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The relationship between unpaid caregiving transitions and health behaviours across the lifecourse

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Declaration

I, Enrico Pfeifer, confirm that the work presented in my thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Acknowledgement of Generative AI Use

I acknowledge the use of the following generative AI tools in the preparation of this academic work. All tools were used in accordance with university guidance and following adequate training received from UCL on the ethical and appropriate use of generative AI in academic settings.

- ChatGPT (version GPT-4, OpenAI, https://chat.openai.com/) was used to rephrase and restructure sentences for clarity and conciseness, check grammar and spelling, and help structure explanatory paragraphs.

- Microsoft Copilot (version GPT-4, Microsoft, https://copilot.microsoft.com/) was used to summarise notes, assist with phrasing and sentence structure, and to generate ideas for overall document structure.

All AI-generated outputs were critically reviewed and adapted for academic integrity and appropriateness. Suggestions were selectively incorporated, with language and content modified to suit the tone and objectives of this thesis. No content was used verbatim without revision.

Abstract

In the UK, demographic and epidemiological shifts have led to an increase in unpaid caregiving. However, the impact of caregiving on caregiver's ability to maintain positive health behaviours remains unclear. This thesis focuses on caregiving transitions and their impact on health behaviours. Four types of transitions were examined: entering caregiving, exiting caregiving, changes in caregiving intensity, and multiple caregiving transitions. Using data from the nationally representative UK Household Longitudinal Study, this thesis employs an interdisciplinary framework that integrates caregiving role theory and health behaviour theories from a lifecourse perspective. Statistical models, including propensity score matching, piecewise growth curve models, and latent class analysis (LCA), are used to model the trajectories of smoking, physical activity, diet and alcohol consumption during caregiving transitions.

The results indicate that caregiving transitions are associated with both positive and negative changes in health behaviours, which are influenced by caregiving intensity and the caregiver's lifecourse stage. Transitioning into caregiving was associated with an increased probability of smoking and a decrease in physical inactivity. Exiting caregiving was linked to an increase in physical activity but was not associated with other health behaviour changes. LCA revealed five distinct classes of caregiving intensity. An increase in caregiving intensity was not associated with changes in health behaviours, while stable high-intensity caregiving was linked to increased physical inactivity, lower fruit and vegetable consumption, higher odds of smoking, and lower odds of problematic drinking.

Regarding multiple transitions, a count variable of the number of transitions and LCA showed conflicting results, but generally, recurrent caregiving was associated with more positive health behaviour changes compared to non-caregiving. These findings highlight the complex relationship between caregiving and health behaviours that is influenced by caregiving intensity and lifecourse stage of the caregiver, suggesting the need for targeted interventions to support caregivers in maintaining healthy behaviours.

Impact Statement

This thesis investigates the relationship between unpaid caregiving and health behaviours across the lifecourse and is based on large-scale UK longitudinal datasets. By focusing on the dynamic nature of caregiving roles, including transitions into and out of caregiving, changes in caregiving intensity, and multiple caregiving transitions, this thesis offers novel insights into how these patterns influence smoking, alcohol consumption, healthy diet and physical inactivity over time. Advanced quantitative methods, including propensity score matching and latent class analysis, were employed to model these associations longitudinally.

Academic impact is evidenced by dissemination of findings at key national and international events, including presentations at the Centre for Care Summer School in Sheffield, the Transforming Care Summer School in Milan, and the 2024 annual conference of the Society for Longitudinal and Lifecourse Studies in Essex. Additionally, the research was recognised through winning the Three Minute Thesis (3MT) competition at the UCL Institute of Epidemiology and Health Care. These activities have fostered interdisciplinary dialogue and positioned this research within global debates on caregiving, health, and inequality.

Non-academic impact has also been central to this research. A blog post was published for Power to Persuade, a social policy platform aimed at lay audiences, extending the reach of the findings beyond academia. Furthermore, the research informed co-produced public engagement workshops with Camden Carers, a London-based organisation supporting unpaid caregivers. These workshops played a crucial role in shaping how findings from this thesis are framed, ensuring they resonate with the language, priorities, and realities of those with lived experience. The discussions helped refine the interpretation of results in a way that is meaningful and accessible to caregivers themselves, strengthening the relevance and authenticity of the research.

In the longer term, this work aims to support a policy environment that both acknowledges the public health implications of unpaid caregiving and promotes the wellbeing of unpaid carers. The findings generated by this thesis are novel in their investigation of caregiving trajectories over time and their associations with health behaviours across the lifecourse. This represents a significant and underexplored area within lifecourse epidemiology and caregiving research. As such, the research offers a strong foundation for peer-reviewed academic publications that can advance theoretical and methodological approaches to understanding unpaid caregiving.

As part of my doctoral journey, I undertook a three-month placement with the Open Innovation Team, a cross-government unit that connects academic expertise with policy development. Although the placement was not directly related to the aims of my PhD, it significantly enriched my understanding of the research–policy interface. Through my contributions to live policy projects with departments such as the Ministry of Housing, Communities and Local Government, and the Department for Energy Security and Net Zero, I developed key skills in evidence synthesis, stakeholder engagement, and communicating research to non-specialist audiences. I also gained insight into how academic research can inform and influence policymaking, and this experience has deepened my appreciation of the broader societal relevance and potential impact of my own research.

Acknowledgements

I would like to dedicate this thesis to my parents, Ute and Gerhard, who have been caregivers for most of their lives. Despite facing many barriers and hardships, they raised my brother and me with unwavering love, always putting our needs before their own to ensure we were safe and supported. They always believed in me, and that belief gave me the confidence to make brave decisions. Without those decisions, this thesis would not have been possible.

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Table of Contents

List of Tables

List of Figures

Abbreviations

Abbreviation	Meaning
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
CV	Coefficient of Variation
FE	Fixed Effect (Models)
FMI	Fraction of Missing Information
IC	Information Criterion
LCA	Latent Class Analysis
MAR	Missing at Random
MCAR	Missingness Completely At Random
NHS	National Health Service
OR	Odds Ratio
RCT	Randomised Controlled Trial
SEP	Socio Economic Position
STROBE	Strengthening Reporting of Observational Studies in Epidemiology
UK	United Kingdom
UKHLS	UK Household Longitudinal Study
VCE	Variance-Covariance Estimator

1 Introduction

Due to ongoing demographic and epidemiological changes, unpaid caregiving has become increasingly common and consequently of growing public health concern. This is because unpaid caregiving represents a central but often under-recognised dimension of social life which shapes the wellbeing, health behaviours, and economic circumstances of millions of caregivers across the lifecourse. This thesis examines how caregiving transitions influence key health behaviours across the lifecourse, with the aim of making novel contributions to existing knowledge, advancing methodological approaches, and informing the wider policy debate. This introductory chapter begins by outlining the researcher's positionality and the overall thesis structure. It then provides background context, presents the theories and conceptual framework underpinning the study, and emphasises the importance of examining caregiving transitions. The chapter concludes by addressing the policy relevance of the research, highlighting its implications for public health and social policy.

1.1 Researcher positionality

As a researcher with lived experience as an unpaid caregiver from a young age, my interest in exploring the relationship between caregiving and health behaviours is both personal and academic. This dual perspective has shaped the development of this research project and may influence my interpretation of findings. While this study draws on secondary quantitative data from a large population-based survey, I recognise that my own positionality may influence the way I frame, prioritise, and interpret certain aspects of the analysis.

Further, my professional background in nursing and population health has further informed my understanding of the structural and social determinants that shape caregivers' experiences across the lifecourse. I am mindful that, despite the statistical objectivity afforded by the use of large-scale survey data, all research is situated within broader contexts, including the researcher's values, assumptions, and experiences. Throughout the research process, I have sought to engage critically with the data and remain aware of my own interpretive lens, particularly when drawing policy-relevant conclusions.

1.2 Thesis structure

This thesis is structured in nine chapters. Chapter 1 provides an overview of the research topic, introducing the concept of unpaid caregiving and its prevalence across the life course. It outlines the significance of studying caregiving transitions and their potential impact on health behaviours from a lifecourse perspective. Chapter 1 also highlights the study's relevance to public health and policy.

Chapter 2 consists of a literature review and this chapter critically reviews existing literature on unpaid caregiving and health behaviours, emphasising gaps in understanding how caregiving transitions affect health behaviours. In Chapter 3, the key research aim is presented alongside the thesis objectives and hypotheses.

Chapter 4 will introduce the data source, the UK Household Longitudinal Study (UKHLS), also known as "Understanding Society". Details on variable definitions and measures are provided, and Directed Acyclic Graphs (DAGs) are used to guide confounder selection. The chapter also outlines ethical approval and funding.

Chapter 5 is the first analytical chapter and investigates the relationship between transitioning into caregiving and changes in health behaviours. The methods in this analysis include fixed-effect models as well as piecewise growth curve models on a propensity score-matched sample. After, Chapter 6 will take a similar methodological approach to examine how exiting caregiving influences changes in health behaviours.

Next, Chapter 7 will explore the changes in caregiving intensity and its association with health behaviours using latent class analysis and multivariate regression. This will be followed by Chapter 8 which will investigate multiple caregiving transitions and their relationship to health behaviours comparing two different methods.

Lastly, Chapter 9 will synthesise findings from the previous analytical chapters and discuss critically how the results from this thesis fit into the wider evidence-base. Strengths and limitations will be discussed in this chapter as well as recommendations for policy and further research will be drawn followed by concluding remarks.

1.3 Background

Long-term trends in population health suggest that improvements in life expectancy have failed to translate into a rise of disability free years of life.[1] As a result, more people require assistance or care to manage their activities of daily life. This care is often provided unpaid and informally by family, friends or neighbours, so-called 'unpaid caregivers'. According to the Department of Health and Social Care, an informal or unpaid caregiver is *"...someone who provides unpaid help to a friend or family member needing support, perhaps due to illness, older age, disability, a mental health condition or an addiction"* (Department of Health and Social Care, 2018, p.4).[2] This support may include assisting with activities of daily living such as bathing, toileting and eating but also instrumental activities of daily living such as managing finances. Throughout this thesis, the term 'caregiver' will refer to those who provide unpaid or informal care to others.

In the UK, around 5.8 million people provided unpaid care in 2021,[3–5] While this overall prevalence of caregiving has remained relatively stable in the UK, descriptive data from UK Household Longitudinal Study (UKHLS) 2010-2020 revealed that around 7% of adults become caregivers each year while around 6% stop being a caregiver which suggests that caregiving is a highly dynamic role.[6] The economic value of unpaid caregiving was estimated to be £162 billion per year in 2021 in England and Wales.[7]

Despite the tremendous benefits of caregiving to our society and economy, unpaid caregiving has emerged as the individuals who provide this care might risk their own health as previous research has suggested an association between caregiving and higher disease risk, psychological stress and mortality.[8,9] Although detrimental effects of caregiving on health are well recognised, previous research has important limitations such as potential residual confounding and reliance on cross-sectional analyses.[10] In contrast, a review of population-based studies found that caregiving was associated with reduced mortality compared to non-caregiving which challenges the belief that caregiving is harmful to one's health.[11,12] Importantly, caregiving is now recognised as a social determinant of health, highlighting its broader relevance beyond individual caregivers to population health and health equity.[13]

Relatively little progress has been made in understanding the mechanisms for the differences in health outcomes between caregivers and non-caregivers despite some evidence that caregiving intensity, relationship between caregiver and care recipient and residential status of the caregiver are influential.[10] In addition, among caregivers, women have generally worse outcomes compared to men which is consistent across studies.[14] These differences are believed to be the result of greater caregiving intensity in women, but further studies are needed to establish whether these gender inequalities are explained by differences in caregiving intensity or whether other mechanisms such as gendered social roles, reduced access to support, and structural factor also contribute to these gender inequalities.[15]

Nonetheless, it must be stressed that outcome measures in most existing studies are based on older populations and limited to the incidence/prevalence of chronic diseases, symptoms or mortality. While ageing with caregiving responsibilities is an important issue that deserves more attention from researchers and policymakers, the focus on the older population has excluded caregivers in youth and earlier adult life from the discourse, resulting in a knowledge gap. Studies often lack a focus on young and young adult carers although a growing evidence-base highlights that caregiving in early adulthood is associated with worsening physical and mental health trajectories.[16–18] Therefore, the lifecourse approach represents an important perspective to address this knowledge gap.

From a lifecourse perspective, caregiving may contribute to differences in health outcomes in later life through cumulative exposures and interconnected pathways that develop over time.[19–21] One key mechanism may be health behaviours. For example, if caregiving influences behaviours such as smoking, alcohol consumption, diet, and physical activity, these changes can accumulate across the years, shaping long-term health trajectories. Given that health behaviours are well-established determinants of chronic disease and mortality,[22,23] understanding how caregiving impacts these behaviours at different life stages is crucial for identifying intervention points to mitigate long-term health risks for caregivers.

1.4 Theories

Scholars have proposed a wide range of theories and conceptual frameworks about caregiving, health behaviours as well as the lifecourse approach. Theories that are relevant in view of caregiving transitions for the conceptual framework are discussed in this section.

1.4.1 Caregiving role theory

A crucial theory to conceptualise caregiving transitions is the role theory of caregiving. Montgomery et al.[24] conceptualised caregiving in five phases (**Figure 1.1**). The first phase represents the onset of caregiving in which the caregiver begins to perform tasks for the care-recipient that are outside of their normative social role (e.g. as a child or partner). However, the caregiver might not be aware that they are acting as a caregiver and might only self-identify as a caregiver in phase two. In phase three, the care needs of the care-recipient exceed the usual boundaries of the established relationship between caregiver and care recipient and caregiving increasingly dominates the relationship between caregiver and care-recipient. In phase four, caregiving may have existed over an extended period until the needs of the care-recipient exceed what the caregiver can provide. In phase five, the caregiver may be relieved of the primary responsibilities of caregiving because the care-recipient moves to a formal care setting. However, other scenarios are possible as well, for example due to the death of the care-recipient or improvement in the care-recipients health conditions. However, it must also be acknowledged that caregiving is a very individual experience and not every caregiver might experience all these stages to the same extent.[24]

Due to the new role as caregiver and with increasing dependency of the care-recipient, a change of identity may occur in which the tasks of the caregiver become inconsistent with the caregiver's standard identity. Hence, the initial relationship between caregiver and recipient is transformed into a care-giving relationship. Theorists have argued that caregiving tasks may not be inherently stressful, but rather that caregiving stress may be caused by caregiving activities that are inconsistent with their standard identity and own view of self and the transitioning between different roles and caregiving phases.[25] Stress may also result from the difficulty of managing existing responsibilities, such as employment or family obligations, alongside the new demands of caregiving, which can lead to role overload.[26] Besides, caregiving takes time, emotional resources and potentially financial resources that must be managed alongside the other family roles.[25] These experiences can result in a loss of self-esteem, as caregivers may struggle to maintain their personal identity while meeting intensive and perhaps prolonged care responsibilities. **Figure 1.1** below depicts the role theory of caregiving

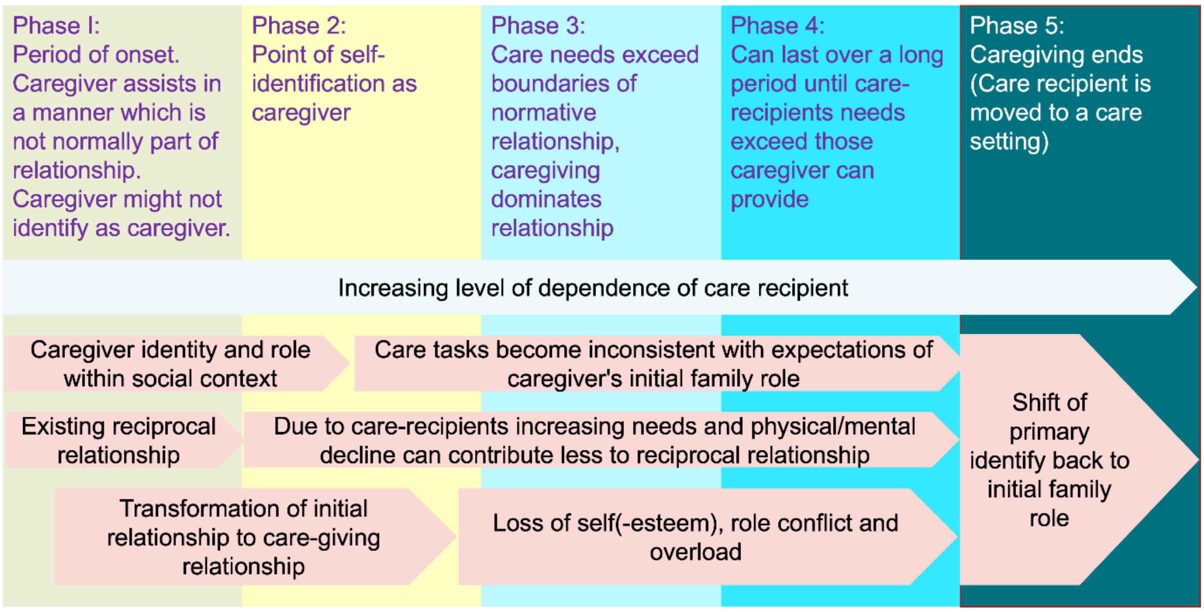


Figure 1.1 Role Theory of caregiving adapted from Bruhn & Rebach, 2014[25]

While caregiving role theory might be useful in conceptualising how individuals adapt to caregiving responsibilities over time, it has several notable limitations. First, it tends to oversimplify the caregiving experience by assuming a linear and uniform progression through predefined phases. In practice, caregiver concerns are dynamic and vary considerably across individuals, with some not experiencing all phases or encountering them in a different order.[27] Second, the theory places a strong emphasis on negative outcomes such as stress and burden, often at the expense of acknowledging positive aspects of caregiving. These may include personal growth, strengthened relationships, and a sense of fulfilment. This narrow focus risks providing an incomplete account of the caregiving experience.[28,29] Finally, the generalised framework may not be sufficiently sensitive to the diversity of caregiving contexts. Factors such as the nature of the care recipient’s condition, cultural background, and family structure can shape caregiving experiences in ways that are not adequately captured by the theory.[30]

There are additions to role theory such as role acceptance theory[31] and role captivity theory.[32] Role acceptance theory is the process of accepting the caregiving role. It is essential for both the caregiver and the care recipient in managing the demands that arise during caregiving. Acceptance is seen as a vital element throughout the caregiving trajectory, influencing caregivers to initiate necessary actions and maintain their motivation to fulfil their role despite challenges.[31] A prior history and experience of caregiving can significantly assist in the acceptance process and influence psychological resilience.[33]

In contrast, role captivity theory describes the feelings of confinement and emotional distress experienced by caregivers.[32] Role captivity is characterised as a psychological state where caregivers feel trapped in their roles, wishing for the freedom to pursue their lives independently.[34,35] Role captivity may also include exiting caregiving but than having to re-enter caregiving due to family expectations or societal norms that demand the continuation of the caregiving role.[32]

1.4.2 Caregiving feminist theories

The provision of unpaid caregiving is deeply gendered. In most societies, women perform the majority of caregiving tasks, both within and outside the household.[36,37] In the UK, women are more likely to provide care, and do so with greater intensity, often over a longer duration and at earlier points in the lifecourse than men.[38,39] Scholars have long argued that this reflects enduring normative expectations rooted in gender roles, which position women as natural caregivers and men as financial providers.[36,40]

While "sex" refers to biological attributes, "gender" reflects the socially constructed roles, behaviours, and identities associated with femininity and masculinity. These constructs shape how individuals experience and take on caregiving roles.[41–43] The conflation of gender with caregiving has significant implications, affecting how caregiving is distributed and how it is valued or devalued, both socially and economically.[44–47]

Feminist theories of care have critiqued the invisibility and devaluation of unpaid care work.[48] Early feminist scholars, including Carol Gilligan and Joan Tronto, argued that care is not merely a private moral obligation but a societal and political concern.[49,50] Tronto proposed a political ethics of care, outlining a framework that positions care as a central human practice that should be shared more equally and recognised within policy and institutional structures.[49,51] Feminist economists such as Nancy Folbre further emphasised the contribution of unpaid care to the economy and the need for state recognition and redistribution of care responsibilities.[52,53]

Further, care feminism critiques the traditional separation between productive (paid) and reproductive (unpaid) labour, emphasising that caregiving, which is often unpaid and performed by women, is essential to the functioning of society rather than peripheral.[54,55] Feminist literature underscores that care work, whether paid or unpaid, plays a central role in sustaining gender subordination and maintaining social and economic systems, thereby challenging the idea that only paid labour is valuable or productive.[56,57]

Empirical research drawing on feminist theory has shown that caregiving can exacerbate gendered health inequalities.[44,46,58] Female caregivers are more likely than men to report stress, depression, and greater physical strain.[14,15,58–60] Given the gendered nature of caregiving and its unequal social and health impacts, it is important to consider sex as a potential effect modifier in the relationship between caregiving and health behaviours across the lifecourse.

1.4.3 Lifecourse theory

Lifecourse theory provides another important lens for studying caregiving. It recognises that caregiving roles and responsibilities unfold over time, intersect with other life transitions, and that repeated or prolonged caregiving episodes can accumulate to influence health across different stages of life. The theory also emphasises the interconnectedness of people's lives, which is of particular importance for caregiving because the lives of caregiver and care recipient are interconnected.[61] The lifecourse approach has distinct roots in both sociology and epidemiology. In sociology, it emerged in the 1970s as a framework for understanding how social roles, transitions, and historical context shape individual trajectories.[61] In epidemiology, lifecourse thinking gained prominence through the Barker hypothesis, which proposed that in utero and early life exposures could have long-term effects on adult health.[62,63] Despite their independent origins, both strands emphasise that the effect of a hazardous exposure on health is not limited to a single point in time but may lead to a disease at the later life stage.

Over the lifecourse, risk and protective factors can accumulate and become embodied, meaning they are physically incorporated into the body through repeated exposures and behaviours.[64] Health behaviours are central to this process, as patterns of smoking, physical activity, diet, and alcohol use can either lessen or intensify the physiological effects of chronic stress and social disadvantage. The gradual embodiment of these social and behavioural experiences contributes to the development of ill health in later life.[65] Thus, risk factors and protective factors can accumulate and manifest in ill health at more advanced stages of one's lifecourse.[61] Caregiving can occur at various time points in one's life and influence the available resources and challenges at a specific life stage.

Also, the lives of the caregiver and care-recipients are linked and based on a pre-existing reciprocal relationship. The dynamic between caregiver and care recipient can be understood through Elder's life course principle of linked lives, which emphasises that individuals' life trajectories are interconnected.[66] In the context of caregiving, the caregiver and care recipient often share a long-standing reciprocal relationship, where changes in one person's circumstances directly affect the other. Becoming a caregiver might lead to changes in the caregiver's employment, education, housing arrangements or social activities. Hence the consequences of caregivers might be viewed as a significant life event that can be conceptualised as triggering cumulative advantages or disadvantages. The impact of caregiving can vary depending on the nature of the caregiver–recipient relationship and where each individual is situated in their life course. These factors shape the level of involvement, the types of needs that arise, the resources available, and ultimately, the consequences experienced by both parties.[25] Besides, societal norms might be influential depending on the lifecourse stage in which the caregiving occurs. For example, providing care during younger life stages may have a greater impact on the caregiver, as it is less socially normative and often coincides with critical transitions into adulthood, such as completing education, establishing employment, and forming intimate relationships.[25]

To illustrate how the lifecourse of caregiver and care recipient are connected, **Figure 1.2** has been developed. It depicts the caregiver's lifecourse in relation to the care-recipients lifecourse and their relationship with one another. This framework contains five main lifecourse stages of a person and their normative priorities at each stage. The first stage represents childhood and child development. The second stage represents youth in which individuals become less dependent on their parents and spend time in education. In young adult life, most individuals' complete education and enter the employment market. In mid-life, individuals continue to grow their careers, and potentially families, and in later life individuals often stop working and retire. Post-retirement, individuals might experience a certain period of good health and relatively few responsibilities, known as the 'Third Age', while the fourth age is characterised by a decline in health.[67]

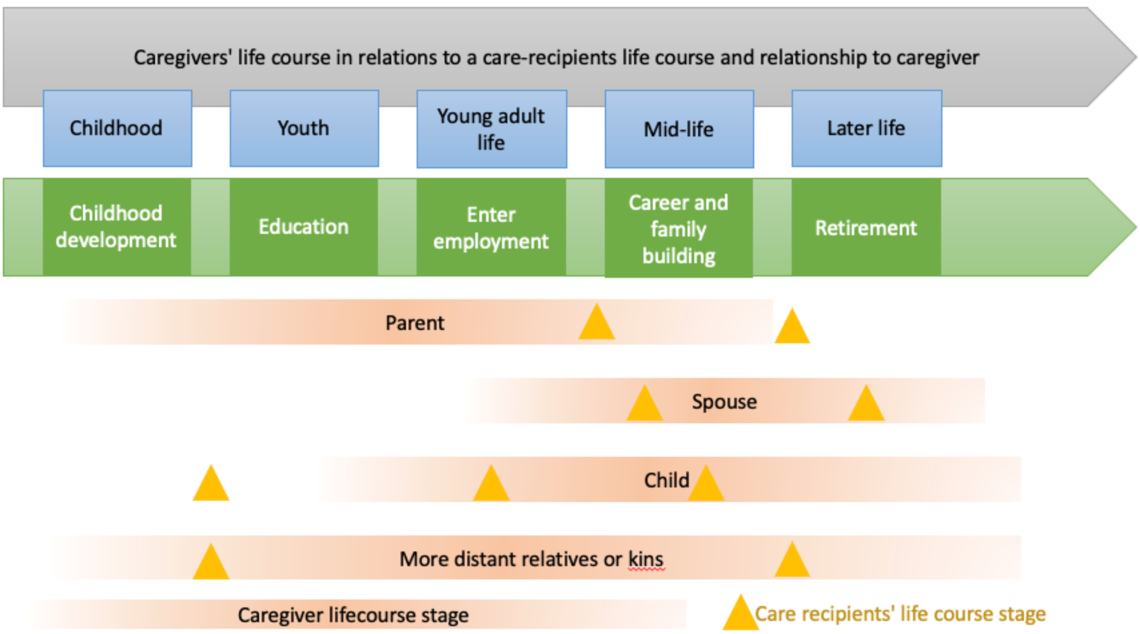


Figure 1.2 Caregivers lifecourse in relation to care-recipient, figure generated by thesis author

1.4.4 Health behaviour theory

Health behaviours refer to actions that individuals take which influence their health outcomes. These include health-promoting behaviours, such as physical activity, balanced nutrition, and preventive screenings. They also include health-risk behaviours, such as smoking, excessive alcohol consumption, or substance misuse which can increase the likelihood of illness or injury.[68] The scholarly literature is rich on health behaviour theories of which many were designed for interventions to improve health behaviours.[69]

The COM-B system represents a comprehensive model that proposes that health behaviours arise from a person's capability, opportunity and motivation to act on it.[70] Physical capabilities include skills, strength and stamina whereas psychological capabilities refer to the knowledge and skills to initiate, maintain or cease certain health behaviour. Opportunities are defined as everything outside of an individual that can either trigger a behaviour or enable action in relation to that behaviour. The theory also distinguishes between physical and social opportunities. Social opportunities are created by the social environment whereas physical opportunities are created by the context in which people are living including time, financial resources and access. The last component of this framework presents motivation which refers to the brain's processes of activating and guiding behaviour including (1) conscious decision-making that manifests in reflective motivation which involves the steps in evaluating and planning a behaviour; and (2) automated motivation which are emotional responses and impulses that are the result of tendencies or associative learning.[69]

1.5 Conceptual framework

Figure 1.3 represents my conceptual framework for the paths between caregiving and health behaviours over the lifecourse. The top green bar represents the caregivers lifecourse and the blue lower bar the lifecourse of the care recipient, both with their individual health status, values and beliefs as well as individual available resources such as educational, social, financial and emotional. Caregiver and recipient exist within policies and legislation at their local and national level. Caregiving evolves as a result of emerging care needs of the care recipient and an existing reciprocal relationship between caregiver and care recipient. Caregiving intensity is a key characteristic of the caregiving experience. It is typically defined by the number of hours spent providing care, the types of tasks performed, and the geographical distance between the caregiver and the care recipient.[17,71,72] Caregiving onset is characterised by role change in which the normative relationship between caregiver and recipient is transformed to a care-giving relationship. The caregiver might appraise this situation as positive or negative or a combination of the two.

The conceptual framework proposes that three main paths might lead to changes in the caregiver's health behaviour. The first is the result of a perceived or subjective burden of caregiving on the caregiver that manifest in stress. This stress can trigger automated emotional responses and result in maladaptive coping strategies such as increased alcohol consumption or smoking. The second path is the result of time demands of caregiving which can be conceptualised as an objective burden. Due to these time demands might have reduced opportunities to enact a certain behaviour such as physical activity or preparing healthy meals. Financial resources of the caregiver might be reduced because of changes of employment status due to caregiving.

However, it must be acknowledged that caregiving might have a positive effect on someone's health behaviour in line with this conceptual framework and its third path. For example, looking after someone who is sick might enhance someone's motivation, skills and knowledge about health, diseases and health behaviour. Besides, caregivers might have closer contact with health professional increasing their access to information and the right resources if they have concerns about their own health. For example, if the care-recipient receives advice or treatment on smoking cessation, this be might a 'teachable moment' for the caregiver and motivate the caregiver to give up smoking as well.[73] The conceptual framework also proposes that the availability of resources, social support, and formal support, including access to formal care and financial assistance, can mitigate both the subjective and objective burden of caregiving.

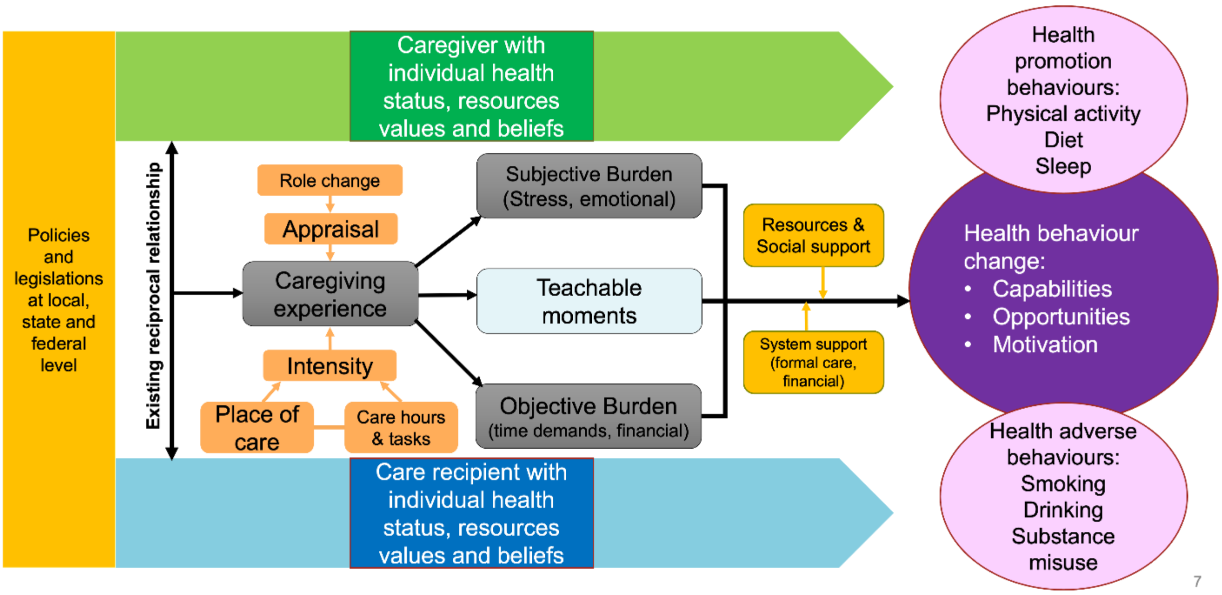


Figure 1.3: Conceptual Framework for the relationship between unpaid caregiving and health behaviour across the lifecourse, figure generated by the thesis author

1.6 Caregiving transitions

By synthesising the aforementioned theories and conceptual framework, it can clearly be seen that caregiving is a dynamic and evolving role, shaped by various types of transitions over time. These transitions include entering into a caregiving role, exiting from caregiving, changes in caregiving intensity, and experiencing multiple caregiving transitions across the lifecourse.

Each transition represents a shift in responsibilities, subjective burdens, and time demands, which may have significant implications for caregivers' health behaviour.

From a lifecourse perspective, transitions are key moments of change that can disrupt existing routines and reshape health behaviours.[20,63,74] According to health behaviour theory, such transitions create windows of vulnerability or opportunity, where individuals may be particularly susceptible to adopting or abandoning health-prompting and health-adverse behaviours.[69,70] By focusing on these transitions, this research aims to identify when and how caregivers' health behaviours change, highlighting in which situations caregiving may be linked to positive health behaviour changes and when it is linked with negative health behaviour changes. A better understanding of these caregiving transitions is essential for developing policies and interventions that recognise caregiving not as a singular experience but rather as a dynamic role with critical turning points that influence health behaviours and ultimately overall health of those who provide unpaid care.

1.7 Policy relevance

Findings from this thesis may have vital implications for public health because unpaid caregiving is a common phenomenon in the UK and will affect most people during their lifecourse, either as caregiver themselves or someone that is cared for. This research has the potential to highlight how caregiving transitions are associated with changes in health behaviour such as physical activity, diet, smoking and alcohol consumption. These behaviour changes may have may have lasting long-term health consequences which makes it essential for public health initiatives to consider unpaid caregiving as a social determinant of health. Findings from this thesis will contribute to a more nuanced understanding of health behaviour trajectories among unpaid caregivers, a population often overlooked in health promotion and disease prevention strategies.

From a policy perspective, this thesis may support the development of more preventative and equitable systems of support for unpaid caregivers. Insights generated through this research could support the development of tailored public health interventions and broader policy measures that enable caregivers to sustain their own health and health behaviours while providing care. This may include financial support, and regulatory or social policy reforms aimed at mitigating the burden of care and promoting healthier behaviours among caregivers. By identifying key periods of vulnerability and change, this thesis seeks to contribute to more equitable, preventative, and carer-inclusive approaches to health and social care policy.

1.8 Chapter conclusion

In summary, this introduction aimed to provide an overview of unpaid caregiving as a societal and public health concern, highlighting its prevalence and significance as well as implications for caregiver's health and wellbeing. While much research has focused on the mental and physical health outcomes of caregiving, particularly in later life, less is known about the behavioural pathways through which these outcomes may emerge throughout the lifecourse. By drawing on caregiving role theory, feminist theory, life course theory, and health behaviour theory, an interdisciplinary conceptual framework was developed that integrates these theoretical viewpoints and offers a novel approach to understanding how caregiving can influence health behaviours over time. The next chapter will provide an overview of the existing literature on caregiving and health behaviours.

2 Literature review

2.1 Introduction

A scoping review was initiated to gain an understanding of what is known about the relationship between health behaviours and unpaid caregiving. A scoping review was seen as more suitable than a systematic review to map the breadth and extent of the research on the topic of interest[75] which spans over multiple disciplines such as public health, psychology, gerontology, nursing and epidemiology. Besides, a scoping review would enable the synthesis of literature of 'caregiving' and 'health behaviours' which are broad and complex constructs.

To enable a consistent and structured approach, this scoping review followed the framework by the Joanna Briggs Institute[75] and is a refined version of the scoping review framework that was initially developed by Arksey and O'Malley.[76] To align with these best practice guide, the following steps were followed:

Identifying the research question

This step involved defining the research questions, aims, and objectives of the review to ensure clarity and focus.

Identifying relevant studies

A structured search strategy was developed to identify relevant literature. This search strategy involved an initial exploratory search to identify keywords followed by a comprehensive search across selected databases included searching electronic databases and screening reference lists. The search terms and inclusion criteria were developed iteratively to capture studies related to unpaid caregiving and individual health behaviours, such as physical activity, diet, smoking and alcohol consumption, as well as studies that used composite measures of overall health behaviours.

Study selection

Titles and abstracts were screened, followed by full-text reviews using predefined inclusion and exclusion criteria. Screening and selection were conducted by a single reviewer, acknowledging that a second reviewer may have enhanced rigour, reliability and credibility of the review. The selection process was documented using a PRISMA flow diagram.

Data charting

Data from the selected studies were systematically extracted and organised. This stage involved the development of data extraction forms, the creation of flowcharts to illustrate the study selection process, and the synthesis of key study characteristics. A quality assessment of the included studies was performed to provide context about the strengths and limitations of the available evidence.

Collating, summarising, and reporting results

The findings from the included studies were analysed and synthesised in relation to the research aims and objectives. This step provided a structured overview of the available evidence, highlighting key themes, research gaps, and implications for future studies.

2.2 Aims of the review

The aim of this literature review was to determine what is known and unknown about the quantifiable relationship between (unpaid) caregiving and health behaviour outcomes. Objectives include:

1. To review what theoretical frameworks were used to investigate the relationship between caregiving and health behaviour.
2. To gain a better understanding of what methods, data and study designs were used in the analysis of quantitative data for the relationship between caregivers and health behaviours. This includes the measurement of outcome (health behaviour) and exposure (caregiving), what statistical tests were used and how third variables were accounted for, the representativeness of the study samples, and the types of comparison groups used.
3. To assess if there is a positive or negative direction of association, or no association, between caregiving and the different health behaviours.
4. To assess the quality of existing quantitative evidence and identify limitations and gaps in what is known about the relationship between caregiving and health behaviour.

2.3 Review methods

Search strategy

The search was conducted on the Cumulative Index to Nursing and Allied Health Literature (CINAHL), Medline, Embase, PsycInfo, Web of Science and Scopus. The search terms for caregiving were combined with the search terms for health behaviours (see Appendix 2.1 for details). To reflect different spelling and to allow words to be in various orders, proximations and truncations were used throughout the search. Medical Subject Headings (MeSH) terms or subject headings were included when they were available for each search term. An additional search of grey literature in OpenGrey was omitted because some of the data bases include grey literature (CINAHL, Embase, PsychINFO). Lastly, reference lists of relevant studies were screened to identify additional literature. The search strategy was developed with the support and review by a subject librarian from University College London.

Inclusion and exclusion criteria

Quantitative studies were included if they were published in English or German between 2002 and March 2025; if caregiving or an aspect of caregiving were a predictor and if health behaviour including physical activity, diet, smoking, alcohol consumption or sleep or a summary measure of health behaviour was an outcome. There were no restrictions in view of age groups, care-recipient characteristics or the residential status of the caregiver. Studies were excluded if they were published before 2002; if they investigated paid caregiving or childcare of healthy children; if they were qualitative or if they focused on biomarkers (for example if they used Body-Mass-Index as an indicator for diet or physical activity).

Quality assessment Critical appraisal of studies

To allow a systematic analysis of the quality and risk of bias, the Specialist Unit for Review Evidence (SURE) checklist was used for each study[77] (see Appendix 2.3). Although this tool has not been externally validated, it was developed in line with recommendations from the Cochrane Collaboration which considers the risk of bias as crucial to the assessment of validity in studies.[78] Besides, the SURE checklists have been devised with reference to the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology, Appendix 4.2) checklist.[79] The appropriate tools for this review were the SURE checklist for cross-sectional studies and the SURE checklist for cohort studies.[77] If a study received a ‘no’ response on any checklist item, it was marked with a red flag, indicating a potential risk of bias in that domain.

In addition to the SURE checklist, further criteria were considered to strengthen the quality assessment. These included the representativeness of the study sample, the presence of a non-caregiving control group, and sample size classification. Sample sizes were categorised as small (fewer than 1,000 sampling units), medium (between 1,000 and 9,999 sampling units), or large (10,000 or more sampling units).

Based on these quality assessment criteria, studies were classified into three levels of risk of bias. A study was judged to have a low risk of bias if it was longitudinal, representative, included a control group, had at least a medium sample size, adequately accounted for confounding or effect modification, and showed no red flags from the SURE checklist. A red flag was defined as any instance where a question from the SURE checklist was answered with "no", for example when the study lacked a clearly stated research question, did not select study participants using transparent or appropriate sampling techniques such as random or probability sampling or failed to use validated measures. Studies were categorised as having some risk of bias if they met more than half but not all of these criteria or if they met all of the criteria but were cross-sectional studies. Finally, studies were considered to have a high risk of bias if more than half of the quality criteria were not met, for example, studies with non-representative samples, an absence of a control group, and insufficient adjustment for confounding.

It is acknowledged that this assessment was conducted by a single reviewer, which may introduce an element of subjectivity. However, the criteria were systematically applied across all studies to enhance transparency, consistency, and reliability in evaluating study quality and risk of bias.

Synthesis of findings

To synthesise the findings from the included studies, a narrative synthesis was performed. The main feature of this approach is that it primarily relies on words to summarise and describe the results of multiple studies or sources.[80] As this serves as a fairly broad definition, narrative reviews have been criticised in the literature for lacking transparency and requiring more sufficient description of how the data and the narrative summary are related.[81] For the purpose of this review, a broad overview of all included studies will be given, organised by study design, health behaviour outcomes and populations studied. Then, findings of studies for each health behaviour will be synthesised by assessing the relationship between the main findings, measurement of outcomes and caregiving as well as the quality of the study and the risk of bias.

2.4 Study selection

For this scoping review, two systematic searches were conducted. The initial search (**Figure 2.1**) was carried out in September 2022 and included studies published from 2002 up to that date. In total 9450 records were identified through databases and 5,993 records were removed because they were duplicates, leaving 3457 records that were title and abstract screened using Rayyan.[82] This resulted in 242 records which were full-text screened. In total, 56 records met the inclusion criteria, and an additional 27 records were retrieved after screening of reference list of included articles. Hence, 83 studies were included in this review.

The initial search strategy incorporated terms related to physical activity, diet, alcohol consumption, smoking, overall health behaviours, and sleep. However, the initial review highlighted substantial gaps in the literature regarding physical activity, diet, alcohol consumption, and smoking, whereas research on sleep was more consistent, with fewer identified gaps. Given the availability of a more comprehensive evidence base on sleep in caregivers, it was decided that sleep would not be a primary focus of this thesis. As a result, 29 studies focusing exclusively on sleep were removed from this review, leaving 54 studies that examined physical activity, diet, alcohol consumption, smoking, and overall health behaviours. The literature review for sleep can be found in Appendix 2.2.

To ensure the inclusion of the most recent research, an updated literature search was conducted in March 2025 (**Figure 2.2**) using the same search strategy as the initial search. This updated search identified an additional 16 relevant studies, bringing the total number of studies synthesised in this scoping review to 70.

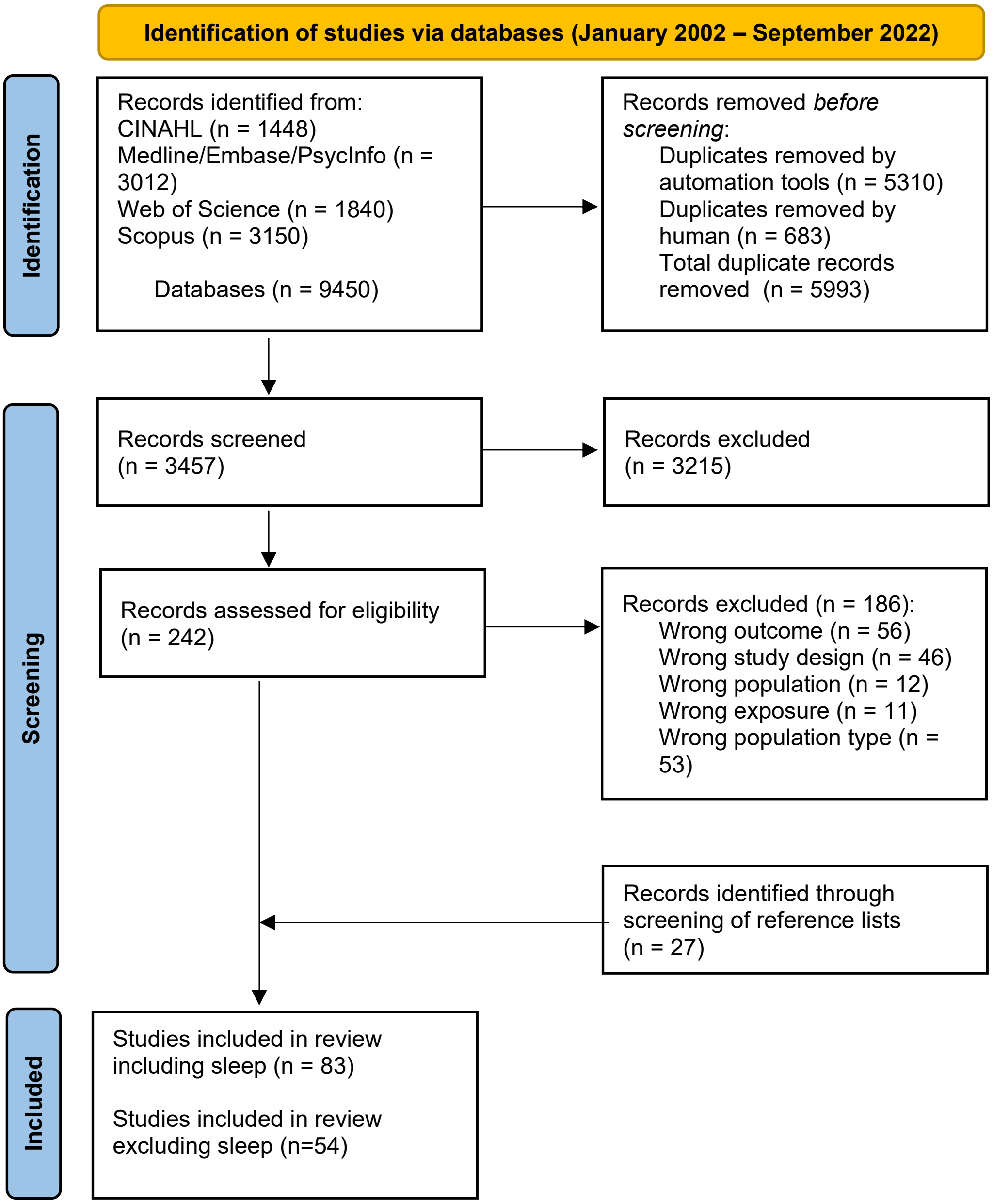
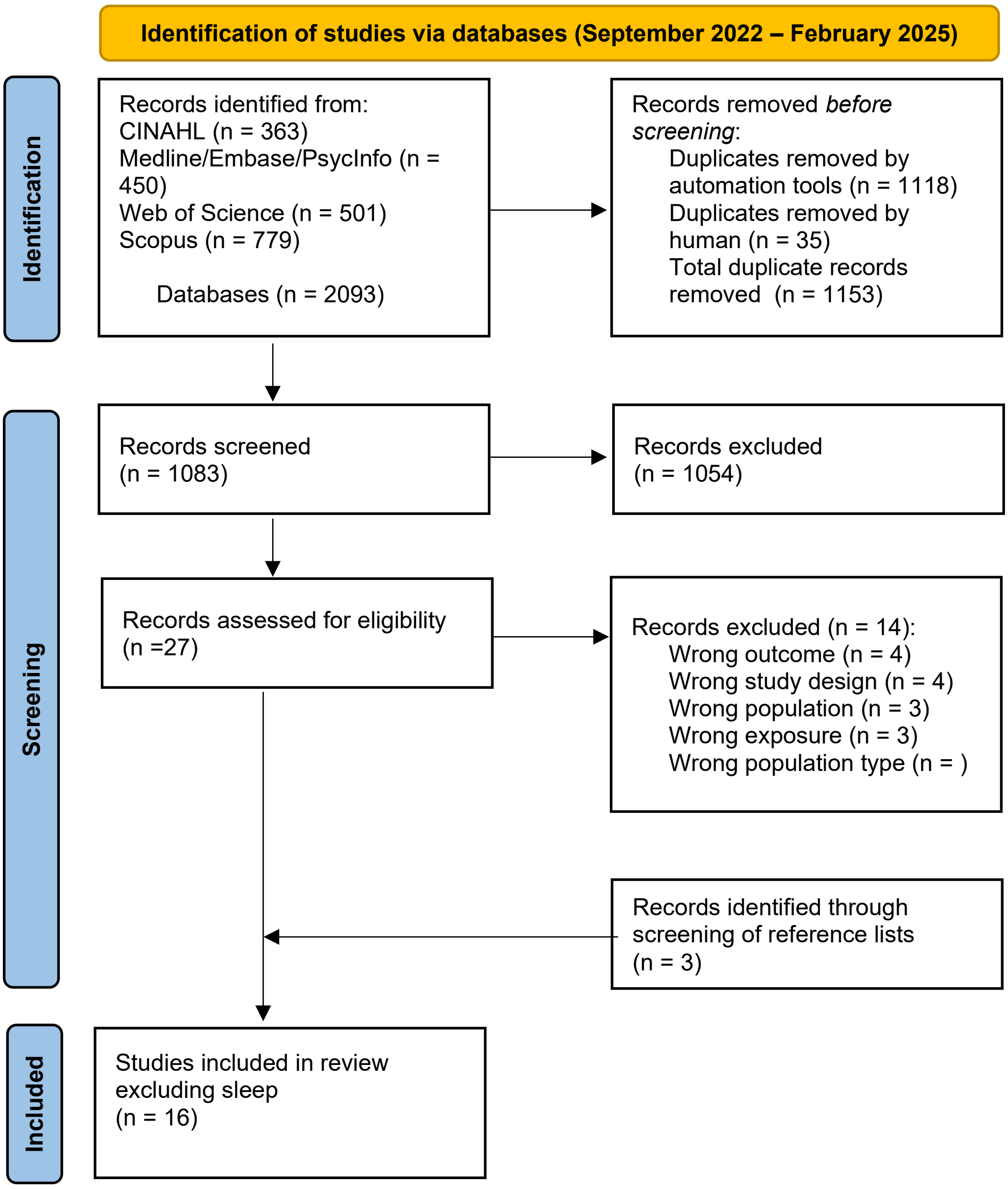


Figure 2.1 PRISMA flow chart for the initial literature search (2002 to September 2022) on unpaid caregiving and health behaviours. The chart illustrates the process of identification, screening, eligibility assessment, and inclusion of studies based on predefine



Adapted from Page et al, 2021 [83]

Figure 2.2 PRISMA flow chart for the updated literature search (September 2022 to February 2025) on unpaid caregiving and health behaviours. The chart shows the updated process of study identification, screening, eligibility assessment, and inclusion based on the

2.5 Summary of studies

This section aims to provide a detailed overview of the studies included in this literature review. It begins with a high-level summary of the key characteristics of the studies, followed by an overview of the theoretical frameworks they employed, what populations were studied, as well as how caregiving was measured. The section then presents a structured synthesis for each health behaviour outcome. For each outcome, the relevant measures are described, and the findings are discussed in relation to the study designs.

2.5.1 Overview of included studies

Out of the 70 included studies in this review, 5 were literature reviews and 65 were primary studies which included 8 longitudinal studies as well as 57 cross-sectional studies (Appendix 2.6). Because some of the 65 primary studies investigated more than one health behaviour, a total of 136 caregiving-health behaviour associations were studied. The majority of the 65 primary studies had a low sample size; were appraised to have a high risk of bias and were not representative of the wider population. Only around half of the included studies had a non-caregiving control group and adjusted for potential confounders such as sex, age and socioeconomic position. In contrast, only twelve studies had a sample of 10.000 participants or more and were classified by the reviewer to have a low risk of bias after completion of the SURE checklist.

2.5.2 Populations studied

Around one third of primary studies (n=21) were based on the general population on either regional,[84–91] national[92–94,94–102] or international[103–106] levels with or without probability samples while the remaining studies focused on sub-populations such as dementia caregivers or cancer-caregivers. Over half of the included studies (58%) used a sample from North America (n=38) and the remaining studies used samples from Europe (n=12), Asia (n=8), Australia (n=4) and multinational samples (n=3). Generally, there was a lack of studies with a sample from the UK as only one international study with a small sample included some data from UK caregivers[103] and one systematic review on physical activity and caregiving with only three studies that were less recent or qualitative.[107]

In total, seven studies (n=7) were restricted to spousal caregivers,[108–114] 17 studies (n=17) were on caregivers above the age of 50,[91,101,102,104,109,110,112–122] and seven (n=7) were all female samples.[108,109,112,117,118,123,124] Researchers justified this with a higher prevalence of caregiving in females compared to males in their respective countries. Ten studies with a larger sample stratified by age and/or sex or adjusted for it.[84,92–94,96,99–101,104,105] There were only two cross-sectional studies that investigated the health behaviour of caregivers in youth or young adult populations,[84,97] both of which were from the USA.

2.5.3 Theories & concepts

Only 19 out of the 70 reviewed studies used theories for their hypothesis and the remaining studies justified their research questions with reference to previous literature. Most studies focused on one specific theory that was either related to caregiving theory,[100,104,116,124–126] health behaviour theory,[127–133] life course theory,[102] stress and coping theories,[123–125,128,134] or other theories.[84,114,135] Three studies used more than one theory.[124,125,128] An overview of these theories can be found in Appendix 2.4.

2.5.4 Measurement of caregiving

Studies varied in their way to measure caregiving and the measures can be summarised broadly into four categories: (1) Single-item measure of caregiver status in which participants were asked a single question that would reveal their caregiver status; (2) Measures that can be considered as 'objective characteristics' of the caregiving experience such as hours spent caring, care tasks performed, relationship to care recipient, duration of caregiving and whether the caregiver resided with care-recipient or not; (3) validated tools that measure how the caregiving experience is perceived by the caregiver which is often labelled as 'subjective burden or strain'; and (4) care-recipient characteristics as a proxy for caregiving stress as it has been conceptualized that, for example, more severe dementia symptoms would lead to higher stress levels for the caregiver.

Smaller studies and studies with defined sub-populations tended to utilise scales as a measure of caregiving and usually had no non-caregiving control group. The most frequent scale used was the Zarit Burden Interview[136–139] which was used by six studies[108,119,140–143] and the caregiver strain index[144] which was used by two studies.[145–147] Further, seven studies used alternative instruments to measure the quality aspects of caregiving such as the cost of care index,[148] Portuguese version of the caregiving burden assessment questionnaire,[149] caregiving burden scale,[125] caregiving self-efficacy instruments[124,132] and caregiving reaction assessment.[131] In contrast, studies with larger population-based sample tended to use more objective characteristics of the caregiving experience such as self-reported caregiving status, residential status with care-recipient, hours spent caring, tasks performed and duration of caregiving.[84–97,99–105,114]

2.5.5 Physical Activity (PA)

Physical activity was the most frequently studied outcome, and 53 included studies investigated physical activity, of which 43 were cross-sectional studies, seven were longitudinal studies, and three were reviews.

There was large variation in how PA was measured across studies including subjective and objective measures. Most studies used subjective measures based on self-report such as the short version International Physical Activity Questionnaire (IPAQ)[150] in which participants were categorised as physically active if they spend at least 150 min per week with moderate to vigorous physical activity.[85,90,92,95,96,100,105,115,117,123,140,146,151–153] Other studies[93,103,109,116,121,127,129,133,149,154,155] used other self-reported scales or alternative questionnaires, for example the Godin Leisure time exercise Questionnaire (GLTEQ)[156] or items from the Health Promoting Lifestyle Profile (HPLP-II).[157] Around one fourth of studies used self-reported PA with definitions that deviated from the IPAQ definition on PA.[84,94,99,101,102,104,112,114,118,128,141,158,159] Fewer studies used self-reported sedentary behaviour as measure of physical activity[86,160] and four studies used objective measures of PA[108,113,121,147] or sedentary behaviour[91] usually measured via accelerometer either placed on wrist, ankle or around the waist.

Reviews

The first review was published in 2013 and included only cross-sectional studies without non-caregiving controls of cancer caregivers. They found that results were inconclusive and that further studies are required.[130] Another review, published in 2021 focused on caregivers in the UK to investigate PA levels as well as facilitators and barriers for PA. They included only three studies, two of which were qualitative and one quantitative. None of these studies reported PA levels in UK caregivers but their synthesis suggests that increased ageing, the routine around the care recipient and lack of time were the main barriers to partaking in PA whereas previous participation in PA, appreciation for the benefits of PA and group activities with similar people are facilitators for PA in caregivers.[107]

An international systematic review of the prevalence of PA levels in caregivers by Linday and colleagues[161] included 77 observational studies and 20 interventional studies. The 20 interventional studies were limited to small sample sizes and included predominantly older female, dementia caregivers. The quality assessment of the authors indicated that 10 interventional studies were classified as low quality, and 10 studies classified as medium quality whereas no interventional study was classified as high quality. Despite the methodological limitations of the included studies, the authors suggested that PA interventions could potentially increase PA levels among caregivers. With regards to evidence from observational studies, of the 77 observational studies, one was qualitative and 76 were quantitative. Out of the 76 quantitative studies, only five employed a longitudinal design and just one of these longitudinal studies included a non-caregiving control group, comparing spousal dementia caregivers with spousal non-caregivers. However, the total sample size in this study was fewer than 250 participants. The quality assessment of the authors indicated that only three of the observational studies were of high quality, 45 medium quality and 28 low quality. All studies classified as high quality were cross-sectional in design and included control groups; however, none of them employed a longitudinal approach. The synthesis from the observational studies revealed that results were overall inconsistent which might be due to different outcome measures used and that not all studies distinguished between leisure time PA, exercise PA and occupational PA from caregiving.[161]

Longitudinal studies

In total, there were six studies that investigated physical activity in caregivers longitudinally, three of which were based on small samples between 53 and 484 participants and certain caregiving sub-groups[110,135,162] while three studies were based on larger population-based samples.[101,104,114] For example, Roddy and colleagues[162] conducted a very small study with 22 caregivers of early-stage lung cancer patients following surgery and found that PA was reduced at 3-months follow up in caregivers but reached baseline levels at 6 months follow up.[162] Another study with 484 caregivers-recipient dyads amongst advanced cancer patients found evidence of an actor effect, whereby caregivers' own physical activity levels at baseline significantly predicted higher levels of PA at 3 months and 6 months follow up. Further, higher perceived social support predicted greater engagement in physical activity over time. Specifically, social support at three months mediated the effect of earlier social support on later exercise, suggesting that consistent perception of support may help sustaining caregivers' engagement in physical activity.[135]

The third small-scale longitudinal study had a non-caregiving control group and was based on 122 caregiving spouses of dementia patients and 117 non-caregiving spouses of care-recipients with dementia.[110] The study estimated longitudinal mediation models and consisted of three repeated measurements over a period of two years. The PA score was calculated based on the self-reported activity, effort and time spent. The caregiving measure included the hours of care provided and a screening of caregiving burden based on 25 caregiving activities or experiences. They found that caregivers had more pronounced improvements of PA over time compared to non-caregivers which was mediated by the hours of care. However, this sample consisted predominantly of older, white, female participants with relatively high income. Besides, the average time caring at baseline was 44 months and participants might have already adjusted to the caregiving role at recruitment of this study.

Further, three longitudinal population-based studies were identified during the search, all of which were studies of ageing and had participants from mid-adulthood (50+) or late adulthood (65+). The samples were from the Health and Retirement Study (HRS) based in the USA[114] with 9,173 participants; the Survey of Health, Ageing and Retirement in Europe (SHARE) from 17 European countries (excluding the UK) with 57,962 participants;[104] and the Longitudinal Survey of Middle-aged and Older adults in Japan with 30,530 participants.[101]

All three studies measured physical activity and caregiving in a slightly different way. The European study distinguished between co-residential and out-of-home-caregiving and used questions about the frequency of moderate to vigorous physical activity. They classified participants as 'lacking physical activity' if they reported engaging in neither moderate nor vigorous physical activity more than once per week, and did not report engaging in both types at least once per week.[104] In contrast, the US study focused on spousal caregiving involving assistance with the daily activities of living. They measured the frequency and intensity of moderate and vigorous physical activity and created an indicator variable when moderate or vigorous PA was initiated between waves.[114] In the Japanese study, participants were classified as physically active if they engaged in moderately energetic or highly energetic exercise at least once a month.[101]

In view of statistical analysis and results, the European study used fixed effect logistic regression and found that providing out-of-home care was associated with a decline in the odds of lacking physical activity while there was no difference when co-residential caregiving was provided.[104] Likewise, the US study utilised individual fixed-effect models and a two-stage least squares instrumental variable approach to strengthen causal inference, using spousal falls as the instrument to predict the probability of providing unpaid care. They found that spousal caregiving was linked to an increased probability of initiating moderate or vigorous probability.[114]The researchers found that becoming a caregiver was associated with an increased probability of reporting a lack of exercise.[101] In contrast, the Japanese study used multivariable logistic regression with correlated random effects to account for observed time-varying and unobserved time-invariant confounding. The researchers found that becoming a caregiver was associated with an increased probability of reporting a lack of exercise.[101]

All of these three studies are fairly strong in view of sample size and measures. However, the methodological difference in each of these studies and the different definitions might explain some of the variation in the reported results. Moreover, it must also be acknowledged that it is possible that cultural differences can significantly differ between Europe, Japan and the USA.[101] Further, the difference in the healthcare system and access to formal care support services may influence the demands on unpaid caregivers and their ability to engage in physical activity.[104] One limitation that these studies have in common is that the focus is on caregiving in later adulthood and that it remains unclear how caregiving may affect health behaviours of caregiving in early adulthood or early mid-adulthood.

Cross-sectional studies with control group

Cross-sectional studies with larger samples and control groups also reported contradictory findings. Results from four studies reported that caregivers were less likely to be physically inactive compared to non-caregivers,[94,96,100,105] and that greater caregiving intensity was associated with even lower odds of inactivity.[105] These findings were observed across different subgroups, including female caregivers providing fewer than 20 hours of care per week[94] and white caregivers, but not among non-white caregivers.[100]

A large representative population-based US study by Kilmer and colleagues [99] with 445,703 individuals compared two independent cross-sectional samples in 2015/16 and 2021/22 in view of the health behaviours of caregivers and non-caregivers. They considered participants as physically inactive if no leisure time physical activity was reported in the last 30 days. The study found a lower prevalence of physical inactivity in the 2021/22 sample compared to 2015/16 for both caregivers and non-caregivers. However, as this analysis is based on two cross-sectional samples at different time points, it does not allow conclusions about individual-level change over time.[99]

In contrast, seven studies did not find a statistically significant difference in PA between caregivers and non-caregivers[84–86,91,95,111,121] while nine studies found that caregivers were at higher odds of being physically inactive compared to non-caregivers.[90,92,93,102,115,117,118,141,158]

These inconsistencies in findings could be explained by the measures used. Most studies relied on self-report and asked participants how often and how long they engaged in moderate or vigorous activity. It may well be that respondents considered certain caregiving tasks to be moderate or vigorous activities. Hence, studies should distinguish between PA from caregiving and other, beneficial forms of PA such as sports or exercise. This is often referred to as the physical activity paradox, which highlights that occupational physical activity, often involving prolonged standing, repetitive tasks, heavy lifting, and insufficient recovery time, may have adverse effects on health.[163,164] This contrasts with the well-documented benefits of leisure-time physical activity, which is typically voluntary, dynamic, and performed at moderate-to-vigorous intensity with adequate rest.[163,165,166]

Cross-sectional studies without control group

Out of the 43 cross-sectional studies, 22 were small-to-medium-scale studies based on specific sub-populations or care recipients without non-caregiving controls. Findings from these studies were inconsistent as some reported that a higher caregiving burden was associated with less physical activity,[119,142,149] whereas another study claimed that more self-reported caregiving burden was associated with more PA in caregivers.[108] It was also reported that the caregiver decreased physical activity since becoming a caregiver[129] while in a study by Beesley and colleagues,14% of caregivers self-reported an increased their PA levels after a caregiver.[152]

There was large variation between reported levels of physical activity. Two US studies found that around half of caregivers would meet national physical activity recommendations,[123,159] while an international study with 384 caregivers from five English-speaking high-income countries found that 99% of caregivers did not meet the Australian recommendation for physical activity.[103] However, the study did not specify how comparable these national guidelines are across countries, which limits the interpretation of cross-country difference in adherence to physical activity guidelines. Other studies explored variables associated with PA levels in caregivers and found that upsetting recipient behaviour or financial strain were associated with lower PA in caregivers[146] or that the lack of willpower and time were the main barriers to PA in caregivers.[113]

In addition, two studies found that higher physical activity in caregivers was associated with a lower levels in quality of life.[140,147] However, given the cross-sectional nature of these studies, it is unclear whether physical activity contributed to reduced quality of life or whether caregivers who experienced poorer quality of life were less able to engage in physical activity. Further, all the above studies had a very low sample size and may be biased because to the lack of a non-caregiving control group such and a more meaningful comparison could be made in larger, longitudinal studies with control groups.

Summary

In conclusion, the existing evidence remains inconsistent and is heavily based on cross-sectional studies or longitudinal studies of caregiving in advanced lifecourse stages. The longitudinal studies from Japan, USA and Europe focused on the transition into caregiving but did not explore other caregiving transitions and none of the studies looked at caregiving in younger age groups or used a sample from the UK. The relationship between transitions of unpaid caregiving and physical activity across the lifecourse in the UK remains a gap in knowledge and further longitudinal studies with large diverse samples are needed to enhance our understanding of the relationship between unpaid caregiving and physical activity.

2.5.6 Healthy diet

In total, 26 studies reported results concerning diet or eating habits, of which 20 were cross-sectional, four were longitudinal and two were reviews. All of these used self-reported measures of diet and 10 studies measured fruit and vegetable intake as indicator for a healthy diet albeit cut-offs and definitions varied.[85,93,94,100,103,104,122,142,152,158] Most studies, however, used different scales or self-reported eating indexes that measured various aspects of diet including calorie intake, saturated fat intake, soda and fast-food intake.[84,86,109,126,127,129,135,141,145,146] In four studies food diaries were reviewed and coded by a nutritionist.[88,110,120,122] Two studies measured food insecurity or poverty.[87,122]

Reviews

There were two reviews that both focused on diet in cancer givers. The first was published by Ross and colleagues in 2013[130] and comprised of eight cross-sectional studies of caregivers without control groups. They found that studies reported conflicting results and stated that this could be due to the lack of uniformity and definitions of healthy eating across different studies. They recommend conducting large-scale longitudinal studies to determine if and to what extent caregiving might be detrimental or beneficial for a caregiver's diet.[130]

More than 10 years after this review, another review was published in 2025 by Ayre and colleagues.[167] It included 22 studies and focused also on cancer caregivers. The sample size of the included studies for review ranged from 21 to 672 of which 68% were from the USA, 77% were cross-sectional studies and 68% of studies were conducted on spousal cancer caregivers. They found that there was a great variation in how dietary intake and quality were measured and that 32% of studies reported negative changes in diet while 23% of studies reported positive changes, 18% reported no changes and 9% of studies did not specify the direction of change. The researchers concluded that the available evidence remains inconclusive and recommended longitudinal studies with validated measures and repeated observations be conducted.[167]

Longitudinal studies

Four studies used a longitudinal approach to investigate diet in caregivers. The first was a US-based study by Ellis and colleagues[135] with 484 dyads of patients with advanced cancer and their caregivers without non-caregiving controls. The study was a secondary exploratory analysis from an interventional study and included baseline data and data from the three-month and six-month follow-up using a longitudinal structural equation model. They found that there was overall no association between the diet of the caregiver and the recipient at any time point. However, there was evidence for an "actor effect" meaning that an individual's previous health behaviour was a strong predictor of their health behaviour in the future.[135] This study lacked a non-caregiving control-group and is specific to caregiving of people with advanced cancer. The baseline observations were taken after the cancer diagnosis, and we cannot make any inference about a caregiver's diet prior to becoming a caregiver.

The second longitudinal study was conducted by Snyder and Vitaliano[110] and included 122 spousal dementia caregivers and 117 spousal non-caregiving matched controls over a period of two years using longitudinal mediation models. They found that caregiving predicted less than recommended micronutrient intake (vitamins and minerals) but that this association was not mediated by hours of care or psychological distress.[110] However, it must be noted that the average time of being a caregiver was 44 months and caregivers in this sample might have already adapted to their role by the time they were recruited to this study. Besides, the sample comprises mainly older females with higher income, and results cannot be generalised to the general population due to the non-representative nature of this study.

The third study was published by Hossain and colleagues[88] and analysed 1674 participants longitudinally using a socioeconomically diverse sample with African-American and White participants of working age. They stratified their analysis by ethnicity/race and were interested in the differences between unpaid elderly care and care of grandchildren over time in two waves. They found that elderly care was associated with a faster decline in diet quality in Whites but not in African Americans.[88] However, it must be acknowledged that this study was limited to two waves with a mean follow-up time of 4.1 years between waves. Besides, this study used a broad measure of caregiving and distinguished only between (1) daily or weekly caregiving; (2) monthly or yearly caregiving; or (3) no caregiving at all. It is possible that that combining daily and weekly caregiving into one category makes it more difficult to detect associations between more intensive caregiving and diet.

The fourth and only study that used a population-based longitudinal sample was published by Hiyoshi[104] using a sample of 57,962 from the European Survey of Health, Ageing and Retirement in Europe (SHARE) which excluded data from the UK for this study. They measured diet with a question on daily fruit and vegetable consumption and classified participants on whether they had daily fruit and vegetable consumption or not. They compared non-caregiving with out-of-home caregiving and co-residential caregiving separately and used fixed-effect models to estimate a change within individuals. They found that co-residential caregiving was associated with higher odds of non-daily fruit and vegetable consumption in males but did not find an association in female caregivers or out-of-home caregiving. However, a limitation of this study was that it only included participants aged 50 or older and findings cannot be generalised to younger caregiving populations.

Cross-sectional with control group

Seven studies were larger, population-based cross-sectional studies with a control group.[84–87,93,94,100] Two studies found that caregiving was associated with lower fruit and vegetable intake compared to non-caregiving[85,94] while Hoffman and colleagues[86] found that caregivers consume more soda and fast food compared to non-caregivers. In contrast, one study with females above the age of 41 did not find an association between caregiving and fruit and vegetable intake[100] while Fuchs and colleagues[93] found that low intensity caregiving was associated with higher odds of daily fruit and vegetable consumption. One US study with a representative regional sample found that caregivers were at greater odds of experiencing hunger and food insecurity independent of household income.[87]

A representative health behaviour survey of 10,880 youth between the ages 10 and 18 showed that age moderated the relationship between caregiving and an unbalanced diet: caregiving was only associated with an unbalanced diet in youth caregivers between the age 14 and 18, but there was no significant association for caregiving youth below the age of fourteen.[84] However, this study conducted linear regression using categorical outcomes which is not an appropriate method to analyse categorical data. This raises serious concerns about the validity of the results from this study.

Cross-sectional without control group

Thirteen of the included primary studies were cross-sectional without a control group and that had a small sample size[103,109,120,122,126,127,129,142,145,146,152,158,168] and reported that caregivers fail to meet guidelines in view of fruit and vegetable consumption,[103,120,122,152,158] or that nutrition is one of the least practised health behaviours in caregivers.[109]

Summary

In summary, although there seems to be a trend that suggests caregiving is associated with a less favourable diet, the available evidence is mainly limited to cross-sectional with a high risk of bias and a few longitudinal studies from the USA that were also limited in view of their sample and methods. The only population-based longitudinal study was based on participants in mid-and late adulthood and did not include participants from the UK although it used a European sample. Hence, longitudinal studies are required that include caregiving in earlier lifecourse stages and also consider different caregiving transitions.

2.5.7 Alcohol consumption

Out of the 70 included studies, alcohol consumption was investigated in 24 studies of which 19 were cross-sectional, three were longitudinal, one was a scoping literature review, and one was a literature review. Most studies asked participants to self-report their drinking habits and to quantify the number of drinks or occasions and/or number of alcohol drinks per occasion.[89,93–97,99–101,103,104,111,141,142,152,158] However, there were variations in the utilised terms and how they were defined. For example, Gonzales et al. defined chronic heavy drinking if the mean units of alcohol per week was equal or higher than 27 in men or 14 in women[95] while Son et al defined problem drinking if men had 7 or more drinks per occasion or women had more than five drinks per occasion.[111] One population-cross-sectional study from the USA with a female-only cohort defined mild to moderate drinking as fewer than one drink per day in the last 30 days and heavy drinking if at least one drink per day was consumed on average.[100] Two studies asked participants retrospectively if they changed their drinking behaviour since becoming a caregiver.[141,159] One US study with participants in early adulthood used national definitions for binge and heavy drinking[97] whereas two other studies failed to provide a clear definition of their drinking categories.[90,126]

Further, three studies used the AUDIT-C tool[103,125,134] which is a validated tool to assess hazardous drinking in the population and the clinical setting.[169–173] The original AUDIT-C is a three-item screening tool on a five-point Likert scale and assesses the frequency of drinking, the number of alcoholic drinks and the frequency of binge drinking. The total scores range from 0-12 and interpretation of the score differs by sex: in men a score of 4 or more is considered hazardous drinking while in women a score of 3 or more indicates hazardous drinking or a potential alcohol abuse disorder.[172,173]

Reviews

There were two literature reviews that synthesised evidence regarding alcohol consumption of caregivers. The first one was the previously mentioned literature review by Ross and colleagues[130] that investigated problematic drinking in cancer caregivers. They found that studies reported contradicting findings and stated that it is challenging to compare results due to the different measurements and definitions of problem drinking across studies.[130]

More recently, Hazzan and colleagues[174] published a review in 2024 about alcohol use and abuse in family caregivers of people with Alzheimer's and dementia in the USA. Only five studies were included in this review and the authors found that a variety of measures was utilised to assess alcohol use and misuse in dementia caregivers. The researchers argued that it is challenging to draw firm conclusions but suggest that caregivers may be less likely to misuse alcohol compared to non-caregivers.[174] However, the results from this scoping literature review have to interpreted with caution because the review was restricted to dementia caregivers in the USA.

Longitudinal studies

During the search, three longitudinal studies could be identified one of which was a longitudinal study without a non-caregiving control group by Kearns and colleagues.[125] This study investigated the relationship between caregiving expectations and problematic alcohol use of caregivers of ICU survivors. For this, potential caregivers were recruited at the time of ICU admission of the care-recipient from an acute care hospital. 124 participants completed the baseline questionnaire about their alcohol consumption (AUDIT-C), caregiver burden and their expectation about their role as a caregiver upon discharge of the care recipient. After 6 months, researchers followed the participants up and repeated their measures. They also determined differentials between expected caregiving intensity and actual intensity. They found that caregiving burden was not associated with problematic alcohol consumption but that caregivers underestimated the time and effort that is required to perform the role as a caregiver. Indeed, underestimating the time spent caregiving following care-recipient's discharge home was associated with higher AUDIT-C scores, and hence, problematic drinking.[125] However, this study was only single-centred without control group and only 84 participants completed the follow up. Besides, the recruitment took place at a stressful time of ICU admission of the care-recipient which could have influenced the caregiver's alcohol consumption through maladaptive coping mechanisms.[125]

The other two longitudinal studies were the two population-based studies published by Hiyoshi[104] using an European sample and Tanigushi[101] using a Japanese sample which were both previously mentioned. The European study defined heavy drinkers if respondents indicated that they were consuming alcohol 'once or twice a week' or more frequent.[104] In contrast, the Japanese study defined heavy drinking when participants drank more than 60g of alcohol in men and 30g of alcohol in women.[101] Despite these different measures, both studies reported that there was no significant difference in alcohol consumption between caregivers and non-caregivers.

Cross-sectional studies with control group

The ten cross-sectional studies with control groups reported contradicting findings. Three of these studies found that caregiving was associated with lower alcohol intake[90,141] or lower odds of binge drinking compared to non-caregiving controls.[96] In contrast, one study reported that caregiving women were at higher odds of problematic drinking compared to non-caregiving women and that men who provided care for less than 20 hours a week were at higher odds of drinking compared to non-caregiving men.[94] Six studies found no significant associations of drinking habits between caregivers and non-caregiving controls.[93,95,97,99,100,111] There were no obvious patterns in view of populations studied, countries or sample size and results were inconsistent across these characteristics.

Cross-sectional studies without control group

Nine included studies were cross-sectional and did not have a non-caregiving control group.[89,103,126,134,142,152,153,158,159] They reported that male caregivers were more likely to engage in harmful drinking compared to female caregivers,[158] that young caregivers between the ages 18-45 were at higher odds of hazardous alcohol consumption compared to caregivers over the age of 65, and that caregivers in the UK had the highest rates of drinking compared to caregivers in Australia, USA, Canada and New Zealand[103]. Four studies reported that a high emotional or subjective burden was associated with problematic alcohol use.[89,134,142,153] A study with dementia caregivers found that one third of caregivers increased alcohol use since becoming a caregiver[159] while another study of ovarian cancer caregivers stated that caregivers reported less alcohol consumption since becoming a caregiver.[152]

Summary

In conclusion, the available evidence is limited to cross-sectional studies, one longitudinal study with considerable limitations and two population-based longitudinal ageing studies outside the UK. Due to the lack of robust longitudinal evidence, it is not possible to ascertain causal associations between caregiving and alcohol consumption in earlier lifecourse stages. Hence, further longitudinal studies with a larger, diverse sample are needed.

2.5.8 Smoking

Smoking was reported in 22 studies of which 18 were cross-sectional studies, three were longitudinal and one was a literature review. Around half of these studies used a representative sample from the general population used. Smoking status was assessed by all studies using self-report.

Reviews

As outlined in previous sections, the study from Ross and colleagues on eight cross-sectional studies of cancer caregivers without non-caregiving controls was the only review commenting on smoking in caregivers. They found that results were inconsistent and that in some studies no differences in smoking were observed while in other caregivers had higher smoking rates compared to controls or smoked less since becoming a caregiver.[130]

Longitudinal studies

In total, three longitudinal studies were identified, one of which was a small-scale study without control group and two were large population-based studies. The small-scale longitudinal study published by Roddy and colleagues[162] was based on a very small sample (n=22) and a very specific population of caregivers of early-stage lung cancer patients following their surgery which reported only marginal changes in smoking rates at 6-months follow up. Given the small sample, distinct study population and lack of control group, this result should be interpreted with caution.

The two aforementioned longitudinal studies by Hiyoshi[104] and Tanigushi[101] reported conflicting results. Hitoshi and colleagues reported for the European sample that co-residential caregiving was associated with a decrease in the odds of smoking compared to non-caregiving but that there was no difference for out-of-home caregiving.[104] In contrast, Tanigushi reported for the Japanese that caregiving was associated with higher odds of smoking, but this was not statistically significant in the fully adjusted model (OR= 1.12, 95% CI: 1.00-1.26, p=0.053). However, the findings of these two longitudinal studies would be restricted to caregiving in an advanced life-course stage and studies outside the UK.

Cross-sectional studies with control group

From the 11 studies with a control group, four found no difference of smoking habits between caregiver and non-caregiver.[85,93,95,141] Six reported that caregivers were more likely to be a smoker compared to controls,[86,96,97,99,100,175] and that this difference was more pronounced in female caregivers.[94] Two studies revealed that caregivers are less likely to be current smokers compared to controls.[90,111] One US study with participants in early adulthood found that being a caregiver was associated with higher prevalence of cigarette smoking but not e-cigarette smoking.[97]

Cross-sectional studies without control group

Six of these cross-sectional studies did not have a control and two reported only smoking rates in caregivers.[103,158]. One study with 200 Dementia caregivers reported that 35.5% of participants increased use of marijuana;[159] one study with ovarian cancer caregivers reported only few changes in smoking behaviour since the cancer diagnosis of the family member.[152]

Summary

It can be concluded that results from all these studies are overall inconclusive. Nevertheless, there seems to be a trend that suggests caregivers are at higher odds of being a smoker, although there is a lack of robust longitudinal evidence from more diverse samples. Hence, larger studies are needed that investigate the trajectories in smoking at more diverse age groups in the UK.

2.5.9 Overall health behaviour

In total, 13 studies used a summary measure of health behaviours or a cumulative measure of health behaviours which can be conceptualised as 'overall health behaviour'. All of which were cross-sectional and used two main approaches to measure the overall health behaviour: three studies[103,124,152] dichotomised health behaviour such as diet, PA, smoking or alcohol consumption into positive or negative health behaviours and added these to create a cumulative sum of positive and negative health behaviours. Eight studies[109,127,129,131,132,143,148,154] used health promoting behaviour scales that had several dimensions to measure health behaviours.

For example, the Health Promoting Lifestyle Profile (HPLP-II) consist of 52 items and contains six dimension: PA, nutrition, health responsibility, spiritual growth, interpersonal relations, stress management.[157] One study[86] created a composite health behaviour index based on the Scharlach Index of health behaviours.[176]

Cross-sectional studies with control group

Slightly higher quality evidence was provided by two cross-sectional studies with a control group. The first was a Spanish study that used a nationally representative sample of 44,755 participants from the Spanish National Household Survey.[94] Researchers from this study measured five health behaviours, dichotomised each outcome and calculated the sum of risk factors. They also stratified the analysis by sex, age group with a cut-off at 45 years and by hours of care provided. They found that only caregivers who provided less than 20 hours of care per week had lower odds of a high sum of risk factors compared to non-caregivers which was also the case for the age group above 45 years in the age-stratified analysis.[94] In contrast, the second cross-sectional study with a control group was a representative study with Californian "baby boomers" who were born between 1949 and 1964. They found that caregivers had greater odds of negative overall health behaviour compared to non-caregivers.[86] In this study, they also measured and dichotomised different health behaviours and created a composite index based on the Scharlach criteria.[176] No study included in this review investigated 'overall health behaviour' longitudinally.

Cross-sectional studies without control group

All? of these eleven studies were limited to small sample size with no control group of caregiving sub-populations. These studies reported mainly associations between caregiver's characteristics and overall health behaviour. For example, they found highly educated caregivers had better overall health behaviour compared to less educated caregivers.[132,154] An international online survey of 384 caregivers found that caregivers from the UK had the highest proportion of caregivers with an overall negative health behaviour compared to caregivers from Australia, Canada, USA and New Zealand.[103] Other findings included that the strength of the family relationship[129] and higher levels self-efficacy[124] were associated with positive overall health behaviour in caregivers while lower self-efficacy, burden and perceived stress were associated with lower practice of health promotion behaviours.[131] There was no difference between rural or urban caregivers in a small study with 77 female, spousal caregivers[109] while a study with 155 caregivers of people with disabilities found no correlation between burden and health promoting lifestyles.[143]

Summary

In conclusion, the evidence on the relationship between overall health behaviour is weak and limited to cross-sectional studies. Longitudinal studies with a diverse sample are warranted if and to what extent trajectories of overall health behaviour change if people transition into- and out of the caregiving role.

2.6 Discussion

2.6.1 Health promoting and health risk behaviours

It was found in this review that caregivers might be at higher odds of unhealthy diet and smoking, but these results were restricted to mainly cross-sectional studies. Besides, findings for physical activity and problematic drinking were inconsistent. While some studies found that caregivers were more physically active and drank less alcohol, others did not find a difference or reported that caregivers were less physically active and at higher risk of problematic drinking. However, there were large variations in how outcomes were measured and defined which created challenges to synthesise evidence due to variations in the measurement of caregiving as well as outcome measures. There were also considerable differences in the population studies and many studies were restricted to certain sub-populations. This finding is consistent with other review in the field that found that the available evidence remains inconclusive due to study limitations and heterogeneity of outcome measures.[130,161]

Moreover, different paths of health behaviours amongst caregivers have been hypothesised. For example, caregivers might be at risk of increased alcohol consumption in response to psychological distress or a maladaptive coping mechanism.[153] Others have argued that the increased responsibilities as caregiver would explain lower odds of binge drinking[96] because the lack of time and the demand on the caregiver to remain vigilant to the care-recipient's needs.[125]

2.6.2 Research gaps

There is a considerable gap in view of population studies, and there is currently no robust UK study that has investigated the relationship between caregiving and health behaviours. Also, this review highlighted numerous gaps in the literature in view of PA, diet, smoking and alcohol consumption in caregivers. It remains unknown how transitioning into the role of a caregiver influences the trajectories of each of these health behaviours over time and to what extent trajectories change when caregiving ends due to the care-recipient's death, recovery or transition into formal care. Within caregiving, it is also unknown how a change in caregiving intensity influences trajectories of health behaviour. Additionally, it remains unexplored how sex and age affect these caregiving transitions. Research recommendations from the reviewed papers include conducting longitudinal analysis with larger and diverse samples.

2.6.3 Limitations of review

This review has several limitations. First, the search strategy for caregiving was designed to minimise the inclusion of studies focused on parenting or childcare. To achieve this, the concept of care was combined with terms such as "informal", "unpaid", "family", "relative", "spouse", or "elder", and the words had to occur within three characters of each other in the search string. Due to this, it is possible that some studies were not identified that used more specific terms such as 'dementia caregiver' or 'cancer caregiver'. However, it was attempted to mitigate this risk by conducting a thorough screening of reference lists which revealed an additional 25 studies that were included in this review. Second, the search was limited to studies published in English or German which have increased the risk of bias in this review. This restriction increased the risk overrepresenting findings from English- and German-speaking contexts and the exclusion from relevant studies published in other languages.

Third, the review was restricted to mainly quantitative research and contains only a few insights from qualitative findings that came from reviews. The decision not to include primary qualitative studies was made to maintain a clear focus on quantifiable associations between caregiving and health behaviours, as the primary aim of the review was to assess patterns and strength of associations. While the inclusion of qualitative research might have been useful to generate hypotheses and provide contextual understanding, this was beyond the scope of the current review. Fourth, the inclusion and exclusion criteria were stringent as caregiving had to be the predictor and a health behaviour the outcome. This 'one-directional approach' was preferred to keep the outputs of the search to a manageable level as there were no restrictions in view of populations or age groups. However, it is possible that health behaviour outcomes influence caregiving outcomes, for example evidence from interventional studies suggest that PA might reduce burden or stress in caregivers.[177] Despite these limitations, this was the first review to summarise the existing evidence of health behaviours in caregivers without restrictions to population or caregiving characteristics. A transparent methodology and a sophisticated search strategy allowed a structured approach despite not being a formal systematic review which would not have been possible due to the breadth of the research question of this review.

2.7 Chapter conclusion

This review aimed to explore what is known and unknown about the relationship between caregiving and health behaviour outcomes which might represent an important link between caregiving and health inequalities. It was found that most studies were limited to cross-sectional evidence or low-quality longitudinal studies that differed in measurement out outcomes and caregiving. The few higher quality longitudinal studies focused on older age groups and only looked at transition into caregiving, outside the UK. Larger, longitudinal studies are required to establish causal paths between caregiving and health behaviours.

3 Thesis aims and objectives

Given the growing recognition of unpaid caregiving as a public health concern, and the existing gaps in the literature regarding its relationship with health behaviours, the following aims and objectives have been established.

3.1 Overarching aim

It is the overarching aim of this study to investigate lifecourse associations between caregiving transitions and health behaviour in the UK population.

3.2 Objectives of the study

1 To investigate the relationship between transitioning into unpaid caregiving and changes in trajectories of health behaviours across the lifecourse in the UK.

1a. To explore whether transitioning into caregiving is associated with changes in health behaviours (physical inactivity, fruit and vegetable consumption, smoking and problematic drinking).

1b. To compare trajectories of health behaviours between individuals who transition into caregiving roles and those who remain non-caregivers.

1c. To assess whether the intensity of caregiving, measured by caregiving hours and place of caregiving, is associated with the magnitude of change in health behaviours among those who transition into caregiving roles.

1d. To investigate if these associations between transition into caregiving and health behaviours are modified by sex or age group.

2 To investigate the relationship between exiting unpaid caregiving and changes in health behaviours across the adult life course in the UK.

2a. To investigate whether exiting caregiving is associated with changes in health behaviours (physical inactivity, healthy fruit and vegetable consumption, smoking and problematic drinking)

2b. To compare trajectories of health behaviours between individuals who exit caregiving and those do not experience a cessation to caregiving as well as those who never provide care.

2c. To assess whether the intensity of caregiving or place of caregiving prior to exit is associated with the magnitude of change in health behaviours amongst those who exit caregiving.

2d. To examine whether the above associations between exiting caregiving and health behaviours are modified by sex or life course stage of the caregiver.

3 To investigate if and to what extent the trajectories of caregiving intensity influence health behaviours amongst caregivers.

3a. To characterise different trajectories of caregiving intensity and examine their characteristics.

3b. To assess whether these trajectories are associated with changes in health behaviour outcomes.

3c. To examine if the above relationships are modified by sex or life course stage of the caregiver.

4 To investigate the relationship between multiple caregiving transitions and changes in health behaviours across the lifecourse.

4a. Comparing different methodological approaches to identifying patterns of multiple transitions into and out of unpaid caregiving over time.

4b. Investigating the association between multiple caregiving transitions and changes in health behaviours over time.

4c. Assessing whether the association between multiple caregiving transitions and health behaviours is modified by sex or lifecourse stage of the caregiver.

3.3 Research hypotheses

The following hypotheses were developed in line with the research objectives. They are stated in a non-directional form because existing evidence on the relationship between caregiving and health behaviours is inconsistent. From a life course perspective, the impact of caregiving may vary depending on the timing and context in which it occurs, with plausible pathways leading to both positive and negative behavioural changes. Role theory similarly suggests that caregiving can act as both a source of role enrichment, promoting healthy behaviours, and a source of role strain, leading to less healthy behaviours. In line with health behaviour theory, caregiving may alter a caregiver's capabilities, opportunities, or motivation to engage in certain health behaviours. Given these theoretical considerations, the hypotheses are framed to allow for associations in either direction.

H1: Transitioning into caregiving is associated with changes in the trajectories of health behaviours (physical activity, diet, smoking, and alcohol consumption).

- Physical activity: It is hypothesised that transitioning into caregiving leads to greater physical inactivity due to objective burden, such as reduced time for exercise and competing responsibilities. Alternatively, it is hypothesised that transitioning into caregiving reduces physical inactivity, since caregiving tasks may increase overall physical activity levels.

- Diet: It is hypothesised that transitioning into caregiving results in poorer dietary behaviours because of stress and reduced time and resources for meal preparation. Alternatively, it is hypothesised that caregiving improves diet through increased motivation of the caregiver to prepare healthy meals for the care recipient and themselves.
- Alcohol consumption: It is hypothesised that transitioning into caregiving increases alcohol consumption due to subjective burden, where stress encourages alcohol use as a coping strategy. Alternatively, it is hypothesised that caregiving reduces alcohol consumption because of the added responsibilities for the caregiver and fewer opportunities for social drinking.
- Smoking: It is hypothesised that transitioning into caregiving increases smoking as a coping mechanism in response to subjective burden, particularly stress and emotional strain. Alternatively, it is hypothesised that caregiving decreases smoking, as looking after a loved one who became unwell increases the caregiver's motivation to refrain from smoking.

H2: Termination or exit from caregiving is associated with changes in the trajectories of health behaviours.

- Physical activity: It is hypothesised that exiting caregiving increases physical activity, as the release from objective burden provides more time and energy for exercise. Alternatively, it is hypothesised that exiting caregiving reduces physical activity, since daily caregiving tasks may have contributed to higher incidental activity that is lost after exit.

- Diet: It is hypothesised that exiting caregiving improves diet, as the reduction of both subjective burden (stress) and objective burden (time and financial constraints) allows for healthier food choices and meal preparation. Alternatively, it is hypothesised that diet remains poor following exit, because dietary habits established under burden persist even after caregiving ends.
- Alcohol consumption: It is hypothesised that exiting caregiving reduces alcohol consumption, since the stress of subjective burden is alleviated. Alternatively, it is hypothesised that alcohol consumption increases after exit, as relief from objective burden restores time and opportunities for social drinking.
- Smoking: It is hypothesised that exiting caregiving reduces smoking, as relief from subjective burden lowers the need to use smoking as a coping mechanism. Alternatively, it has been hypothesised that smoking continues after exit, since behaviours adopted during caregiving may become entrenched and remain even when caregiving ends.

H3: It is hypothesised that greater caregiving intensity or increases in caregiving intensity are linked to adverse health behaviour changes, reflecting both subjective burden (stress and emotional strain) and objective burden (time constraints, reduced resources, and restricted social opportunities).

- Physical activity: it is hypothesised that higher intensity or increases in intensity decrease physical activity due to reduced time and energy.
- Diet: it is hypothesised that higher intensity or increases in intensity worsen diet through stress, time constraints, and reduced financial resources.

- Alcohol consumption: it is hypothesised that higher intensity or increases in intensity increase problematic drinking through stress, although reduced opportunities for social drinking may alternatively lead to lower alcohol use.
- Smoking: it is hypothesised that higher intensity or increases in intensity increase smoking as a coping response to stress.

H4: It is hypothesised that experiencing multiple transitions into and out of caregiving is linked to changes in health behaviours, due to repeated exposure to both subjective burden (stress and emotional strain) and objective burden (time constraints, reduced resources, reduced social opportunities).

- Physical activity: It is hypothesised that multiple transitions decrease physical activity, as repeated reorganisation of responsibilities disrupts stable exercise routines. Alternatively, it is hypothesised that caregiving tasks increase incidental activity, mitigating a decline in physical activity.
- Diet: It is hypothesised that multiple transitions worsen diet, since repeated cycles of stress and shifting time/resources disrupt meal preparation and increase reliance on unhealthy foods. Alternatively, it is hypothesised that multiple caregiving transitions improve the caregiver's diet by fostering increased awareness of their own health and nutritional needs.
- Alcohol consumption: It is hypothesised that multiple transitions increase problematic drinking through repeated stress exposure. Alternatively, it is hypothesised that multiple caregiving transitions reduce drinking due to multiple changing roles and constraints on time and social opportunities to engage in drinking behaviour.

- Smoking: It is hypothesised that multiple transitions increase smoking as a coping response to recurrent stress. Alternatively, it is hypothesised that recurrent exposure to caregiving increases the motivation of the caregiver to refrain from smoking.

H5: It is hypothesised that the associations between caregiving transitions and health behaviours differ by sex and by the life stage at which caregiving occurs.

- Sex: It is hypothesised that women may experience stronger negative changes in health behaviours due to greater exposure to subjective burden (emotional strain, stress) and objective burden (longer hours, fewer social opportunities), compared with men. For example, women may be more likely to increase smoking or decrease physical activity when transitioning into caregiving, whereas men may show weaker or different patterns.
- Life stage: It is hypothesised that younger adults who transition into caregiving may experience more negative health behaviour changes due to sharper objective burdens (disruptions to education, employment, and social opportunities). In contrast, older adults may experience smaller changes or even improvements in some behaviours, since caregiving may be more consistent with existing social roles and routines.

4 Data and measures

4.1 Aim of this chapter

This chapter aims to provide a general overview of the data sources and key measures used throughout this thesis. This will include an overview of the data used, the definitions of measures and variables, and ethical considerations. While some details in this chapter are relevant across analytical chapters, additional variable definitions and methodological information specific to each research question are presented in the respective analytical chapters.

4.2 Study design

The project is a quantitative secondary longitudinal data analysis and reporting will be in line with the STROBE guidelines[79] (Appendix 4.2).

4.3 Data

The data comes from the UK Longitudinal Household Study (UKHLS), also known as "Understanding Society" which has collected data on over 40.000 households in 14 waves to date. It is the largest household study in the UK and uses a complex survey design with clustering and stratification to achieve a nationally representative sample. It was initiated in 2009 and interviews annually all adults in each household who are aged 16 and older. Response rates in UKHLS were around 57% in the first wave and levelled off between 80% and 90% of initial study members in subsequent waves while attrition was comparable to other longitudinal household studies.[178] Also, its sample includes data from the British Household Panel Study (BHPS) which commenced in 1991. Using UKHLS data enables the proposed objectives to be addressed as it includes repeated measures on caregiving activity and intensity the proposed objectives because it has collected repeated data on caregiving characteristics and health behaviours.

All analyses draw on data from the UKHLS. The specific waves used vary depending on the analysis; some use four selected waves, while others use data from Waves 2 to 13. While this data set contains caregiving characteristics at every wave, data on health behaviours are not present in all waves.

Table 4.1 shows the measures for health behaviours and caregiving in the long-term content plan from UKHLS.[179] Variables for smoking are available in wave 2 and from wave 5 to wave 13. Variables for alcohol consumption, physical activity and nutrition are available in waves 2, 5, 7, 9, 11 and 13. However, it must be noted that the questions for these non-smoking outcomes change from wave 7 onwards. Due to the change in questions, it was not possible to fully harmonise certain variables across earlier waves which may affect comparability of these measures over time. The implications of this constraint for each analysis are addressed in the relevant analytical chapters. It must also be acknowledged that wave 12 will be excluded from data analysis. This was because the questions for physical activity and alcohol consumption were only added mid-fieldwork in response to the emerging Covid-19 pandemic.

Table 4.1 UKHLS long term plan, adapted from University of Essex

Module	**Waves**												
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Diet		x			x		x		x		x		x
Physical activity		x			x		x		x		x	(x)	x
Smoking		x			x	x	x	x	x	x	x	x	x
Alcohol consumption		x			x		x		x		x	(x)	x
Caregiving	x	x	x	x	x	x	x	x	x	x	x	x	x

(x) added mid-field in response to Covid-19 pandemic

4.4 Measures

The variables of interest have been defined and coded as follows (Appendix 4.1).

Outcomes

<u>*Physical activity (PA):*</u>

A physical activity variable was constructed based on questions regarding participant's vigorous to moderate physical activity from UKHLS. These questions aligned with questions from the International Physical Activity Questionnaire.[150] With regards to vigorous physical activity, participants were asked how many days they engaged in vigorous physical activity: *"Now, think about all the vigorous activities which take hard physical effort that you did in the last 7 days. Vigorous activities make you breathe much harder than normal and may include heavy lifting, digging, aerobics, or fast bicycling. Think only about those physical activities that you did for at least 10 minutes at a time. During the last 7 days, on how many days did you do vigorous physical activities?"*(University of Essex, p.269).[180] Then, participants were asked to estimate the average duration of vigorous PA on those days: "*How much time did you* *usually spend doing vigorous physical activities on one of those days?" (*University of Essex, p.269).[180] If participants were unsure about the typical daily duration, they were instead asked: "*How much time in total did you spend over the last 7 days doing vigorous physical activities?"* (University of Essex, p.270).[180]

With regards to moderate physical activity, participants were asked how many days they engaged in moderate physical activity: "*Now think about activities which take moderate physical effort that you did in the last 7 days. Moderate physical activities make you breathe somewhat harder than normal and may include carrying light loads, bicycling at a regular pace, or doubles tennis. Do not include walking. Again, think only about those physical activities that you did for at least 10 minutes at a time. During the last 7 days, on how many days did you do moderate physical activities?"* (University of Essex, p.272).[180] Afterwards, participants were asked to estimate the average duration of moderate PA on those days: "*How much time did you usually spend doing moderate physical activities on one of those days?"* (University of Essex, p.272).[180] If participants were unsure about the typical daily duration, they were instead asked: "*How much time in total did you spend over the last 7 days doing moderate physical activities?"* (University of Essex, p.272).[180]

Based on the responses, total weekly minutes of moderate and vigorous physical activity were calculated. If participants provided both the number of days and the usual time spent per day, total weekly minutes were calculated by multiplying the two. If they instead answered the total time question, this value was used directly. Binary variables were then created to classify participants as physically active or inactive, in line with recommendations from the UK's Chief Medical Officer (CMO).[181] Participants were classified as physically active if they met at least one of the following criteria: (1) 75 minutes or more of vigorous activity per week; (2) 150 minutes or more of moderate activity per week; or (3) a combined total of 150 minutes per week of both moderate and vigorous activity. The walking variable was omitted to derive this binary variable for PA because the definition of moderate PA from the UK's CMO includes 'brisk walking'[181] while the question from UKHLS includes all walking for at least 10 minutes, including walking to work. A binary variable was preferred to align with international definitions of physical activity. Besides, modelling physical activity on continuous scale was challenging due to its non-normal distribution and excess zeroes.

Diet – fruit and vegetable consumption:

To measure healthy diet, a continuous variable was derived based on participant's daily number of fruit and vegetables. Firstly, participants were asked how often in a week they would eat fruits: "*Including tinned, frozen, dried and fresh fruit, on how many days in a usual week do you eat fruit?"* (University of Essex, p.267)[180] and how many portions they would eat on a typical day: "*On the days when you eat fruit, how many portions (e.g. an apple, an orange, some grapes) do you eat*?" (University of Essex, p.267).[180] Secondly participants were asked how often in a week they eat vegetables: "*Not counting potatoes, crisps or chips but including tinned, frozen, dried and fresh vegetables, on how many days in a usual week do you eat vegetables?"* (University of Essex, p.267)[180]and how many portions they would eat on a typical day "*On the days when you eat vegetables, how many portions (i.e. 3 heaped tablespoons) do you eat? Please do not include potatoes*" (University of Essex, p.267).[180] Based on the responses to these four questions, the average number of portions of fruits and vegetables consumed per day was computed for each observation

For diet, a continuous measure of fruit and vegetable consumption was preferred because the values approximated normal distribution which would make it possible to model daily portions of fruit and vegetable on continuous scale. Besides, the literature review in Chapter 2 revealed a lack of consensus in previous literature regarding the cut-off despite recommendations with guidelines from the WHO[182] and UK's public health authority[183] which state that adults should consume at least 5 servings of fruit and vegetables every day.

Smoking:

Participants were asked: "*Do you smoke cigarettes? Please do not include electronic cigarettes (e-cigarettes*)?" (University of Essex, p.268).[180] Based on their response, participants were coded as smoker or non-smoker. Those who indicated that they currently smoked, a second continuous variable was generated about the number of cigarettes they usually smoked which was based on the question: "*Approximately how many cigarettes a day do you usually smoke, including those you roll yourself?"* (University of Essex, p.268).[180]

Alcohol:

To measure problematic drinking, the Alcohol Use Disorders Identification Test – Consumption (AUDIT-C) was used which consists of three items that ask about the frequency of drinking alcoholic drinks ("*Thinking about the past 12 months, how often do you have a drink containing alcohol*?" (University of Essex, p.665)[180] the number of drinks consumed on a typical day of drinking ("*How many drinks do you have on a typical day when you are drinking?""*(University of Essex, p.666)[180] and the frequency of binge drinking("How often have you had 6 or more units (female) / 8 or more units (male), on a single occasion in the last year?" (University of Essex, p.666)[180] which is defined as having 6/8 or more drinks on one occasion.[172] Each item is scored on a scale from 0 to 4, with response options corresponding to increasing frequency or quantity. The scores for the three items are summed to produce a total AUDIT-C score ranging from 0 to 12 with higher scores indicating more problematic alcohol use. Participants were coded as 'problematic drinkers' if they had a score of 3 or greater in females or if they had a score of 4 or more in male participants. These cut-off scores for problematic drinking are in line with previous research[172,173,184] and were introduced in recognition of sex-specific differences in alcohol-related harm.[185] Evidence indicates that women are at higher risk of alcohol-related diseases and reach higher blood-alcohol concentrations than men after consuming equivalent amounts of alcohol relative to body weight.[186]

Exposure

Caregiving residential status:

Participants were asked: "*Is there anyone living with you who is sick, disabled or elderly whom you look after or give special help to (for example, a sick, disabled or elderly relative, husband, wife or friend etc*)?" (University of Essex, p.321).[180] If respondents answered with yes, they were coded as 'household caregivers.' Additionally, participants were asked: "*Do you provide some regular service or help for any sick, disabled or elderly person not living with you?"* (University of Essex, p.322).[180] If respondents answered with yes, they were classified as 'non-residential caregivers. A fourth category was created for caregivers who were household AND non-residential caregivers.

Care giving status:

Based on the responses from the questions about providing care to someone inside the household and to someone outside the household, a binary variable was created to classify participants as caregivers if they reported either type of care, or as non-caregivers if they reported neither.

Caregiving hours:

The number of hours spent caregiving was measured by asking: "*Now thinking about everyone who you look after or provide help for, both those living with you and not living with you - in total, how many hours do you spend each week looking after or helping them?" (*University of Essex, p.324).[180] Responses were collected as categories: (1) 0-4 hours; (2) 5-9 hours; (3) 10-19 hours; (4) 20-34 hours; (5) 35-49 hours; (6) 50-99 hours; (7) 100 or more hours / continuous care; (8) varies under 20 hours; and (9) varies over 20 hours. This variable was re-categorised depending on the analysis and the specific research question. Details of the re-categorisation are provided in the relevant analytical chapters.

Confounders

Confounders were selected based on existing literature and theoretical considerations and further refined using directed acyclic graphs (DAGs) to identify the sufficient adjustment set for each research question. Covariates were drawn from the relevant baseline wave prior to the caregiving transition, to minimise the risk of adjusting for potential mediation. As the research questions and analysis techniques varied across chapters, details how each covariate was treated in each analysis will be described in more detail within the individual chapters. The variables cohabiting with partner, household size, measures of socioeconomic position (education, income quintiles, occupational class), employment status, general self-rated health, psychological distress were considered as potential confounders when measured as baseline but could also act as mediators if measured after the caregiving transition. Hence, these variables were included as baseline measures to ensure appropriate temporal ordering in the adjustment strategy in line with Directed Acyclic Graphs which is discussed in the next section (Section 4.5) Additionally, physical health functioning was considered a confounder for the analysis for physical activity because limitations in physical health are directly related to an individual's ability to engage in physical activity. In contrast, physical health functioning may have less direct influences on diet, alcohol consumption and smoking. Age and sex were hypothesised to either confound or modify the relationship between caregiving and health behaviour.

Sex:

A binary measure of sex was used, with respondents categorised as male or female based on the derived variable `sex_dv` provided in the cross-wave files. This variable reflects a longitudinally consistent classification derived from information collected across all waves. While this binary categorisation excludes non-binary gender identities, it was employed with an awareness of the gendered nature of caregiving and with the aim of exploring gendered associations between caregiving and health behaviours.

Age / Age groups:

A continuous variable for age was available and different age groups were created to account for possible non-linearity. A lifecourse stage variable consisted of 4 categories groups and was aligned with the hypothesis that associations between caregiving and health behaviours might differ according to typical life course stages of participants: (1) participants in early adulthood aged between 16 and 29; (2) early mid-adulthood between 30 and 49; (3) late mid-adulthood aged between 50 and 64; and (4) participants in late adulthood aged 65 or above. This age-categorisation aligns with previous literature on caregiving across the lifecourse.[17]

Ethnicity

For this variable, groups were combined to reflect the following groups: (1) white; (2) black; (3) Indian; (4) Pakistani/Bangladeshi; and (5) other Asian or other ethnicity. More detailed categorisation by ethnicity were not possible due to limited sample sizes in the sub-groups.

Relationship status:

The derived variable of 'de-facto marital status' was used to categorise participants into those who were cohabiting with a spouse or partner or those who were non-cohabiting. Participants who were single, divorced, widowed, or separated were categorised as 'non-cohabiting' whereas those who were married, in a civil partnership or living with a partner were categorised as cohabiting.

Household size:

Information on the household size was available and participants were categorised into 1-person household, 2-person household, 3 to 4-person household and 5 or more people living in the same household.

Number of children

This is a derived variable which specifies the number of own children living in the household which includes natural children, stepchildren and adopted children under the age of 16. The responses can be (1) no children; (2) one child; (3) two children; or (4) three or more children.

Education:

UKHLS provides a derived variable about the highest educational attainment in each wave. It is updated with each wave to reflect the most recent qualification of panel members. Participants were categorised to either having (1) no qualification; (2) A-Levels, GCSE, other qualifications; and (3) degree or other higher degree.

Employment status

A variable on employment status was created with three response categories based on the question whether people were in paid employment and the derived variable whether participants were in full-time or part-time employment. Working full-time was defined as working at least 30 hours of more per week The categories were (1) full-time employed; (2) part-time employed; and (3) not in paid employment.

Occupational class:

For those in paid employment, occupational class was derived using the three-class version of the National Statistics Socio-economic Classification (NS-SEC), which categorises occupations into: (1) managerial and professional; (2) intermediate; and (3) routine and manual occupations.[187] Participants not in employment at the time of data collection—including those unemployed, retired, or otherwise economically inactive—were assigned to a separate *"not employed"* category in the occupational class variable. This allowed these individuals to be retained in the analysis while acknowledging that NS-SEC is not applicable to individuals with no current or recent occupational history.

Household income quintiles:

Household income was based on a derived variable which contains data on the overall net household income. This value was divided by OECD equivalised income scale to compute the household income accounting for household size and composition.[188] Based on this, income quintiles were generated.

Self-rated general health

Respondents were asked how they would rate their general health and could respond: excellent, very good, good, fair or poor. Responses were recoded into a binary variable with participants who rated their health as fair or poor in one group and participants who rated their health as excellent to good in the other group.

General Health Questionnaire (GHQ):

The GHQ is a validated and reliable questionnaire with 12-items that measure psychological distress.[189] Participants were asked how they have been feeling over the last few weeks and includes questions about sleep, ability to concentrate, general happiness, and other symptoms. Respondents could answer each question with not at all (score: 0), not more than usual (score: 1), rather more than usual (score: 2), or much more than usual (score: 3). Total scores range from 0 to 36 with higher scores indicating more symptoms of psychological distress or non-specific psychiatric morbidity.

SF12-PCS:

The physical component score of the SF12 is a shortened scoring system from the longer SF36 and serves as a validated measure of physical health functioning.[190] Participants were asked 12 questions about their physical health, for example, whether they suffered from health conditions that limited their moderate physical activities. The score ranges from 0 to 100 with higher scores indicating better physical functioning.

4.5 Directed Acyclic Graphs (DAGs)

Recent developments in epidemiology have challenged the way in which confounders in observational studies are identified. Scholars have argued that traditional methods of identifying confounders potentially introduce selection bias,[191] collider bias[192] and confounding bias.[193] To enable researchers to better understand if conditioning on a covariate is potentially reducing or increasing bias, graphical depiction of causal effect in the form of so-called Directed Acyclic Graphs (DAGs) has been proposed.[194] As caregiving represents a conceptually challenging topic with a high risk of confounding and bias, a DAG was produced to answer the research question in his thesis.

The DAG is presented in Appendix 4.3 (**Figure A4.1**). and depicts a causal model for the impact of caregiving transitions on health behaviours while accounting for time-varying and time-invariant confounding. The main exposure is caregiving transition, and the outcome of interest is health behaviour. Time-invariant covariates are sex, education, ethnicity and age at baseline / first observation. The time-varying variables are measured at several timepoints and include household income, occupational class, marital status, household size, psychological distress and general self-rated health. Time A of the time-varying covariate is considered as period prior to the caregiving transition whereas time B of the time-varying covariate is conceptualised to be the period after the caregiving transition occurred. According to this DAG,[192] any further analysis should be adjusted for the time-invariant covariates as well as the time-varying covariates prior to the caregiving transition. However, time-varying covariates after the caregiving transition should not be adjusted for as they may lay on the causal pathway between caregiving transition and health behaviour.

4.6 Ethical approval & Funding

This project is funded by the UBEL-DTP (UCL, Bloomsbury and East London Doctoral Training Partnership) and is registered under the grant reference ES/P000592/1. The funder is not involved in project design, analysis or write up of findings. The project uses data which are publicly available from the UK Data Service (https://ukdataservice.ac.uk/) and uses data from the UKHLS, also known as 'Understanding Society', which has received ethical approval from the University of Essex Ethics Committee for all data collection activities.[188]

4.7 Chapter conclusion

In conclusion, this chapter had the aim of outlining the data source and key measures underpinning this thesis. UKHLS was identified as the most appropriate dataset for exploring the relationship between unpaid caregiving and health behaviours due to its rich longitudinal design, nationally representative sample, and inclusion of detailed caregiving information on participants from age 16 onwards. Key measures of caregiving characteristics, health behaviours and third variables of interest were described and justified. The use of DAGs was also introduced to guide analytical decisions and ensure appropriate adjustment for confounding. Finally, the chapter addressed ethical considerations. A detailed description of the methodical strategies will be discussed within the analytical chapters that follow.

5 Transitioning into caregiving and changes in health behaviours

5.1 Introduction

In the literature review in Chapter 2, it was established that while there is a substantial number of studies examining the health behaviours of unpaid caregivers, only a few population-based studies have investigated this relationship longitudinally.[101,104,114] However, none of these longitudinal studies have been conducted in the UK, despite the rise in the prevalence of unpaid caregiving in the UK.[6] The influence of caregiving on health behaviours may differ in the UK due to distinct features of its welfare state, health and social care systems, and labour market.[195] Furthermore, the few existing longitudinal studies that investigated transitions into caregiving focused largely on people over 50 with samples outside the UK.[101,104,114] This is an important gap, as the transition into caregiving in earlier stages of the lifecourse can be considered an unexpected, non-normative, and often undesired role change, as conceptualised in lifecourse theory and caregiving role theory.[25,61,196]

Therefore, this study aims to investigate the relationship between transitioning into unpaid caregiving and changes in health behaviours across the lifecourse in the UK. The central focus of this chapter is to examine the trajectories of physical inactivity, fruit and vegetable consumption, smoking and alcohol consumption and how these are affected when study participants transition into the role of an unpaid caregiver. To allow rigorous analysis of these complex relationships, longitudinal quantitative techniques such as fixed effect models and piecewise growth curve models will be employed along with matching approaches that have the aim to reduce bias caused by differential selection into caregiving.

5.2 Chapter aims, objectives & hypotheses

It is the aim of this chapter to address Objective 1 and Objective 5, namely, to investigate the relationship between transitioning into unpaid caregiving and changes in trajectories of health behaviours across the lifecourse in the UK. Chapter objectives include:

1a. To explore whether transitioning into caregiving is associated with changes in health behaviours (physical inactivity, fruit and vegetable consumption, smoking and problematic drinking).

1b. To compare trajectories of health behaviours between individuals who transition into caregiving roles and those who remain non-caregivers.

1c. To assess whether the intensity of caregiving, measured by caregiving hours and place of caregiving, is associated with the magnitude of change in health behaviours among those who transition into caregiving roles.

1d. To investigate if the associations between transition into caregiving and health behaviours are modified by sex or age group.

5.3 Methodology

5.3.1 Data

The data for this study comes from the UKHLS, also known as "Understanding Society" which is the largest household (panel) study in the UK, collecting in over 40.000 households across 14 waves since 2009. Using this data set allows for an analysis of caregiving characteristics and health behaviours longitudinally as described in Chapter 4.3 Data.

5.3.2 Measures

Outcomes

The outcomes of interest will be physical inactivity, fruit and vegetable consumption (as a measure of a healthy diet), problematic drinking at waves 7,9,11 and 13 as well as smoking from wave 5 to wave 13 as described in Chapter 4.3.

Exposure

The exposure of interest for this chapter is the transition into caregiving or caregiving onset. This captures the point at which an individual begins providing unpaid care, typically observed when caregiving status changes from non-caregiver ("0") in one wave to caregiver ("1") in the following wave(s). How this change in caregiving status is operationalised varied depending on the analytical strategy and will be described in more detail in the statistical analysis section. Among participants who became caregivers, further details on caregiving hours and place of care (within or outside the household) at the time of transition is used for subgroup analysis.

Covariates

Covariates will be divided into time-invariant covariates such as sex, education, ethnicity and time-varying covariates such as occupational class, employment status, de facto marital status, quintiles of household income, household size, number of children living in the household, general self-rated health and psychological distress. All these measures are described in detail in 4.4 Measures.

5.3.3 Statistical analysis

5.3.3.1 Overview

To address the chapter objectives, FE models and piecewise growth curve models based on a propensity score matched sample were considered as two appropriate statistical methods. These two approaches have been considered in the spirit of triangulation with the notion that two analytical methods generate more confidence in the research findings.[197]

5.3.3.2 Fixed Effects (FE) models

As a first analytical step, FE models were estimated to examine whether transitioning into caregiving is associated with within-individual changes in health behaviours. These models are well-suited to longitudinal panel data because they focus on changes within individuals over time.[198] By using each participant as their own control, FE models adjust for all time-invariant characteristics, whether observed or unobserved.[199,200] This reduces the risk of bias due to stable individual traits, such as personality or early-life circumstances.[201] A known limitation of fixed-effect models is their inability to estimate the effect of time-invariant variables.[202] However, this is not the concern in the present analysis which focuses on a time-varying exposure and outcome.

5.3.3.3 Propensity Score Matching

Propensity Score Matching (PSM) is used in this study to reduce caregiver selection bias. Entry into unpaid caregiving is not random; rather, it is influenced by a range of sociodemographic and contextual factors that make some individuals more likely to transition into a caregiving role than others.[25,72] PSM addresses this by estimating the probability (propensity score) of becoming a caregiver based on observed baseline characteristics, such as age, sex, employment status, and health. Caregivers are then matched with non-caregivers who have similar propensity scores, helping to balance the distribution of these confounding variables between the two groups. The matched sample is subsequently used in the piecewise growth curve models to compare changes in health behaviours between those who transitioned into caregiving and those who did not (see 5.3.3.6 Preparatory steps for piecewise growth-curve models).

To enable propensity score matching, a binary treatment variable was created to distinguish participants who transitioned into unpaid caregiving from those who did not. For this, participants were assigned to either the treatment group ("1" = transitioned into caregiving) or the control group ("0" = no transition into caregiving). Matching was performed at a 1:3 ratio, with each participant in the treatment group matched to up to three participants in the control group.

Participants were matched on a range of baseline characteristics, including socioeconomic factors (occupational class, household income, highest educational attainment, working status), demographic characteristics (household size, ethnicity, number of children living in the household), health indicators (psychological distress, self-rated health, baseline health behaviour of interest), and the number of waves they had participated in the study and the number of the wave which was the baseline wave. Exact matching was applied for sex, age at baseline, and the wave at which participants entered the study. Matching on the baseline wave was used to account for potential period effects, and changes in population-level health behaviours over time, for example declining smoking rates. This ensured that caregivers and non-caregivers were compared within the same temporal context. To assess the quality of the matching, balance diagnostics were conducted using statistical tests (e.g. t-tests and chisquared tests) and standardised mean differences to ensure covariates were adequately balanced between the treatment and control groups.

5.3.3.4 Entropy balancing

While PSM is an increasingly popular method in observational studies, it may be difficult to identify a PSM model with an adequate covariate balance.[203] To tackle the issue of potential covariate imbalance in the analytical sample, entropy balancing was used in conjunction with propensity score matching in this study. While propensity score matching estimates the probability of “receiving treatment”, entropy balancing reweights the control sample observations to align them with the treated sample in terms of observable covariates.[204,205] Entropy balancing has demonstrated promising results in estimating treatment effects especially in scenarios involving a binary exposure, outperforming methods solely focused on propensity score estimation.[206,207]

To assess and address potential covariate imbalance in the analytical sample, covariate balance was evaluated both before and after matching using standard statistical test such as t-test and chi-square test. Imbalance was considered present if covariates were statistically different between participants who transitioned into caregiving (treatment group) and those who did not (control group). Statistical difference was assessed using hypothesis testing and a p-value of 0.05 or smaller was taken to indicate a statistically significant difference between the groups.

In the propensity score matched sample, several covariates showed evidence of imbalance, such as baseline health behaviour, ethnicity, number of people living in the household, education and income quintiles (Appendix 5.2; **Table A5.1**).

5.3.3.5 Piece-wise growth curve models

To examine potential changes in health behaviours following transitions into caregiving, piecewise growth curve models were employed. This approach was well-suited to addressing the research objectives, as it allows for the modelling of the health behaviour trajectories before and after the transition into caregiving. Piecewise growth curve modelling is a statistical modelling technique that allows for the setting of knot points or intercept at the beginning of a caregiving period (for example, the first wave caregiving is reported), allowing to assess if and how trajectories differ when study participants enter caregiving. Hence, this is a suitable method to study transitional periods and changes over time[208] and can be applied to meet thesis objective 1 and 2 (transitioning in-and out of caregiving).

To test the statistical significance of changes in trajectories before, during, and after the transition into caregiving, the Stata package mkspline was used.[209] Three knot points were specified to divide the trajectories into distinct periods or 'pieces': the first piece captured the pre-transition trajectory; the second piece captured the transition period which was defined as the interval between the wave before caregiving was first reported and the wave it was first reported; and the third piece captured the post-transition trajectory. Additionally, the option 'marginal' was specified to estimate the change in slope from the preceding interval.

These spline components were then included in the regression model through an interaction term between the spline variables and the caregiving transition variable. While these models produced multiple estimates, two p-values were of interest to answer the research questions which corresponded to the interaction terms between the spline components and the caregiving transition variable. The first p-value of interest represented the difference in the change in slope at the transition point between those who transition into caregiving and those who did not. The second p-values of interest represented the difference in the change in slope in the post-transition period between those who transitioned into caregiving and those who did not. A p-value of ≤ 0.05 for the interaction term was taken as evidence to reject the null hypothesis that the change in slope across caregiving transition was the same across groups. This approach was preferred because piecewise growth curve models allow for the comparison of changes in the slopes of the outcome across distinct time periods such as before, during, and after the transition into caregiving. They also enable testing whether these changes differ between caregiving and non-caregiving groups, rather than assuming a single, continuous trajectory. This structure makes it possible to isolate and test whether the slope of health behaviours changes specifically around the caregiving transition. Additionally, testing differences across the entire growth curves may obscure meaningful variation across these time segments, especially given that, due to matching, caregivers and non-caregivers were expected to have similar trajectories prior to the transition.

5.3.3.6 Preparatory steps for piecewise growth-curve models

The timing of the transition into caregiving, defined as the first wave in which caregiving was reported, was a crucial variable for modelling piecewise growth curves. For participants who transitioned into caregiving, this time point could be directly observed. However, for matched control participants who did not experience a transition into caregiving, the timing of such a transition could not be observed. To enable comparable modelling of trajectories using piecewise growth curves, a transition time point needed to be assigned to matched controls. This was done by assigning each control the same wave of transition as their matched caregiver. This approach allowed for the alignment of time points across groups and ensured comparability in estimating pre- and post-transition trajectories. The procedure involved several steps, outlined below.

First, for participants who experienced a caregiving transition, the sample was restricted to participants who had at least one observation prior and after the caregiving transition. Then propensity score matching was conducted as described above. Additionally, unique identifier for each control unit (no caregiving transition) matched to a treatment unit (caregiving transition) was generated. The next step involved managing the matched data to ensure that each treatment case is aligned with the time of caregiving transition from the matched controls. These steps are repeated for each individual in the control group, generating a new variable for the "time of caregiving transition" for each matched control group. The logic ensures that each treatment subject's "time of caregiving transition" is matched with the first occurring "time of caregiving transition" among the matched controls. This process aligns the timing of caregiving transition between the treated and control individuals. Following this, the final analytic sample was selected based on data availability. To be included, participants in both the treatment and control groups needed to have valid observations both before and after the transition period. Therefore, the inclusion criteria were reapplied to ensure that only participants with sufficient data coverage across the pre- and post-transition periods were retained for analysis.

5.3.3.7 Clustering at household level

UKHLS is a longitudinal household study and a significant methodological challenge represents the clustering of observations within households. This clustering can introduce bias and violate the assumption of independence of observations.[210] Hence, several analytical strategies were explored to account for the clustering at household level.

Initially, multilevel modelling was considered as a potential solution to handle the hierarchical structure of the data, where individuals are nested within households. Multilevel models are particularly useful for accounting for data clustering by estimating random effects that model shared variance within groups.[211] However, despite the theoretical suitability of this approach, practical challenges were encountered such as repeated model convergence failures. This is a known issue in models with complex structures, limited numbers of observations per higher-level unit, or sparse data within clusters.[212]

Although the piecewise growth curve models used in this study are also multilevel in nature, with repeated measures (Level 1) nested within individuals (Level 2), a third level for household clustering could not be included due to convergence issues. This was primarily because most households contained only one participant relevant to the analysis (either a caregiver or a control), and relatively few households included multiple individuals transitioning into or remaining outside of caregiving. As a result, there was insufficient clustering to support a stable three-level model.

Due to the difficulties with fully specifying multilevel models, alternative approaches were explored. One such method was using the Variance-Covariance Estimator '*vce(cluster)*' option in Stata, which adjusts standard errors to account for clustering at the household level. This approach maintains the assumption of independence between clusters (households) while allowing for intra-household correlation, thereby producing robust standard errors.[213]

Another strategy considered was to randomly select one participant per household. While this would effectively eliminate intra-household clustering, it would also substantially reduce the sample size and limit the generalisability of the findings. After careful consideration and comparison of these methodologies, it was decided that the use of the *vce(cluster)* option is the superior approach for the analysis. This decision was driven by the need to retain a large enough sample while adequately addressing the methodological challenge of clustering. Some analysis comparing these different options with smoking as outcome and transition into caregiving as exposure can be found in Appendix 5.3.

5.3.4 Analytical sample

The variation in the availability of outcome measures created the dilemma of whether to perform analysis on complete cases where all outcomes are present for the same number of participants or whether to run separate analysis for each outcome which may differ in sample size. A further challenge was that two types of analysis were performed, namely FE models and piecewise growth curve models based on a propensity score matched sample. To preserve as much sample size as possible, a tailored approach was preferred and each outcome was analysed separately, acknowledging that the sample size varied slightly across outcomes. This allowed that for each analysis, a robust approach and enhanced statistical power and inclusion criteria varied across the two proposed approaches.

Participants were eligible for inclusion if they were aged 16 or older, had completed the full interview, and were non-caregivers at baseline. Caregivers at baseline were excluded from the growth curve analysis, as the focus was on capturing transitions into unpaid caregiving. The sample size varied depending on the outcome measure and the type of analysis conducted. In the FE models, the sample included all eligible respondents across waves who contributed data on caregiving status and health behaviour outcomes in at least two waves to enable estimation of within-individual changes over time. For the piecewise growth curve models, the analysis was based on a propensity score matched sample comparing individuals who transitioned into unpaid caregiving with those who did not. Further details are provided in the section below.

Sample size

FE models

In the FE models of the binary outcomes (physical inactivity, smoking, and problematic drinking), participants who did not have their caregiving status or health behaviour observed were excluded from analysis. Among those remaining, Stata's FE logistic regression model further excluded individuals who showed no variation in the outcome across waves, since they do not contribute to the estimation of within-individual change. As FE models inherently control for time-invariant confounders within individuals, and because some time-varying variables may lie on the causal pathway between caregiving onset and health behaviours, no additional covariates were included in the models. Consequently, no participants were excluded due to missing covariate data. After applying these criteria, the fixed-effect models were conducted on 18,262 participants for physical inactivity **Figure 5.1**, 9,465 for problematic drinking (Appendix 5.1; **Figure A5.2**), and 6,263 for smoking (Appendix 5.1; **Figure A5.3**). Below, in **Figure 5.1** is the sample size flowchart for physical inactivity while the sample size flowchart can be found in Appendix 5.1.

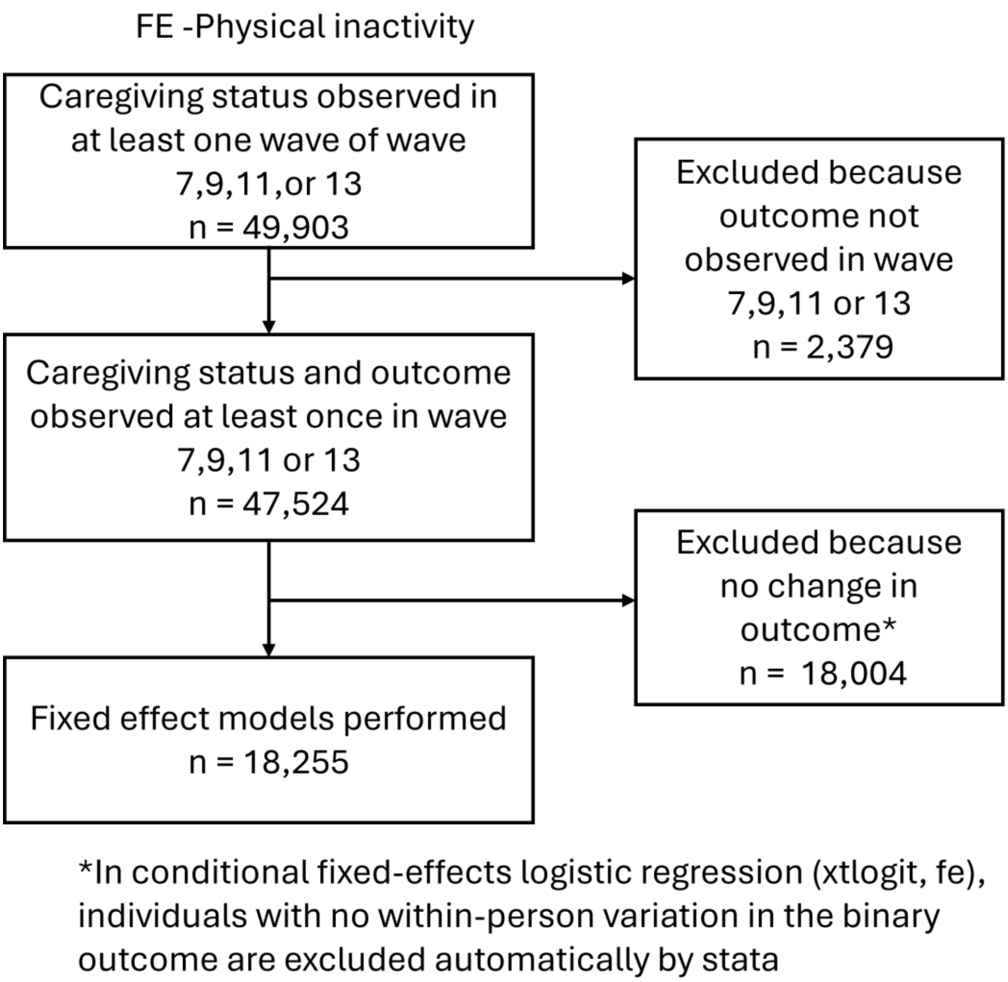


Figure 5.1 Sample size flow chart for physical inactivity using FE models.

In contrast, fruit and vegetable consumption was measured as a continuous outcome, increasing the likelihood of variations in outcome compared to binary outcomes. However, because continuous measures are more sensitive to variations over time, a larger sample size was retained for fruit and vegetable consumption (N=35,779). To address potential outliers in the fruit and vegetable consumption measure, observations above the 99th percentile were excluded from the analysis. Values in the bottom percentile were not excluded as these were considered to reflect plausible low levels of fruit and vegetable consumption rather than outliers. This approach retained 99% of the sample while reducing the influence of extreme values that may reflect reporting errors or atypical responses. Further details on the distribution of the variable are provided in Appendix 4.6.

Propensity score matching & piecewise growth curve models

After matching, the analytical sample sizes varied across outcomes. For physical inactivity, the matched sample included 17,118 participants (4,436 caregivers; 12,682 controls, **Figure 5.2**). The sample for problematic drinking comprised 17,250 participants (4,468 caregivers; 12,782 controls, **Figure A5.5**), and the fruit and vegetable consumption analysis included 16,027 participants (4,468 caregivers; 11,559 controls, **Figure A5.4**). For smoking, where a longer observation period was used, the matched sample was substantially larger at 25,979 participants (8,659 caregivers; 17,320 controls, **Figure A5.6**). Additional matched samples were created for subgroup analyses based on care hours and place of care. Detailed sample selection processes for each outcome are shown in Appendix 5.1. Below, in **Figure 5.2** is the sample size flowchart for physical inactivity while the sample size flowchart can be found in Appendix 5.1.

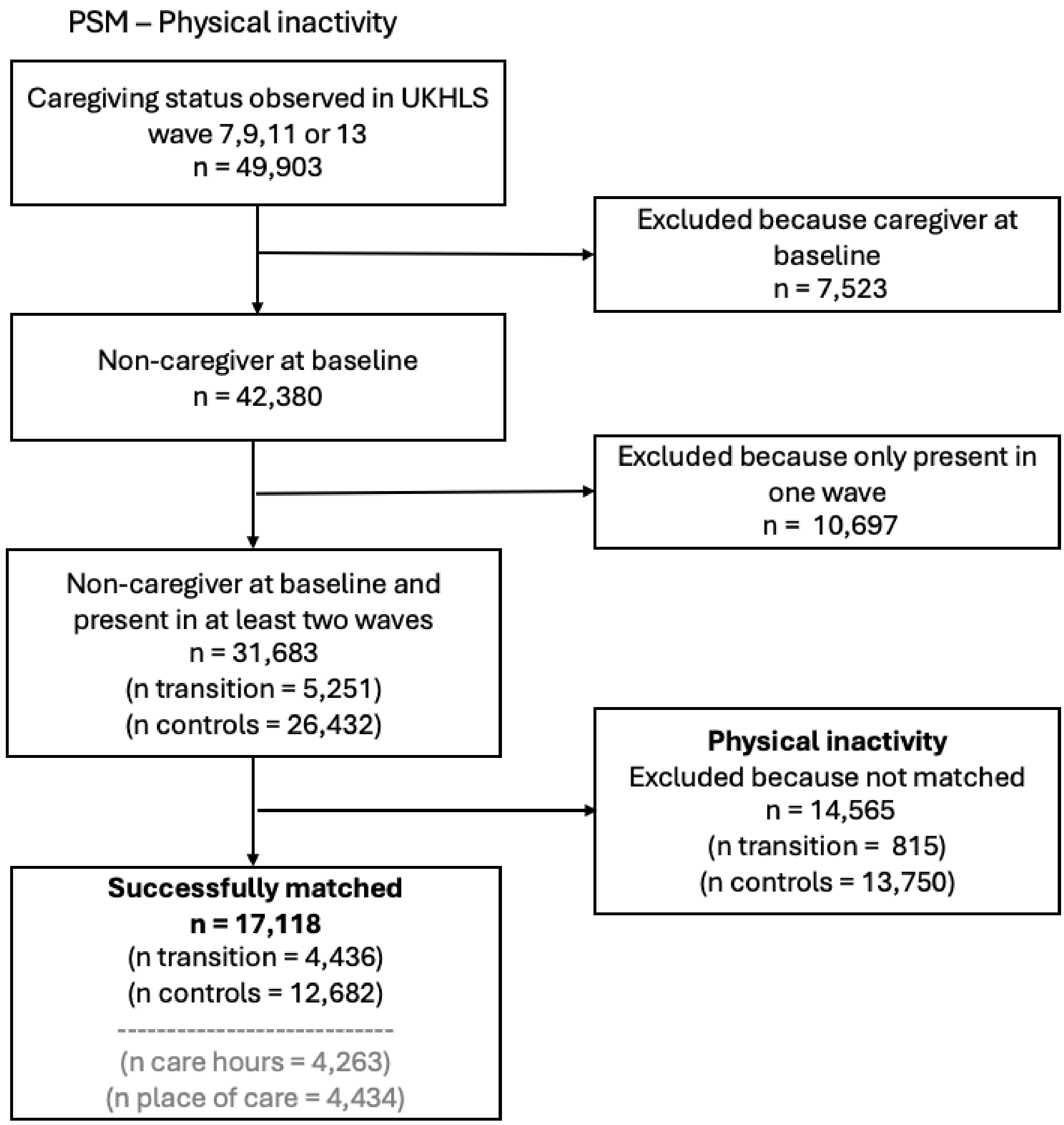


Figure 5.2 Sample size flow chart for propensity score matching and physical inactivity.

5.4 Results

In this section, results are presented to investigate the relationship between transitioning into caregiving and changes in health behaviours. Each outcome is presented separately. For each outcome, descriptive statistics are followed by results from fixed-effect models and piecewise growth curve models based on the propensity score matched sample. Results from the fixed-effect models are shown in tables, while the piecewise growth curve models are presented in graphical form as illustrations of the predicted probability of an outcome at each time point. In addition, a table summarising the p-values for both the transition and post-transition periods in the piecewise regression models, along with references to the corresponding figures, is provided in Appendix 5.7.

5.4.1 Physical inactivity

5.4.1.1 Unadjusted analysis

Table 5.1 presents the prevalence of physical inactivity for wave 7, 9, 11 and 13 of UKHLS and is stratified by caregiving status and caregiving intensity (low intensity for caregivers who provided 20 hours or less of care per week and high intensity if caregivers provided more than 20 hours of care per week). The prevalence of physical inactivity is similar between caregivers and non-caregivers across all survey waves and both groups show a similar trend with physical inactivity decreasing in wave 9 and then gradually increasing in subsequent survey waves. While the reason for this 'dip' at wave 9 is unclear, it must be noted that data for wave 9 was collected between 2017 and 2019, prior to the Covid-19 pandemic. However, this pattern should be interpreted with caution because this graph is based on unweighted data and serves a descriptive purpose only. It may reflect sampling variation or changes in respondent characteristics across waves. In wave 13, the prevalence of physical inactivity was 54.2% for caregivers and 54.0% for non-caregivers. In view of care intensity, low intensity caregivers show consistently a lower prevalence of physical inactivity compared to higher intensity caregivers. In wave 13, low intensity caregivers had a prevalence of physical inactivity of 50.8% whereas high intensity caregivers had a prevalence of physical inactivity of 61.2%.

Table 5.1 Cross-sectional prevalence of physical inactivity in waves 7,9,11 and 13 of UKHLS among participants who reported caregiving status and physical inactivity status at least once during this period by caregiving status and care hours.

UKHLS wave	N= 47,524	Caregiver	Non-caregiver	<20 hrs care	>20hrs care
7	42,120	55.7%	56.4%	53.9%	63.3%
9	36,025	51.2%	49.8%	46.0%	59.6%
11	30,543	53.3%	52.8%	50.1%	59.4%
13	29,907	54.2%	54.0%	50.8%	61.2%

5.4.1.2 FE Models

The full sample consisted of 47,9524 participants but fixed-effect models were only based on around 18,255 participants for the binary caregiving variable and 18,191 participants on the analysis with care hours because they had no change in outcome. In **Table 5.2**, the Model based on caregiving status, revealed that transitioning from non-caregiving to caregiving was associated with lower odds of physical inactivity (OR= 0.84, 95% CI: 0.79/0.89), adjusted for wave. The model with caregiving hours revealed that, compared to non-caregivers, individuals providing less than 20 hours of care per week had significantly lower odds of being physically inactive (OR=0.84, 95% CI: 0.79–0.90). Those providing more than 20 hours of care per week also had lower odds of physical inactivity (OR=0.83, 95% CI: 0.74–0.93).

While there was no evidence for an interaction between caregiving status and sex or caregiving hours and sex, age groups seemed to modify the relationship between caregiving transition and physical inactivity. In view of caregiving status (see **Table 5.3**), transitioning into caregiving was associated with lower odds of physical inactivity, apart from early adulthood (16-29 years) where transition into unpaid care was associated only with a small and non-significant decrease in the odds of physical inactivity (OR=0.95, 95%CI: 0.80/1.13, p=0.56). In view of care hours, transitioning into lower intensity care (<20 hours/week) was associated with a mild decrease in physical inactivity in all age groups apart from early adulthood. In contrast, transitioning into higher intensity care (>20 hours/week) was associated with a greater decrease in physical inactivity in early adulthood (OR=0.66, 95% CI: 0.46/0.95) and late adulthood (OR=0.66, 95%CI: 0.52/0.83) only.

Table 5.2 Fixed-effect regression for physical inactivity and transitioning into caregiving

Model	**Sample**		**OR**	**95% CI**	**p**
Model: Caregiving status + adjustment for wave	$N_{participants}$ = 18,255 $N_{observations}$= 62,824	Non-caregiver Caregiver	1.00 0.84	- 0.79/0.89	<0001
Interaction					
Caregiving-status*sex					0.51
Caregiving-status*age-group					0.03
Model: Caregiving hours + adjustment for wave	$N_{participants}$ = 18,191 $N_{observations}$= 62,485	Non-caregiver < 20 hours care >20 hours care	1.00 0.84 0.83	- 0.79/0.90 0.74/0.93	<0.001
Interactions					
Caregiving-hours*sex					0.81
Caregiving-hours*age-group					0.001

Table 5.3 Stratified fixed-effect regression for physical inactivity by age

Stratified results	**Sample**		**OR**	**95% CI**	**p**
Caregiving status and age groups					
Early adulthood (16-29)	$N_{participants}$ = 3.757 $N_{observations}$= 11.731	Non-caregiver Caregiver	1.00 0.95	- 0.80/1.13	0.56
Early mid-adulthood (30-49)	$N_{participants}$ = 6.276 $N_{observations}$= 21.672	Non-caregiver Caregiver	1.00 0.81	- 0.73/0.90	<0001
Late mid-adulthood (50-64)	$N_{participants}$ = 4.751 $N_{observations}$= 17.079	Non-caregiver Caregiver	1.00 0.90	- 0.81/0.99	0.04
Late adulthood (65+)	$N_{participants}$ = 3.471 $N_{observations}$=12.342	Non-caregiver Caregiver	1.00 0.77	- 0.68/0.88	<0.001
Caregiving hours and age groups					
Early adulthood (16-29)	$N_{participants}$ = 2.743 $N_{observations}$= 11.678	Non-caregiver < 20 hours care >20 hours care	1.00 1.01 0.66	- 0.84/1.22 0.46/0.95	0.07
Early mid-adulthood (30-49)	$N_{participants}$ = 6.258 $N_{observations}$= 21.576	Non-caregiver < 20 hours care >20 hours care	1.00 0.78 0.98	- 0.70/0.87 0.81/1.19	<0.001
Late mid-adulthood (50-64)	$N_{participants}$ = 4.734 $N_{observations}$= 16.976	Non-caregiver < 20 hours care >20 hours care	1.00 0.89 0.91	- 0.80/0.99 0.75/1.12	0.11
Late adulthood (65+)	$N_{participants}$ = 3,456 $N_{observations}$= 12,255	Non-caregiver < 20 hours care >20 hours care	1.00 0.82 0.66	- 0.72/0.95 0.52/0.83	<0.001

5.4.1.3 Trajectories pf physical inactivity

Caregiving status

In the propensity score matched sample for the analysis of physical inactivity, a total number of 4,689 participants transitioned into unpaid care and 12.682 matched non-caregivers. **Figure 5.3** presents the trajectory of the predicted probability of physical inactivity based on a propensity score-matched sample, illustrating the probability of physical inactivity in relation to the transition into unpaid care caregiving. With this approach, it was possible to model up to 7 years before and seven years after the onset of caregiving. Prior to the onset of caregiving, participants who transition into caregiving and those who do not show relatively similar probabilities of physical inactivity with confidence intervals largely overlapping, indicating no significant difference.

At the onset of caregiving, the probability of physical inactivity diverges between participants who transitioned into caregiving and those who remained non-caregivers. Participants who transitioned into caregiving decreased their probability of physical inactivity compared to non-caregivers who had more stable trajectories of physical inactivity. However, in the waves after the transition, the probability of physical inactivity increases gradually for participants who transitioned and reaches the level of non-caregivers after four years of follow up. The interaction term, testing whether slope changes differed between those who transitioned into caregiving onset and the non-caregiving controls was statistically significant (p=0.002) which suggest that there is evidence that transitioning into caregiving decreases the probability of physical inactivity compared to non-caregivers, albeit temporarily.

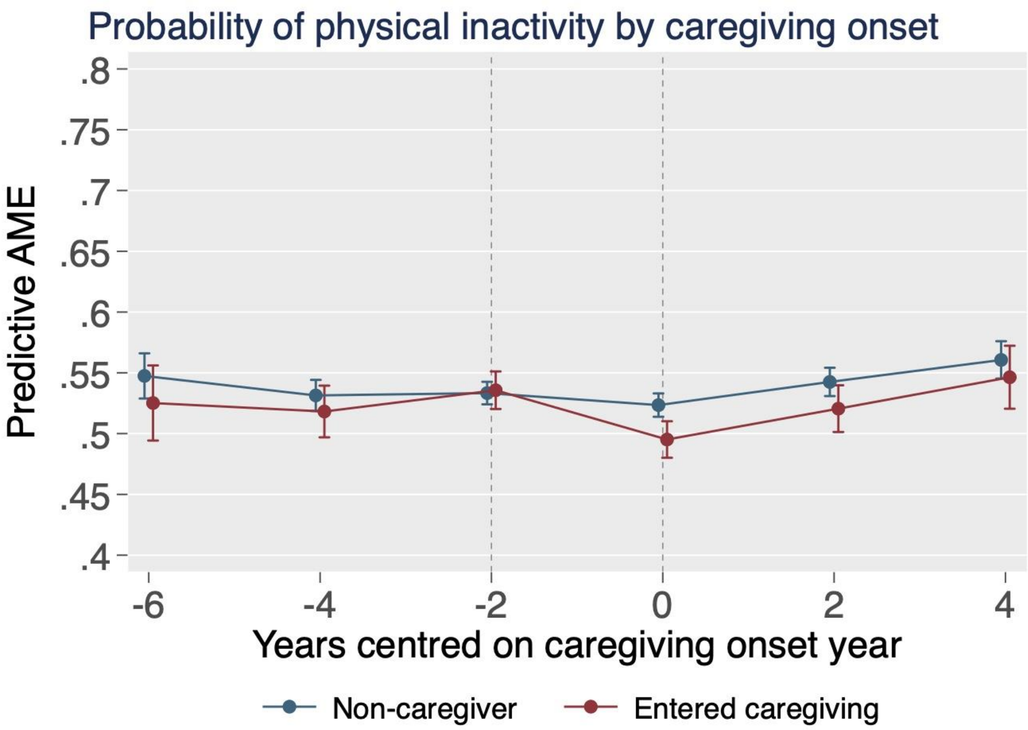


Figure 5.3 Probability of physical inactivity before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, based on a propensity score matched sample (n=17,118;4,436 caregivers,12,682 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

Hours of care

Next, the trajectories of physical inactivity were stratified by caregiving intensity in the first caregiving episode in which low intensity was defined as providing less than 20 hours of care per week and high intensity was defined as providing 20 hours or more care per week. Only 4,263 participants had valid observations in view of hours of care when caregiving was first observed after the transition and 82.9% (n=3,534) of participants transitioned into lower caregiving intensity whereas 17.1% (n=729) of participants transitioned into higher intensity caregiving. **Figure 5.4** shows that while high intensity caregivers started at a higher baseline of physical inactivity, they showed a similar decrease in physical inactivity compared to low intensity caregivers in the wave of transitioning to caregiving while the trajectory of physical inactivity remained stable for people who did not transition in any care category. Although there was some evidence that the caregiving hours after the first transition modified the trajectories of physical inactivity (p=0.05), the declining trajectories looked very similar between low and high intensity caregivers.

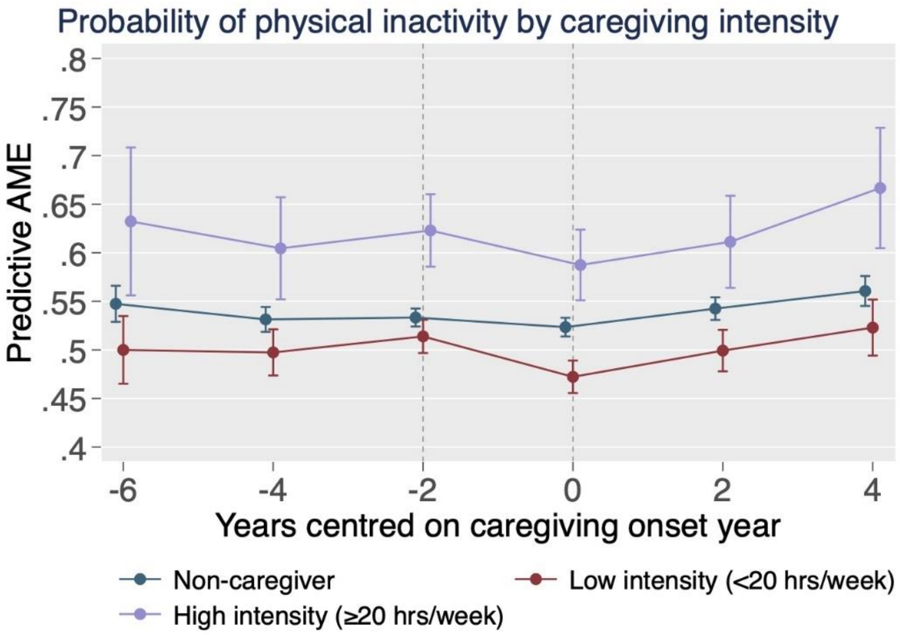


Figure 5.4 Trajectories of physical inactivity by care hours; probability of physical inactivity before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, stratified by care hours at onset, based on a propensity score matched sample (n=16,945; 4,263 caregivers, 12,682 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

Because low- and high intensity caregivers differed with their probability of physical inactivity, a sub-group analysis was conducted in which low intensity caregivers were matched with high intensity caregivers through entropy balancing as shown in **Figure 5.5**. The matching variables were the same as for the analysis that compared participants who transitioned into caregiving and those who did not. After matching, low and high intensity caregivers had similar probabilities of physical inactivity but low intensity caregivers had a steeper decrease in their probability of physical inactivity after the transition to caregiving which may suggest that low intensity caregivers are more likely to engage in more physical activity after the caregiving transition. However, confidence intervals between these two groups largely overlapped and there was not enough statistical evidence to confidently support a difference in slope change between the two groups during the caregiving transition (p=0.12).

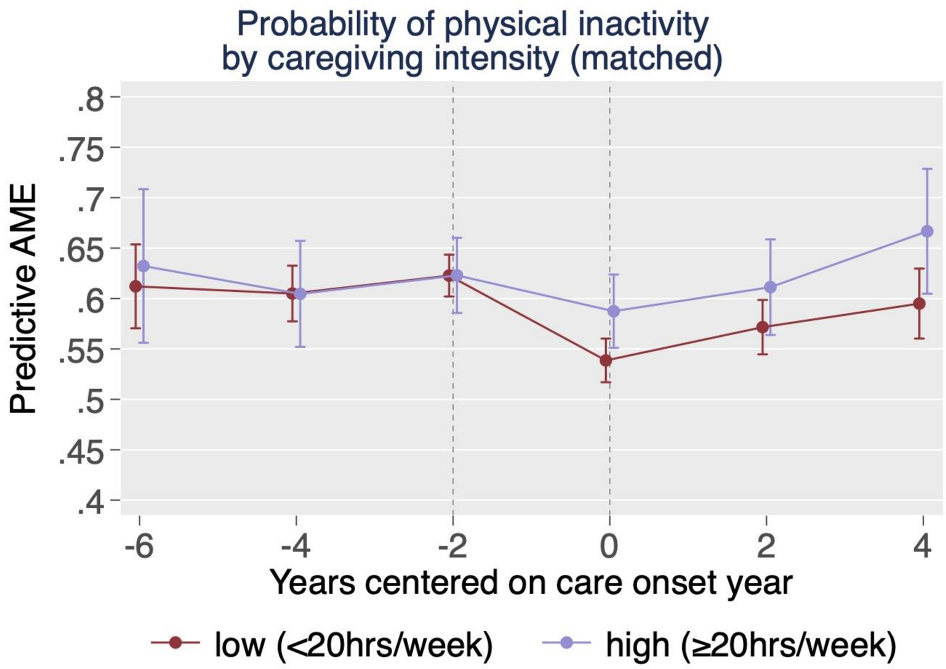


Figure 5.5 Trajectories of physical inactivity by matched care hours; Probability of physical inactivity before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, comparing low-intensity (<20 hours) and high-intensity (≥20 hours) caregivers, based on a entropy balanced matched sub-group sample (n=4,263; 3,534 low-intensity, 729 high-intensity caregivers). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

Place of care

In view of place of care, in total 65.4%% (n=2903) caregivers transitioned into caregiving outside the household, while 29.9% (n=1,325) participants transitioned into caregiving inside the household and only 4.7% (n=206) participants transitioned into dual caregiving (inside and outside the household). **Figure 5.6** depicts the trajectories of physical inactivity by place of care compared to non-caregivers. It can be seen that individuals who transitioned into caregiving within the household, as well as both those who transitioned into caregiving care inside the household as well as outside the household, both show a decrease in physical inactivity following the transition. In contrast, those who provided dual caregiving showed only a marginal change in their probability of physical inactivity immediately following the transition, with a remarkable increase in physical inactivity two years after transition. However, this pattern should be interpreted with caution, as the small sample size for this group limits the reliability of the estimates. The overall interaction term is statistically significant (p=0.01) which suggest that there is evidence that the place of care to which participants transitioned to was associated with slope changes in the probability of physical inactivity.

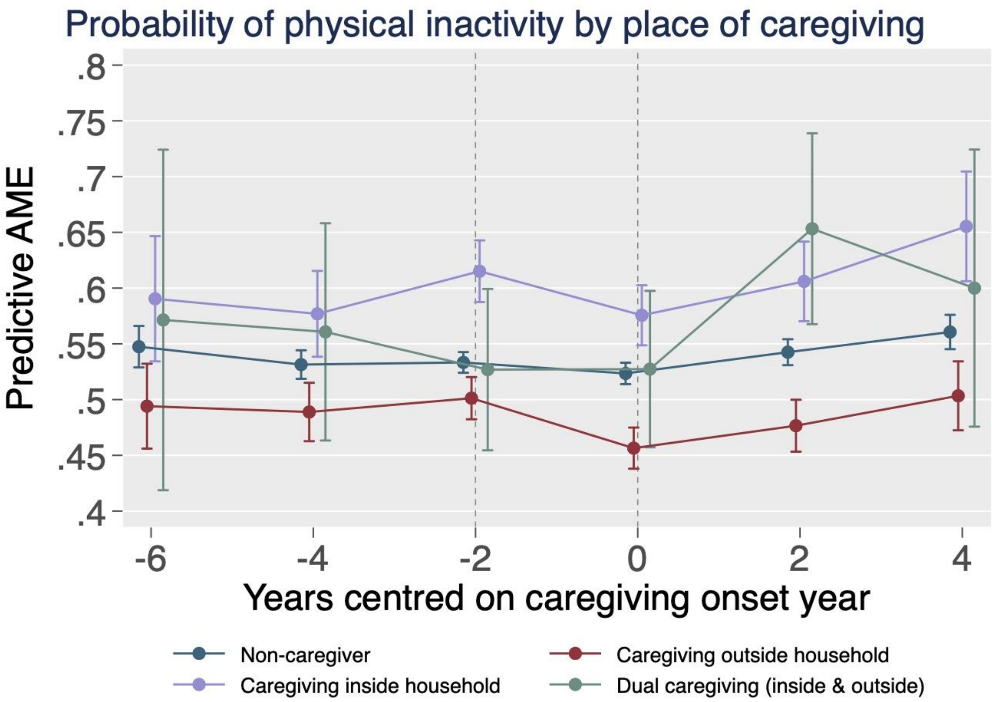


Figure 5.6 Trajectories of physical inactivity by place of care; probability of physical inactivity before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, stratified by place of care at onset, based on a propensity score matched sample (n=17,116; 2,903 outside the household, 1325 inside the household, 206 inside and outside the household, 12,682 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

5.4.1.4 The role of age and sex on trajectories

Sex

Regarding sex, out of all participants who transitioned into caregiving, 40.6% were male (n=1,800) and 59.4% were female (n=2,636). The interaction term between sex and the caregiving transition variable was statistically not significant (p=0.83). Additionally, a graphical comparison of trajectories of physical inactivity by sex in **Figure 5.7** reveals female participants had generally higher prevalence of physical inactivity throughout the study period. However, the trajectories between male and female participants who transitioned into caregiving are almost parallel which suggest that sex did not modify the relationship between transitioning into caregiving and physical inactivity.

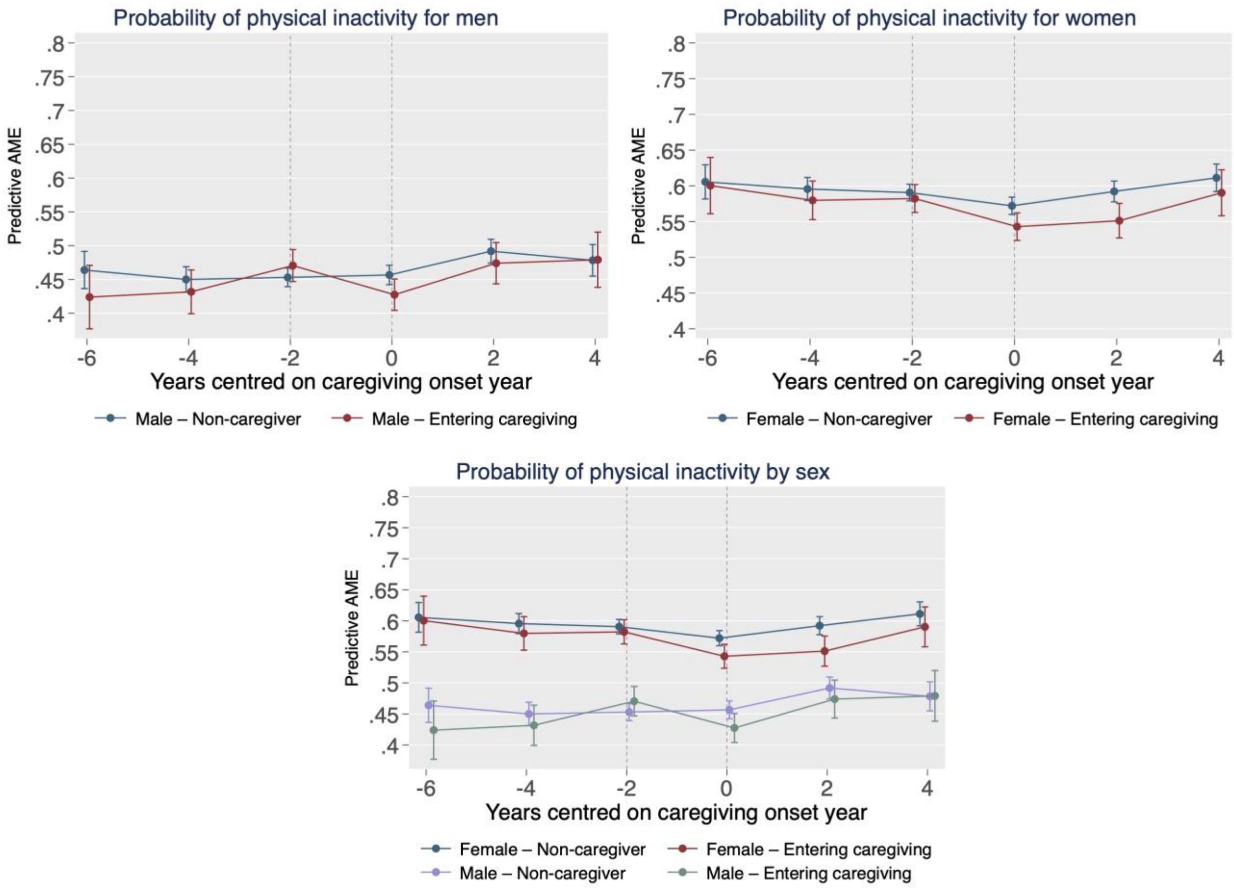


Figure 5.7 Trajectories of physical inactivity by sex; probability of physical inactivity before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, stratified by sex, based on a propensity score matched sample (n=17,118; 2,636 female caregivers, 1,800 male caregivers, 12,682 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

Age groups

In view of age groups, out of all participants who transitioned into caregiving, only 10.4% were caregivers in early adulthood (n= 461) while 34.8% were in early mid-adulthood (n=1.544), 33.9% were in late mid-adulthood (n=1,505) and 20.9% were in late adulthood older caregivers (n=926). Graphical assessment of age stratified trajectories in **Figure 5.8**, suggests a reduction in physical inactivity following entry into caregiving across all age groups apart from participants in early adulthood (16-29) which showed no difference in trajectories. However, the p-value of the interaction term between the transition variable and age-group affiliation at baseline was not statistically significant (p=0.97), likely due to overlapping confidence intervals within each strata. Upon graphical assessment of age stratified trajectories in **Figure 5.8**, it emerged that caregivers in late adulthood had the strongest association between entering caregiving and a slope change in physical inactivity which was statistically significant (p=0.004). However, all age groups showed a decrease in physical inactivity during the transition period, but only caregivers in late adulthood (65+) had the sharpest increase of physical inactivity during the post-transition period.

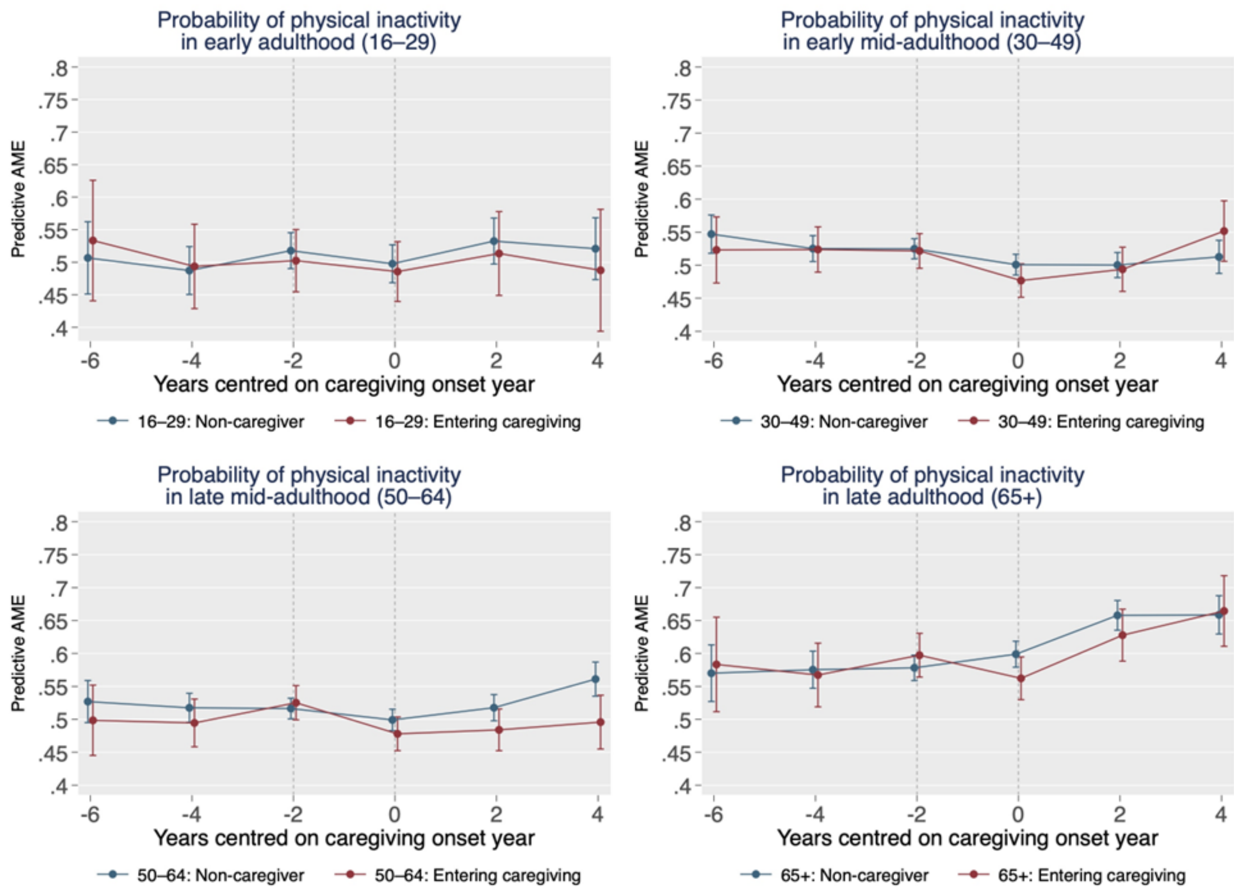


Figure 5.8 Trajectories of physical inactivity stratified by age group; probability of physicalctivity inactivity before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, stratified bygiving age at caregiving onset, among participants who transitioned into caregiving (n=4,436; 4616–29], early adulthood [16–29], 1,544 early mid-adulthood [30–49], 1,505 late mid-adulthood [50–]) and 64], 926 late adulthood [65+]) and non-caregiving matched controls (n=17,118). Time islashed centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

5.4.1.5 Summary

This part of the study investigated the relationship transitioning into caregiving and changes in physical inactivity using data from four waves of the "Understanding Society" study. The unadjusted analysis revealed that caregivers generally had higher prevalence of physical inactivity compared to non-caregivers. However, higher intensity caregiver consistently had a higher prevalence of physical inactivity compared to low intensity caregivers. In the adjusted FE analysis, it emerged that transitioning into caregiving was associated with lower odds of physical inactivity which was in strong contrast to the unadjusted analysis. These findings were confirmed by the trajectories of the piecewise growth curve models which indicated that transitioning into caregiving is associated with lower odds of physical inactivity. In other words, participants who transitioned into caregiving became more physically active. Higher intensity caregivers and lower intensity caregivers had a similar degree of decrease in physical inactivity. The trajectories did not differ between men and women but carergivers in early adulthood had the least decrease in physical inactivity which mirrored the result from the FE interaction analysis. This suggests that transition into caregiving was generally associated with an decrease in physical inactivity.

5.4.2 Fruit and vegetable consumption

5.4.2.1 Unadjusted analysis

The outcome of interest was the mean portions of fruits and vegetables per day as described in Chapter 4.4. Measures. The variable ranged from 0–60 and was right-skewed due to extreme values. Box plots and histograms were generated, and the variable was trimmed at the 99th percentile (Appendix 4.6). Observations above the 99th percentile were excluded from the analysis rather than recoded to the 99th percentile value. No trimming was applied at the lower end of the distribution (0–1st percentile), as these values were considered plausible and reflected very low but realistic levels of fruit and vegetable consumption. This approach resulted in a distribution that was closer to normal distribution, although some skewness to the right remained. Although this variable was censored at zero, there were only 1.5% zeros and following trimming, the mean and median of this variable were more similar (3.7 vs. 3.4 respectively).

Then, **Table 5.4** was generated to illustrate the average portions of fruits and vegetables across the UKHLS waves, stratified by caregiving status and hours of care. Caregivers had an overall slightly higher daily fruit and vegetable consumption compared to non-caregivers, but the difference was fairly small and only between 0.1 to 0.2 portions a day. Further, those providing less than 20 hours of care per week had a higher daily consumption of fruits and vegetables compared to caregivers who provided more than 20 hours of care per week, but the difference was relatively small and between 0.3 and 0.6 portions a day across the four UKHLS waves.

Table 5.4 Cross-sectional average fruit and vegetable consumption in wave 7,9,11 and 13 of UKHLS among participants who reported caregiving status and fruit and vegetable consumption at least once during this period, by caregiving status and care hours.

UKHLS wave	N=47,666	Caregiver	Non-caregiver	<20 hrs care	>20hrrs care
7	39,170	3.6	3.4	3.7	3.3
9	34,375	3.8	3.6	3.8	3.5
11	29,700	3.7	3.6	3.9	3.3
13	27,017	3.6	3.5	3.8	3.3

5.4.2.2 FE models

To assess change within individuals, FE regression was employed on 47,579 individuals for caregiving status and 47,627 participants for the analysis of care hours, with the slightly larger sample for care hours arising because some individuals who did not vary in caregiving status over time still reported variation in caregiving hours and were therefore retained in the fixed-effect estimation. For caregiving status, transitioning into caregiving was associated with an increase of 0.02 portions increase in daily fruit and vegetable consumption, adjusted for wave, but this increase was statistically neither significant (95%CI: -0.01/0.06, p=0.16), nor meaningful from a public health perspective. Similarly, there were no significant associations between transitioning into different hours and care and daily fruit and vegetable consumption (**Table 5.5**). In view of interactions, there was no evidence that sex or age groups modify the association between transitioning into caregiving and the daily consumption of fruits and vegetables although the interaction between care hours and age groups was marginally non-significant (p=0.07). This suggest that there was no relationship between transition into caregiving and the daily consumption of fruits and vegetables.

Table 5.5 Fixed-effect regression for fruit and vegetable consumption and transitioning into caregiving)

Model	Sample		Coeff.	95% CI	p
Model: Caregiving status + adjustment for wave	$N_{participants}$ = 47,579 $N_{observations}$= 130,613	Non-caregiver Caregiver	Ref. 0.02	- -0.01/0.06	0.16
Interactions					
Caregiving-status*sex					0.13
Caregiving-status*age-group					0.93
Model: Caregiving hours + adjustment for wave	$N_{participants}$ = 47,627 $N_{observations}$= 128,744	Non-caregiver < 20 hours care >20 hours care	Ref. -0.01 0.00	- -0.01/0.00 -0.02/0.01	0.54
Interactions					
Caregiving-hours*sex					0.19
Caregiving-hours*age-group					0.07

5.4.2.3 Trajectories of fruit and vegetable consumption

Caregiving status

Next, trajectories of daily fruit and vegetable consumption were estimated based on the propensity score matched sample in which 4,468 participants transitioned into caregiving and 11.559 matched non-caregivers. **Figure 5.10** shows that, before and during the transition, the trajectories of fruit and vegetable consumption were similar for caregivers and non-caregivers throughout the observation period. The confidence intervals largely overlapped, and the interaction term was statistically not significant (p=0.55) which suggest that there was no association between caregiving transition and the consumption of fruit and vegetables.

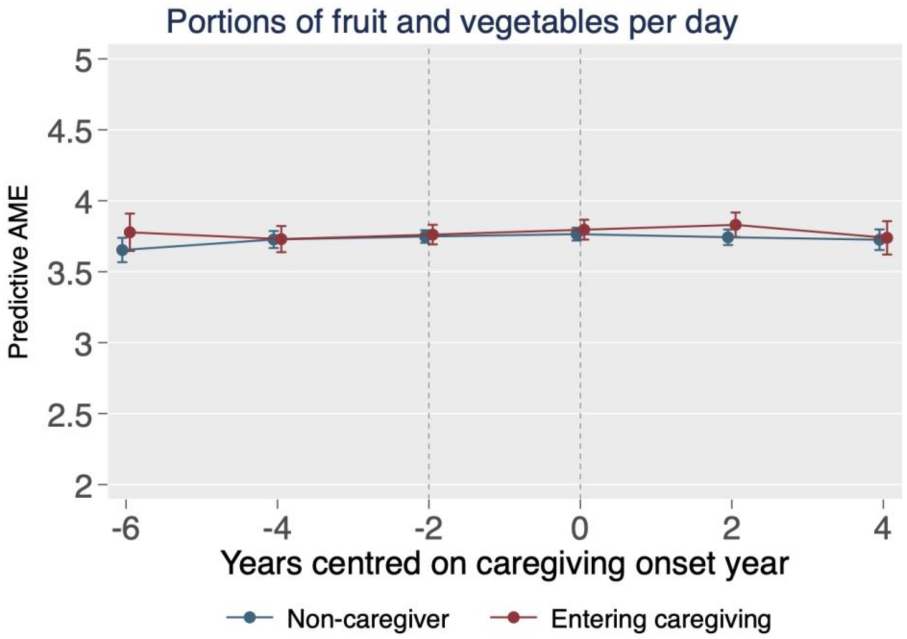


Figure 5.10 Trajectories of fruit and vegetable consumption by transition; average daily portions of fruit and vegetables before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, based on a propensity score matched sample (n=16,027; 4,692 caregivers, 11,559 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

In view of care hours at the first transition into caregiving, only 17.1% (n=736) of caregivers transitioned into higher intensity caregiving with providing 20 hours or more care per week while 82.9% (n=3,559) of caregivers transitioned into lower intensity caregiving with providing less than 20 hours of care per week. **Figure 5.11** represents the trajectories of daily fruit and vegetable consumption by care intensity and shows that high intensity caregivers had the lowest daily fruit and vegetable consumption compared to non-caregivers and low intensity caregivers and this difference began several years before the transition to caregiving. However, the trajectories remained stable during the transition period regardless of the care hours provided and the interaction term was statistically not significant (p=0.92) which suggests that there was no association between caregiving intensity and daily fruit and vegetable consumption.

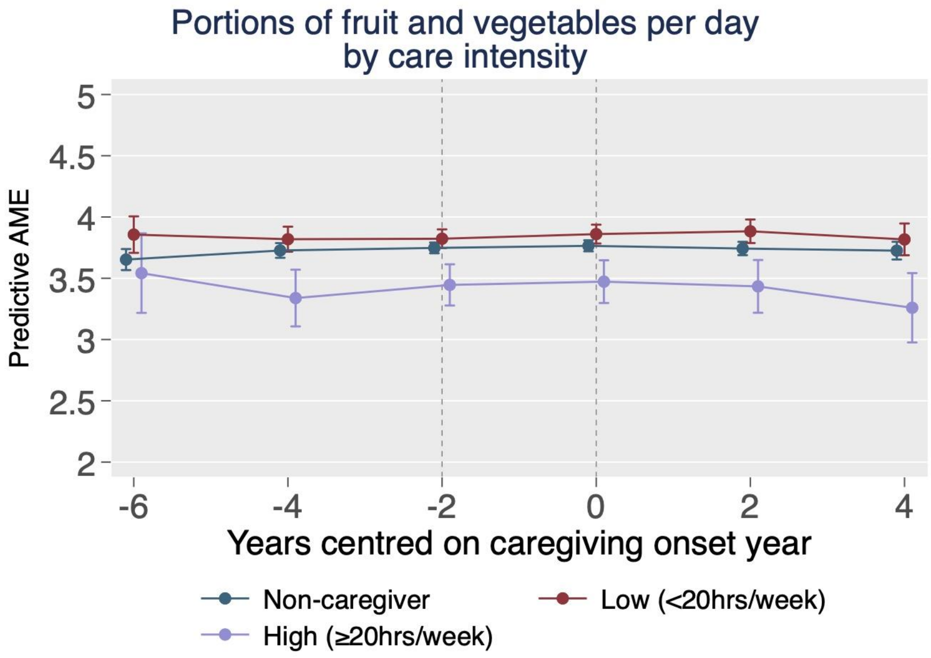


Figure 5.11 Trajectories of fruit and vegetable consumption by care hours; average daily portions of fruit and vegetables before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, stratified by caregiving intensity, based on a propensity score matched sample (n=15,854; 3,559 low-intensity caregivers, 736 high-intensity caregivers, 11,559 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

Because low and high intensity caregivers differed in their fruit and vegetable consumption prior to the caregiving transition, a sub-group analysis was performed in which low intensity caregivers were matched with high intensity caregivers via entropy balancing. **Figure 5.12** represents the trajectories of this sub-group analysis which shows that low intensity caregivers had a slight increase of their fruit and vegetable consumption compared to non-caregivers who had no change in their trajectories during the transition period. However, the increase was small, the confidence intervals were largely overlapping, and the interaction term was statistically not significant (p=0.69) which suggests that there was no association between care intensity and daily fruit and vegetable consumption.

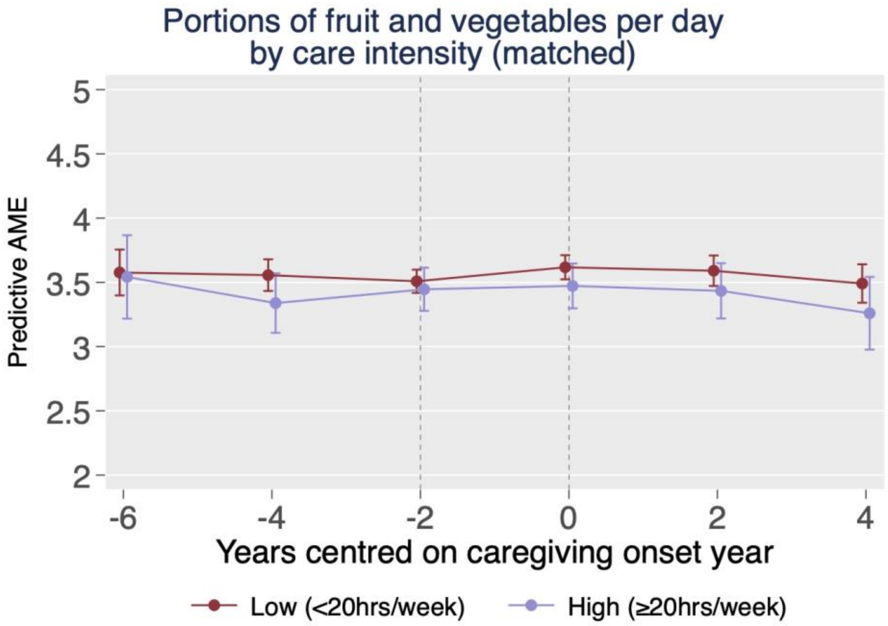


Figure 5.12 Trajectories of fruit and vegetable consumption by matched care hours; average daily portions of fruit and vegetables before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, comparing low-intensity (<20 hours) and high-intensity (≥20 hours) caregivers, based on a propensity score matched sample (n=4,295; 3,559 low-intensity, 736 high-intensity caregivers). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

Place of care

In view of place of care, 65.4% (n=2,924) participants transitioned into caregiving roles outside of their household while 29.9% (1,333) transitioned into caregiving within their household and 4.7% (n=209) transitioned into dual caregiving (inside and outside household). **Figure 5.13** represents the trajectories of fruit and vegetable consumption stratified by place of care during the transition. While caregivers who provide care inside the household and dual caregivers had on average a lower consumption of fruits and vegetables compared to non-caregivers and caregivers who provided care outside the household, the trajectories were similar during the transition period. The interaction term between place of care and the transition variable was statistically not significant (p=0.88) which suggests that the transitioning into a particular place of care was not associated with the daily consumption of fruits and vegetables.

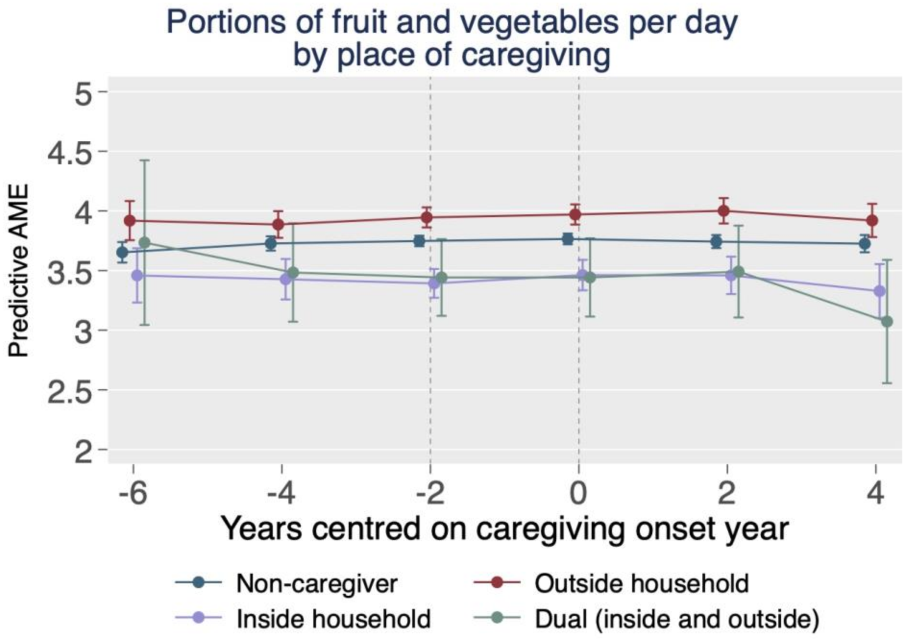


Figure 5.13 Trajectories of fruit and vegetable consumption by place of care; average daily portions of fruit and vegetables before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, stratified by place of care at onset, based on a propensity score matched sample (n=16,025; 2,924 outside household, 1,333 inside household, 209 both inside and outside, 11,559 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

5.4.2.4 The role of age and sex on trajectories

Sex

Regarding sex, 59.4% (n=2,656) of those who transitioned into caregiving were female and 40.6% (n=1,812) were male.

Figure 5.14 represents the trajectories of daily fruit and vegetable consumption stratified by caregiving status and sex. Overall, men reported lower daily fruit and vegetable consumption than women, regardless of caregiving status, but both groups remained stable with their daily fruit and vegetable consumption during the transition into caregiving compared to matched non-caregivers. Only in the years after the caregiving transition, men and women became more similar in view of their daily fruit and vegetable consumption. However, the interaction term of the interaction between caregiving status, transition variable and sex was not statistically significant (p=0.17) which suggest that sex did not modify the relationship between transition into caregiving and daily fruit and vegetable consumption.

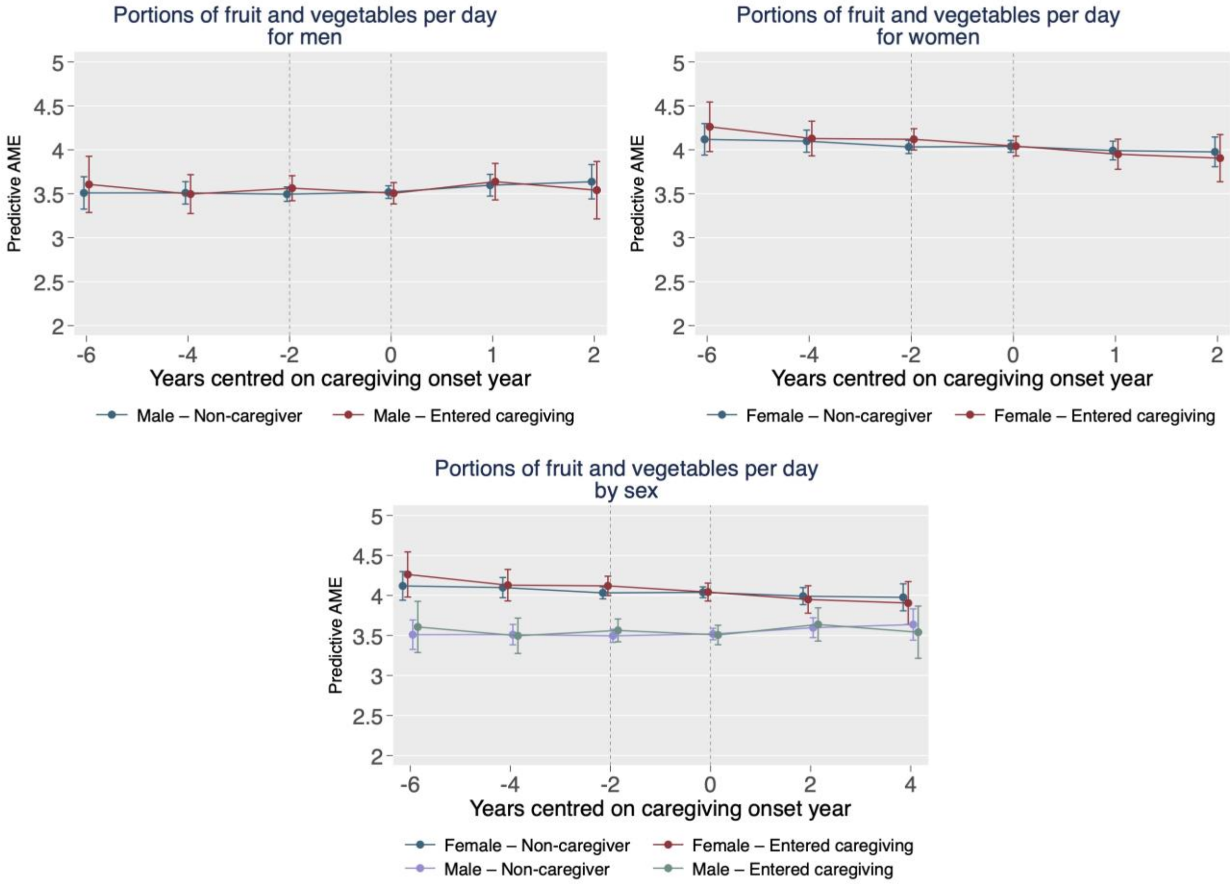


Figure 5.14 Trajectories of fruit and vegetable consumption by sex; average daily portions of fruit and vegetables before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, stratified by sex, based on a propensity score matched sample (n=16,027; 2,656 female caregivers, 1,812 male caregivers, 11,559 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

Age groups

Out of all participants who transitioned into caregiving, 10.5% (n=467) transitioned between the ages 19-29, 34.7% (n=1,550), transitioned between the ages 30-49, 33.9% (n=1,515), transitioned between the ages 50-64, and 21.0% (n=936) were 65 years or older when they transitioned into caregiving. An interaction test was performed between caregiving status, the transition variables and age group at baseline which was marginally non-significant (p=0.06) which suggests that age did not modify the relationship between transitioning into caregiving and daily fruit and vegetable consumption. When analysing trajectories separately by age group, none of the interaction terms testing for differences in slopes before and after the transition into caregiving were statistically significant. The interaction terms for early mid-adulthood and late mid-adulthood approached significance but did not meet the conventional threshold (p=0.07 and p=0.08 respectively) and the magnitude of the association was very small. When comparing trajectories across the age groups of those who transition in **Figure 5.15**, an age effect emerges in which caregivers in early mid-adulthood had the lowest fruit and vegetable consumption compared to the other age groups. However, there was no evidence that transitioning into caregiving was associated with changes in fruit and vegetable intake across any age group.

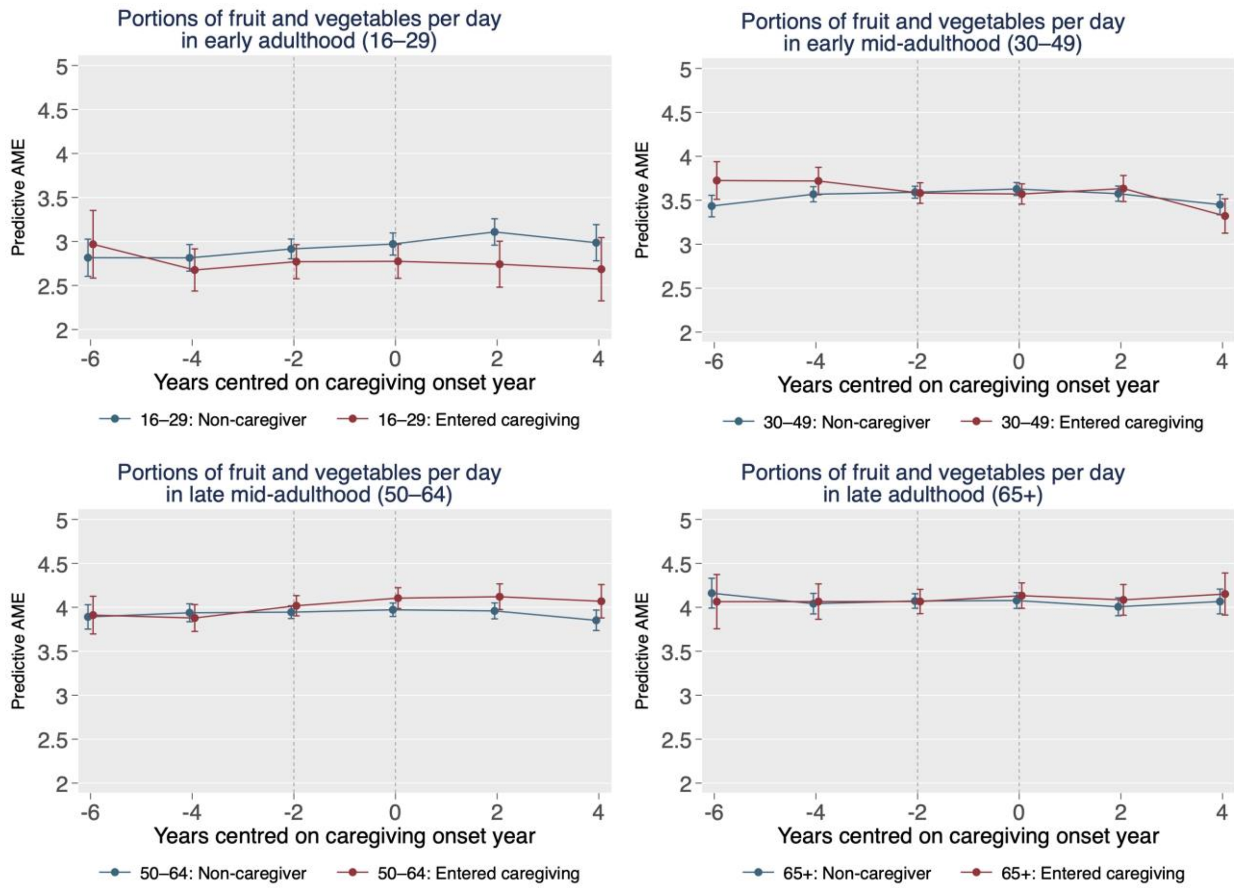


Figure 5.15 Trajectory of diet by age group; average daily portions of fruit and vegetables before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, stratified by age at caregiving onset, based on a propensity score matched sample (n=16,027; 467 early adulthood [16–29], 1,550 early mid-adulthood [30–49], 1,515 late mid-adulthood [50–64], 936 late adulthood [65+], 11,559 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

5.4.2.5 Summary

This analysis investigated the relationship between transition into caregiving and fruit and vegetable consumption, measured as portions of daily fruit and vegetable consumption. The unadjusted analysis revealed that caregivers consumed slightly more fruits and vegetables compared to non-caregivers, with minor differences based on caregiving hours. Participants who provided less than 20 hours of care consumed more fruit and vegetables than participants who provided more than 20 hours of care per week. In the adjusted analysis, FE regression did not reveal any significant association between caregiving transition and fruit and vegetable consumption. Likewise, there were no significant associations when accounting for caregiving hours, sex and age groups. These results were confirmed by the piecewise growth curve models of the propensity score matched sample which failed to identify significant associations between those who transition into unpaid care and those who did not although it could be observed that caregivers in early adulthood had the lowest fruit and vegetable consumption compared to older caregivers. Overall, this analysis suggests that transitioning into caregiving did not significantly change fruit and vegetable consumption.

5.4.3 Problematic drinking

5.4.3.1 Unadjusted analysis

The outcome of interest in this section was problematic drinking based on cut-offs of the Audit-C score as described in Chapter 4.4. Measures. **Table 5.6** shows the prevalence of problematic drinking across the UKHLS waves, stratified by caregiving status and hours of care. Over the study period, caregivers had a lower prevalence of problematic drinking across the four waves and the prevalence of problematic drinking decreased over time for caregivers and non-caregivers. However, when comparing caregivers who provided less than 20 hours of caregiving per week and those providing more than 20 hours per week, stark differences emerged. Caregivers who provided less than 20 hours of care per week had a higher prevalence of problematic drinking compared to non-caregivers and high intensity caregivers. In contrast, caregivers who provided more than 20 hours of care per week had the lowest prevalence of problematic drinking compared to non-caregivers and low intensity caregivers. The difference in the prevalence of problematic drinking was up to 14% between low intensity and high intensity caregivers.

Table 5.6 Cross-sectional prevalence of problematic drinking in waves 7,9,11 and 13 of UKHLS among participants who reported caregiving status and physical inactivity at least once during this period, by caregiving status and caregiving hours

UKHLS wave	N=46,929	Caregiver	Non-caregiver	<20 hrs care	>20hrs care
7	39,600	46.6%	49.1%	50.2%	36.6%
9	35,096	48.0%	49.8%	51.4%	39.1%
11	30,524	43.8%	47.7%	47.7%	34.2%
13	27,809	42.6%	45.0%	47.0%	33.0%

5.4.3.2 FE models

To assess the association of caregiving and problematic drinking within individuals, FE models were estimated on 9,455 individuals for caregiving status and 9,417 individuals on care hours (**Table 5.7**). For caregiving status, transitioning into caregiving was associated with higher odds of problematic drinking which was marginally statistically significant although the lower 95% CI being 1 (OR=1.09, 95%CI: 1.00/1.19, p=0.05) when adjusted for wave. In view of care hours, transitioning into less intense caregiving (<20 hours per week), was associated with increased odds of problematic drinking increased (OR=1.11, 95%CI: 1.01/1.22) while there was no significant association for participants who transitioned into higher intensity (>20 hours per week) caregiving (OR=1.05, 95%CI: 0.89/1.24). However, the magnitude of the association was small and the global p-value for this variable suggest that there was no evidence for a significant relationship between caregiving hours and problematic drinking in the FE models.

In view of interactions (**Table 5.7**), there was no evidence that sex modified the relationship between caregiving status, caregiving hours and problematic drinking (p=0.20 and p=0.13 respectively). Further, there was no evidence for an interaction between caregiving hours and sex. However, there was a significant interaction between care hours and age groups (p=0.01) and the stratified results suggest that transitioning into higher intensity caregiving was associated with higher odds of problematic drinking for caregivers in early mid-adulthood (30-49) (OR=1.38, 95%CI: 1.02/1.38) and late adulthood (65+) (OR=1.36, 95%CI: 1.09/1.69) while there was no evidence for this association in early adulthood (16-29) and late mid-adulthood (50-64) as shown in **Table 5.8**. However, all age groups have overlapping confidence intervals.

Table 5.7 Fixed-effect regression for problematic drinking and transitioning into caregiving

Model	**Sample**		**OR**	**95% CI**	**p**
Model: Caregiving status + adjustment for wave	$N_{participants}$ = 9,455	Non-caregiver	1.00	-	0.05
	$N_{observations}$= 32,484	Caregiver	1.09	1.00/1.19	
Interactions					
Caregiving-status*sex					0.20
Caregiving-status*age-group					0.13
Model: Caregiving hours + adjustment for wave	$N_{participants}$ = 9,417	Non-caregiver	1.00	-	0.09
	$N_{observations}$= 32,296	< 20 hours care	1.11	1.01/1.22	
		>20 hours care	1.05	0.89/1.24	
Interactions					
Caregiving-hours*sex					0.27
Caregiving-hours*age-group					0.01

Table 5.8 Stratified fixed-effect regression for problematic drinking, stratified by age

Stratified results	**N=**		**OR**	**95% CI**	**p**
Caregiving hours and age groups					
Early adulthood (16-29)	$N_{participants}$ = 2,559	Non-caregiver	1.00	-	
	$N_{observations}$= 8,025	< 20 hours care	1.16	0.92/1.47	0.47
		>20 hours care	1.03	0.65/1.63	
Early mid-adulthood (30-49)	$N_{participants}$ = 3.026	Non-caregiver	1.00	-	
	$N_{observations}$= 10,545	< 20 hours care	1.08	0.92/1.28	0.09
		>20 hours care	1.38	1.02/1.85	
Late mid-adulthood (50-64)	$N_{participants}$ = 2,169	Non-caregiver	1.00	-	
	$N_{observations}$= 7,884	< 20 hours care	0.93	0.79/1.10	0.38
		>20 hours care	0.82	0.61/1.11	
Late adulthood (65+)	$N_{participants}$ = 1,663	Non-caregiver	1.00	-	
	$N_{observations}$= 5.842	< 20 hours care	1.36	1.09/1.69	0.01
		>20 hours care	0.91	0.64/1.29	

5.4.3.3 Trajectories of problematic drinking

Caregiving status

In the next step, the trajectories of the probability of problematic drinking were estimated based on the propensity score matched sample in which 4,468 participants transitioned into the role of a caregiver and 12.782 matched participants who remained non-caregivers. **Figure 5.16** represents the predicted probability of problematic drinking that compared participants who transitioned into caregiving (caregivers) vs participants without transition (non-caregivers). Throughout the transition periods, the trajectories between those who transitioned into caregiving and non-caregivers showed no differences. The p-value for the interaction between the slope variable and the transition variable was statistically not significant (p=0.73) which suggest that there was no evidence for a relationship between transitioning into caregiving and the probability of problematic drinking.

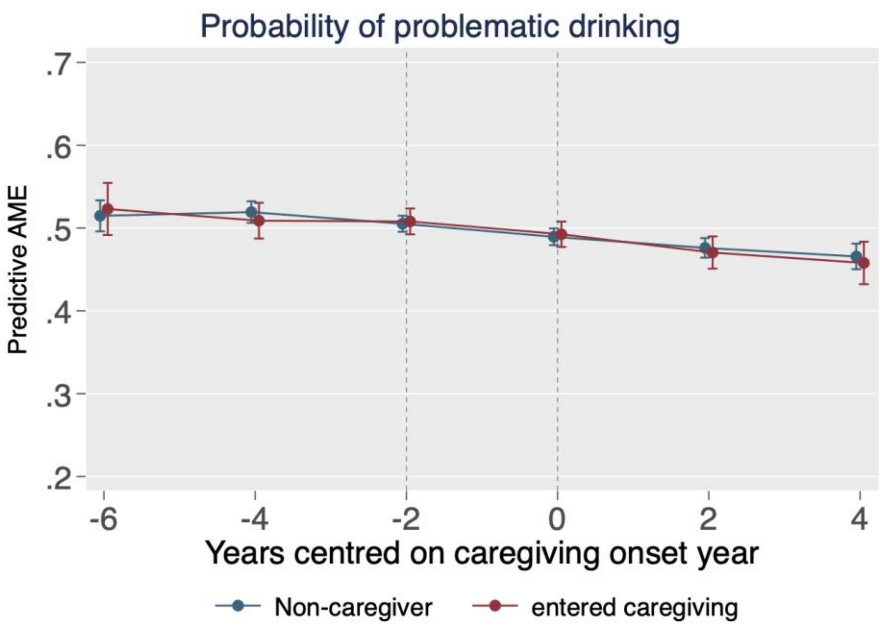


Figure 5.16 Trajectories of problematic drinking by transition; Probability of problematic drinking before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, based on a propensity score matched sample (n=17,250; 4,468 caregivers, 12,782 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

Caregiving hours

Regarding caregiving hours, 82.9% (n=3,560) transitioned into lower intensity caregiving (less than 20 hours per week) while 17.1% (n=735) transitioned into higher intensity caregiving (> 20 hours of care or more per week). **Figure 5.17** depicts the trajectories of problematic drinking, stratified by the hours of care. While higher intensity caregivers had lower probability of problematic drinking compared to non-caregivers and low intensity caregivers, the decrease in problematic drinking across the transition into caregiving looked similar across the strata. However, in the period after the transition, higher intensity caregivers had a more prominent decline in problematic drinking compared to non-caregivers but this difference was not statistically significant (p=0.62). Because low and high intensity caregivers were different in their bassline probability of problematic drinking, a sub-group analysis was performed in which high intensity caregivers were matched with low intensity caregivers in **Figure 5.17**. It can be observed that higher intensity caregivers had a more pronounced decrease in problematic drinking after the transitioning into caregiving, but experienced no differences in slope change during the transition, compared to lower intensity caregivers but this association was statistically not a significant (p=0.21).

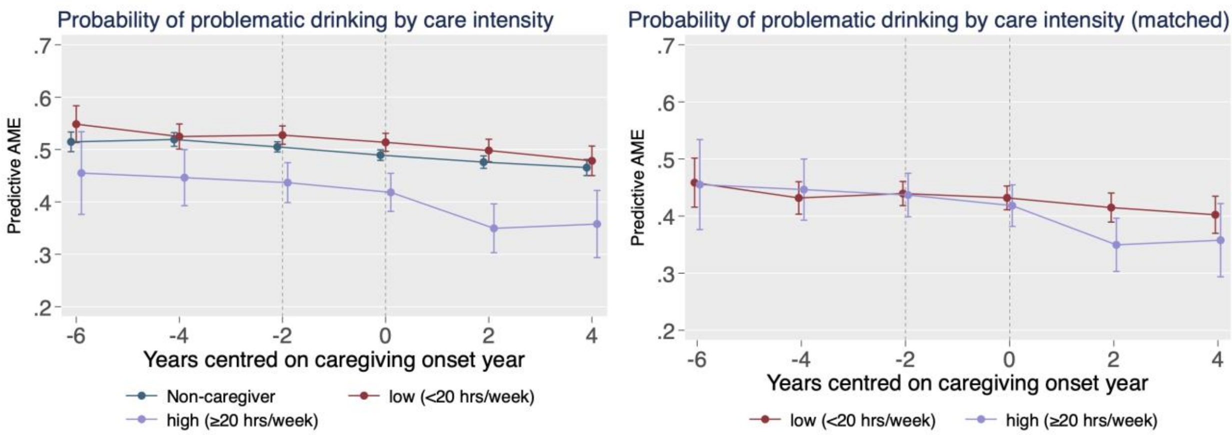


Figure 5.17 Trajectories of problematic drinking by care hours; left panel: probability of problematic drinking before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, stratified by caregiving intensity, based on a propensity score matched sample (n=17,250; 3,560 low-intensity caregivers, 735 high-intensity caregivers, 12,782 controls). Right panel: Probability of problematic drinking before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, comparing low-intensity (<20 hours) and high-intensity (≥20 hours) caregivers, based on a entropy balanced matched sample (n=4,295; 3,560 low-intensity, 735 high-intensity caregivers). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

Place of care

Regarding the place of care, 65.4% (n=2,921) transitioned into caregiving that took place outside of the own household, while 29.9% (n=1,335) participants transitioned into caregiving within the household, and 4.7% (n=210) transitioned into caregiving inside and outside the household. **Figure 5.18** depicts the trajectories of problematic drinking by place of care. Participants who provided care outside the household had the highest probability of problematic drinking before and after the transition compared to non-caregivers, inside household caregivers and dual caregivers. In contrast, caregivers inside the household and dual caregivers had lower probability of problematic drinking before and after the transition compared to non-caregivers and caregivers providing care outside the household. During the transition into caregiving, there were only slight differences between the strata and caregivers inside the household showed a slightly more pronounced decline in problematic drinking. However, confidence intervals were large and overlapped and the test of the overall interaction term between place of care, transition and the time variable was statistically not significant (p=0.60) which suggests that there was no evidence that the place of care modified the relationship between a transitioning into caregiving and problematic drinking.

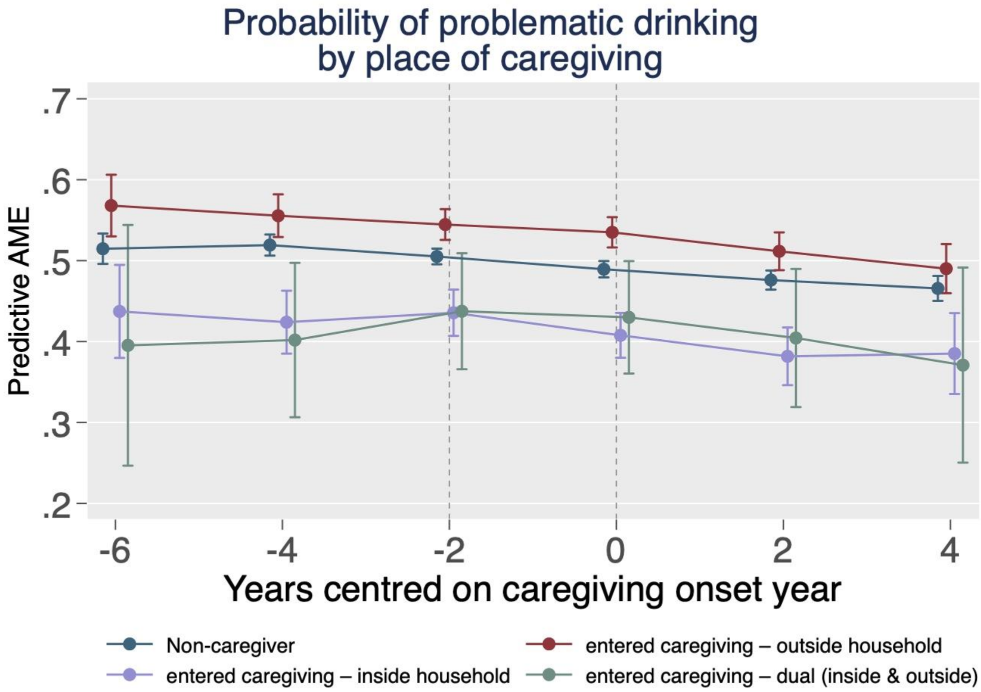


Figure 5.18 Trajectories of problematic drinking by place of care; probability of problematic drinking before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, stratified by place of care at onset, based on a propensity score matched sample (n=17,250; 2,921 outside household, 1,335 inside household, 210 both inside and outside, 12,782 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

5.4.3.4 The role of age and sex on trajectories

Sex

In view of sex, 40.6% (n=1,810) of those who transitioned into caregiving were male and 59.4% (n=2,658) were female. The sex stratified trajectories are depicted in **Figure 5.19**. Trajectories were very similar for male and female caregivers compared to their matched non-caregivers and the interaction term was not significant (p=0.37). This suggests that sex did not modify the association between transitioning into caregiving and problematic drinking.

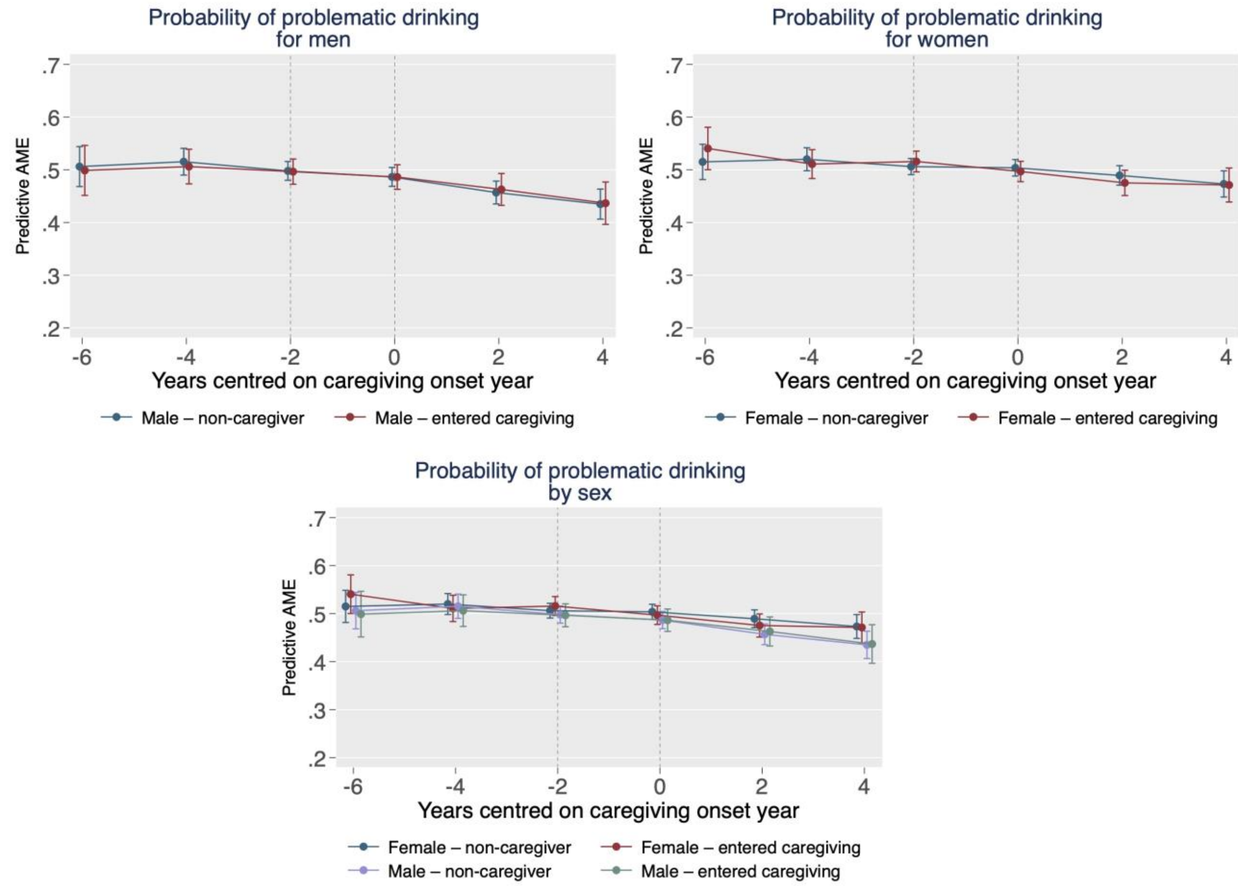


Figure 5.19 Trajectories of problematic drinking by sex; probability of problematic drinking before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, stratified by sex, based on a propensity score matched sample (n=17,250; 2,658 female caregivers, 1,810 male caregivers, 12,782 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

Age groups

Regarding age groups, 10.5% (n=467) transitioned between the ages 16-29 (early adulthood), 34.6% (n=1,548), between the ages 30-49 (early mid-adulthood), 34.0% (n=1,518) between the ages 50-64 (late mid-adulthood), and 20.9% (n=935) when they were 65 or above (late adulthood). **Figure 5.20** depicts the trajectories of problematic drinking by age-group. Participants in late adulthood had the lowest probability of problematic drinking compared to participants in early adulthood had lower probability of problematic drinking compared to adult or participants in late mid-adulthood. However, when comparing the trajectories between those who transitioned into caregiving and those who did not, only transitioning into caregiving in early adulthood was associated with a small decrease in problematic drinking compared to matched non-caregivers, but large overlapping confidence intervals could be observed which may be due to the lower sample size in this age category. In view of the other age groups, there were no notable differences between the strata and similar trajectories between those who transitioned into caregiving and those who did not, could be observed. The interaction term for age-group was statically not significant (p=0.78) which suggest there is no evidence that age modified the association between transitioning into caregiving and the probability of problematic drinking.

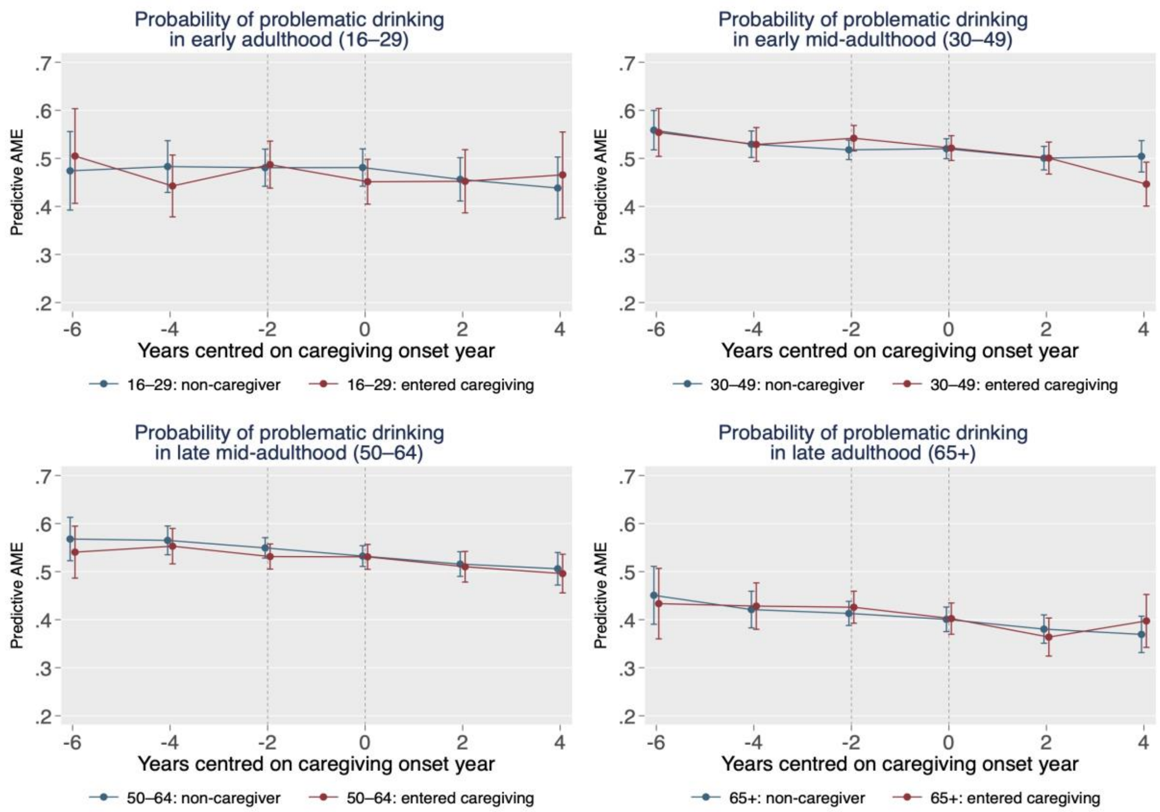


Figure 5.20 Trajectories of problematic drinking by age group; probability of problematic drinking before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, stratified by age at caregiving onset, based on a propensity score matched sample (n=17,250; 467 early adulthood [16–29], 1,548 early mid-adulthood [30–49], 1,518 late mid-adulthood [50–64], 935 late adulthood [65+], 12,782 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

5.4.3.5 Summary

This analysis investigated transitioning into caregiving and changes in problematic drinking. In the unadjusted analysis, caregivers had a lower prevalence of problematic drinking compared to non-caregivers. Notably, the prevalence of problematic drinking between low and higher intensity caregivers was in stark contrast to each other. Participants who provided less than 20 hours of care had the highest prevalence of problematic drinking while caregiver providing more than 20 hours of care had the lowest prevalence of problematic drinking compared to non-caregivers.

The adjusted analysis using FE models revealed that transition into caregiving was associated with higher odds of problematic drinking although this only remained statistically significant for participants who provided less than 20 hours of care when accounting for hours of care. There were no significant differences in associations between caregiving hours and problematic drinking by sex but there were by age groups. Participants in early mid-adulthood (30-49) who transitioned into higher intensity care and participants who transitioned into lower intensity care had higher odds of problematic drinking compared to non-caregivers of the same age.

These findings could not be replicated in the trajectory analysis of the piecewise growth curve models. Which showed that there was no evidence for a significant relationship between caregiving transition and problematic drinking although higher intensity caregivers showed a more pronounced decrease in the probability of problematic drinking after the transition into caregiving took place. Stratification by age group revealed that while there was an age effect of drinking in which caregivers in late adulthood had generally lower probability of problematic drinking compared to caregivers in early adulthood, these associations were not related to the caregiving transition. However, the overall trajectories were similar across all age groups which suggests that the age did not modify the association between transitioning into caregiving and problematic drinking. These overall inconsistent findings suggest that the relationship between caregiving and problematic drinking is complex.

5.4.4 Smoking

5.4.4.1 Unadjusted analysis

Table 5.9 shows the prevalence of smoking in percentage between wave 5 and 9 of UKHLS, stratified by caregiving status and caregiving hours. All groups showed general decline in smoking prevalence over the study period. The smoking prevalence among non-caregivers started at 17.6% in wave 5 and steadily decreased to 10.2% by wave 13. Across all waves, caregivers were consistently slightly more likely to smoke compared to non-caregivers. Caregivers who provided more than 20 hours of care per week consistently had the highest smoking prevalence across all waves, starting at 25.3% in wave 5 and declining to 17.4% by wave 13. In comparison, caregivers providing less than 20 hours per week and non-caregivers had lower and more similar smoking rates throughout, with both groups showing a gradual decline. By wave 13, smoking prevalence among caregivers providing less than 20 hours per week was 9.6%, closely aligning with non-caregivers at 10.2%.

Table 5.9 Cross-sectional smoking in waves 5 to 13 of UKHLS among participants who reported caregiving status and physical inactivity at least once during this period, by caregiving status and caregiving hours

UKHLS wave	N=57,498	Caregiver	Non-caregiver	<20 hrs care	>20hrs care
5	42,729	19.7%	17.6%	17.7%	25.3%
6	39,203	19.7%	16.1%	17.8%	25.2%
7	40,852	17.3%	15.2%	15.4%	22.7%
8	35,509	16.3%	14.2%	14.5%	20.5%
9	35,570	15.4%	13.0%	13.6%	20.7%
10	33,938	14.3%	12.8%	13.0%	17.8%
11	30,542	13.4%	11.9%	11.8%	17.4%
12	29,115	12.2%	10.8%	11.2%	14.8%
13	27,864	11.8%	10.2%	9.6%	17.4%

5.4.4.2 FE models

The full sample consisted of 55,011 participants, but fixed-effects logistic regression models were based on around 6,028 participants for caregiving status and 6,011 for caregiving hours, as only individuals who experienced variation in both smoking status over time contributed to the estimation. The model with caregiving status revealed that there was evidence that transitioning into caregiving was association with higher odds of smoking (OR=1.16, 95% CI: 1.07–1.27) after adjusting for wave to account for the temporal decline in the likelihood of smoking (**Table 5.10**). This association was independent of the intensity of caregiving participants transitioned into. Transitioning into lower-intensity caregiving was associated with a 15% increase in the odds of smoking (OR=1.15; 95% CI: 1.05/1.27), while transitioning into higher-intensity caregiving was associated with a 17% increase in the odds (OR: 1.17; 95% CI: 1.00–1.37). However, the confidence interval for higher-intensity caregiving was wider and included 1 at the lower bound, which may be due to lower sample size as only 14.8% of participants transitioned into higher intensity care (>20 hours per week) while 85.2% transitioned into lower intensity care (<20 hours per week). There was no evidence that the association between caregiving and smoking differed by sex or age group although the interaction between caregiving hours and age group was marginal non-significant (p=0.08).

Table 5.10 FE regression for smoking status and entering caregiving

Model	Sample n=57,498		OR	95% CI	p
Model: Caregiving status + adjustment for wave	$N_{participants}$ = 6,263 $N_{observations}$= 40,084	Non-caregiver Caregiver	1.00 1.16	- 1.07/1.27	 0.001
Interactions					
Caregiving-status*sex					0.84
Caregiving-status*age-group					0.20
Model: Caregiving hours + adjustment for wave	$N_{participants}$ = 6,011 $N_{observations}$= 38,823	Non-caregiver < 20 hours care >20 hours care	1.00 1.15 1.17	- 1.05/1.27 1.00/1.37	<0.001
Interactions					
Caregiving-hours*sex					0.90
Caregiving-hours*age-group					0.08

5.4.4.3 Trajectories of smoking

Smoking status

Figure 5.21 represents the trajectories of the predicted probabilities of smoking based on a sample of 8,659 participants who transitioned into unpaid caregiving and their 17,317 matched non-caregiving controls. With this approach, it was possible to model seven years before to seven years after the onset of caregiving. Prior to the onset of caregiving, participants who transitioned into caregiving and those who did not showed relatively similar probabilities of smoking but the group who transitioned into caregiving showed a slightly lower initial probability of smoking compared to those who did not transition into caregiving. However, their confidence intervals were largely overlapping, indicating no significant difference.

At the onset of caregiving, the probability of smoking for those who transitioned into caregiving began to diverge from those who do not transition. This transition also marked the beginning of a visual increase in the probability of smoking for those who transitioned into caregiving. In the years following the transition into caregiving, the probability of smoking increased further for the caregiving group. The divergence became more pronounced over time, with non-overlapping confidence intervals indicating a significant difference between the two groups. The interaction term between timing of caregiving onset and transition category was statistically significant (p=<0.001) which suggest that there was evidence that transitioning into caregiving is associated with slope changes in the probability smoking status.

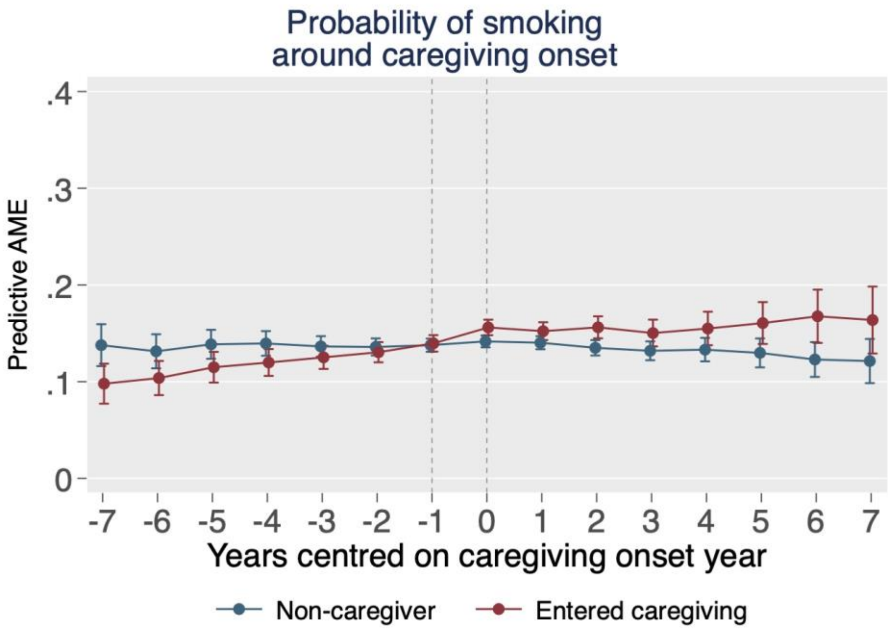


Figure 5.21 Trajectories of smoking by transition; probability of smoking before and after caregiving onset across UKHLS waves 5 to 13, based on a propensity score matched sample (n=25,976; 8,659 caregivers, 17,317 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

Caregiving intensity at initial caregiving episode

Regarding the hours of care, 85.2% (n=7,082) of participants transitioned into lower intensity caregiving which is defined as providing less than 20 hours of care per week while 14.8% of participants (n=1,234) transitioned into higher intensity caregiving (more than 20 hours of care per week). When stratifying by care intensity in **Figure 5.22**, measured by the hours of care, distinct patterns in smoking behaviour emerged. Before the onset of caregiving, participants who transitioned and those who did not showed similar probabilities of smoking with higher intensity caregivers showed slightly higher and more variable probabilities. As the onset of caregiving approached, the probabilities for smoking increased in those providing higher intensity care and remained during the post-transition period. This contrasted sharply with the participants who transitioned into low-intensity caregiving and non-caregivers where smoking probabilities remained stable, and the same as one another, over time. The p-value for the interaction term between timing of caregiving onset and care intensity at the first caregiving episode, which represented differences in slope change during the transition, was statistically significant ($p<0.001$). However, in the matched sub-sample comparing low- and high-intensity caregivers, the slope change was not statistically significant ($p=0.12$).

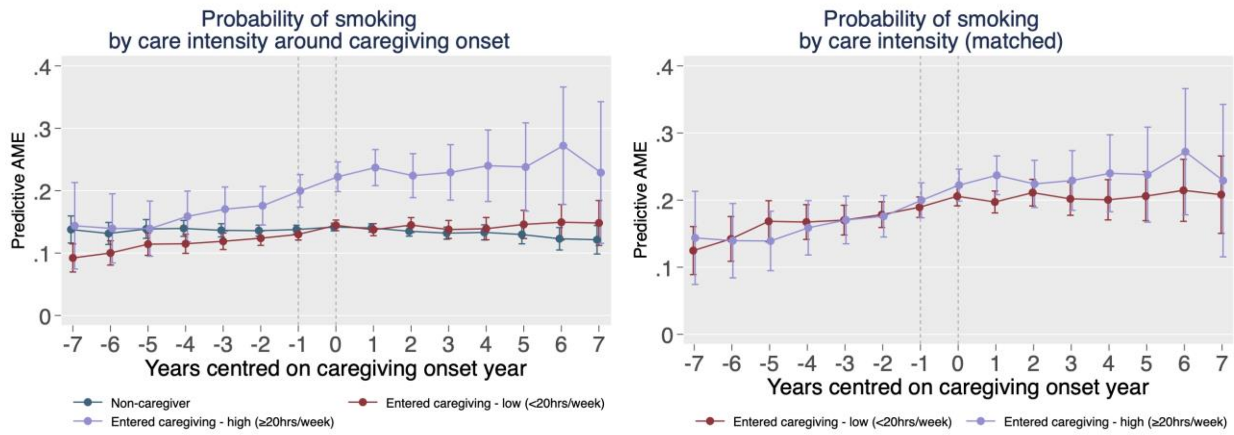


Figure 5.22 Trajectories of smoking by care hours; Left panel: Probability of smoking before and after caregiving onset across UKHLS waves 5 to 13, stratified by caregiving intensity, based on a propensity score matched sample (n=25,976; 7,082 low-intensity (<20 hours) caregivers, 1,234 high-intensity (≥20 hours) caregivers, 17,317 controls). Right panel: Sub-group analysis of probability of smoking before and after caregiving onset across UKHLS waves 5 to 13, low intensity caregivers entropy balance matched with high intensity caregivers.

Number of cigarettes

In addition to smoking status, the trajectories of the number of cigarettes they smoked per day was also assessed. For this, the number of cigarettes was examined regarding normal distribution and outliers. It was found that the number of cigarettes was semi-continuous because it was not normally distributed. Out of all observation, 87.1% had a value of “zero” which means that they were excess zeros for this variable. Additionally, there was a large number of outliers as the number of cigarettes ranged from 0 to 400. To address outliers, the variable was trimmed at 80 cigarettes after graphical inspection of the histogram and box plot (Appendix 4.7). To account for the excess zeroes, two-part models were employed. The two-part model approach is particularly suitable for this analysis due to the semi-continuous nature of the variable that quantifies the number of cigarettes which is characterised by a significant proportion of non-smokers with zero values and a continuous range of cigarettes smoked amongst smokers. The first part of the model assesses the likelihood of smoking using logistic regression while the second part of estimates the number of cigarettes smoked. Based on these estimates, it is possible to calculate predictive marginal effects of the semi-continuous variable that considered both, the regression and also the logistic part.

In **Figure 5.23**, the number of cigarettes per day were modelled by caregiving transition using two-part models. The observed trend was very similar to the trend when examining smoking status and there was increase in the number of cigarettes smoked for those who transitioned into caregiving compared to non-caregiving matched controls during and after the transition period. The interaction term between time of care onset and the transition variable was statistically significant ($p<0.001$). However, it must be acknowledged that this analysis is heavily driven by smoking status because 87.1% of observation had a value of zero.

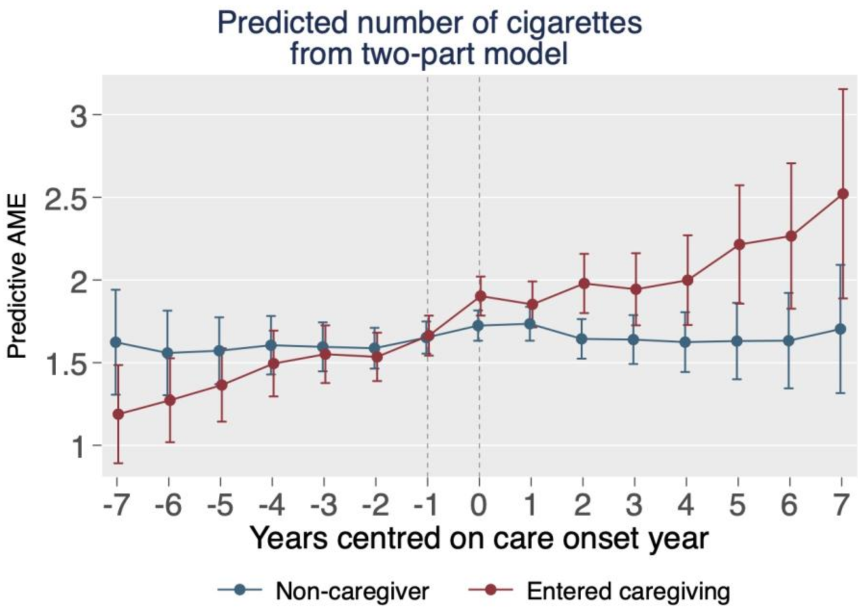


Figure 5.23 Trajectories of number of cigarettes by transition; average number of cigarettes smoked before and after caregiving onset across UKHLS waves 5 to 13, based on a two-part model and a propensity score matched sample (n=25,976; 8,659 caregivers, 17,317 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

Smoker at baseline

Therefore, a sub-group analysis was performed on participants who were smokers at baseline. This sub-group analysis had a sample of 4,278 participants of which 1,492 participants transitioned into caregiving and 2,786 were non-caregiving controls (n=4,275; n-transition=1,492; n-controls= 2,783). For this analysis, two-part models were employed to estimate the average number of cigarettes smoked per day for participants who were smokers at baseline as shown in **Figure 5.24**. Among participants who were smokers at baseline, there was no evidence of a difference in the trajectories of cigarette consumption between those who transitioned into caregiving and those who did not, during or after the transition period. The interaction term representing the slope change during the caregiving transition was not statistically significant (p=0.46), suggesting that for individuals who were already smokers, transitioning into caregiving was not associated with a change in the number of cigarettes smoked.

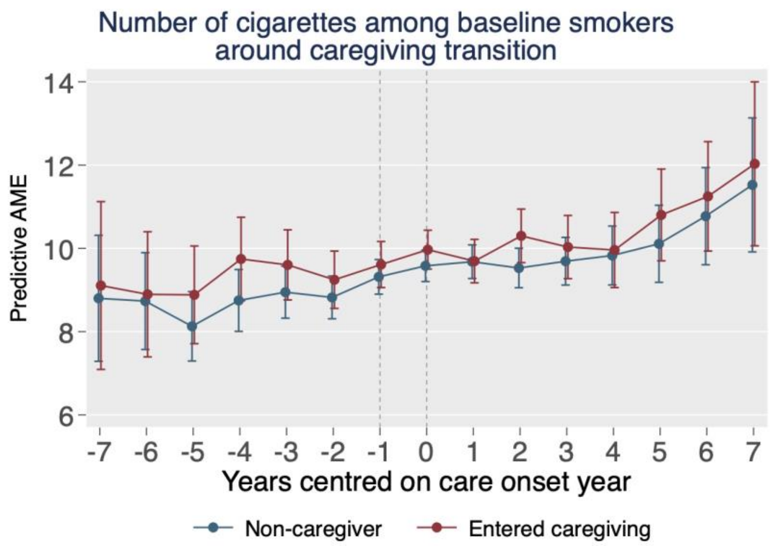


Figure 5.24 Trajectories of number of cigarettes when smoker at baseline; average number of cigarettes smoked before and after caregiving onset across UKHLS waves 5 to 13, among participants who were smokers at baseline, based on a two-part model and a propensity score matched sample (n=4,278; 1,492 caregivers, 2,786 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

Further, when stratifying by care intensity in the first care episode in **Figure 5.25**, participants who were smokers at baseline and who transition into more intense caregiving category seemed to increase the number of cigarettes smoked per day, but this association was statistically not significant (p=0.23) probably due to the large overlapping confidence intervals. Also, the increase in the number of cigarettes already occurred one year prior to the transition into caregiving.

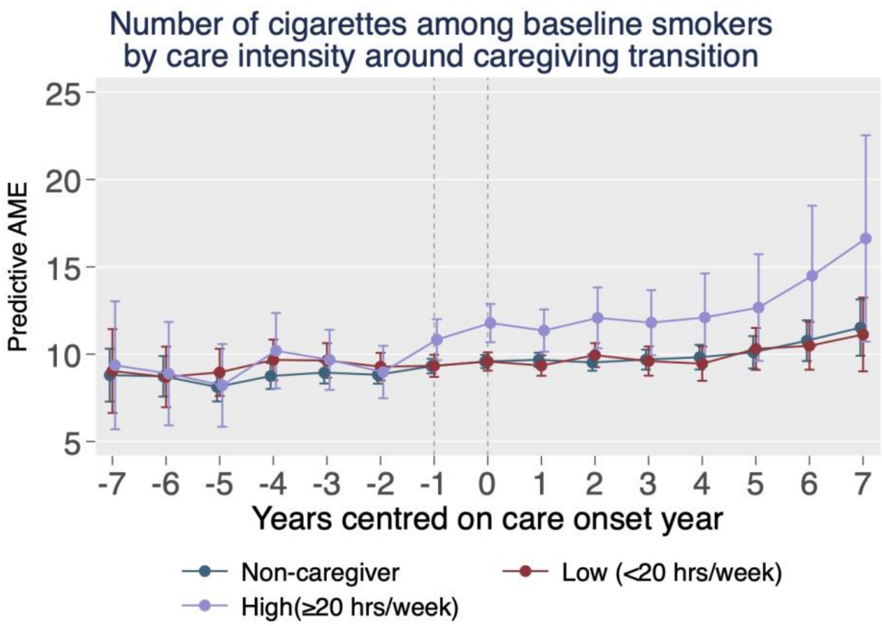


Figure 5.25 Trajectories of number of cigarettes by care hours when smoker at baseline; average number of cigarettes smoked before and after caregiving onset across UKHLS waves 5 to 13 among participants who were smokers at baseline, based on a two-part model and a propensity score matched sample (n=4,216; 1,141 low-intensity (<20 hours) caregivers, 292 high-intensity (≥ 20 hours) caregivers, 2,783 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

Place of caregiving

In view of place of caregiving, 68.5% (n=5,933) participants transitioned into caregiving outside the household while 28.3% (n=2,450) transitioned into caregiving inside the household and 3.2% (n=274) transitioned into caregiving within as well as outside the household. **Figure**

5.26 illustrates the probabilities of smoking comparing participants who transition into caregiving and non-caregivers, stratified by place of care. Participants who provide care outside of the household and non-caregivers show similar probabilities of smoking before and after the transition of caregivers. In contrast, participants who provide care inside the household or dual caregiving (inside and outside the household) showed a pronounced increase in the probability of smoking which began in the wave prior to the onset of caregiving compared to non-caregivers but the slope change was marginally non-significant across groups (p=0.07). However, it must be acknowledged that the sample size for dual caregivers is relatively small (n=274).

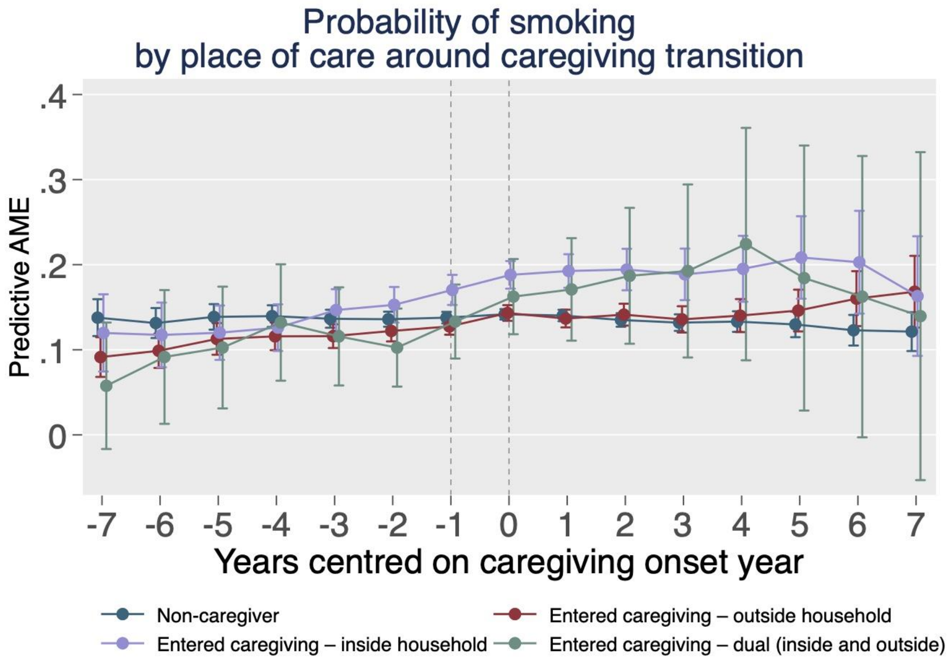


Figure 5.26 Trajectories of smoking by place of care; probability of smoking before and after caregiving onset across UKHLS waves 5 to 13, stratified by place of care at onset, based on a propensity score matched sample (n=25,974; 5,933 outside household, 2,450 inside household, 274 both inside and outside, 17,317 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

5.4.4.4 The role of age and sex on trajectories

Sex

In view of sex, of those who transitioned into unpaid care, 58.4% (n=5,058) were female and 41.6% (n=3,6061) were male. **Figure 5.27** models the probability of smoking seven years before and after the onset of caregiving, stratified by sex. For both male and female participants, the smoking probabilities were quite similar between those who transition into caregiving and non-caregivers before the transition to caregiving, but after the onset of caregiving, those who transition show significant increases in their probability of smoking for both men and women. Although male caregivers tended to have slightly higher overall smoking probabilities than female caregivers, the trajectories for both sexes are largely parallel. The interaction term for sex was not statistically significant ($p = 0.82$), indicating little evidence that sex modifies the relationship between caregiving transition and smoking.

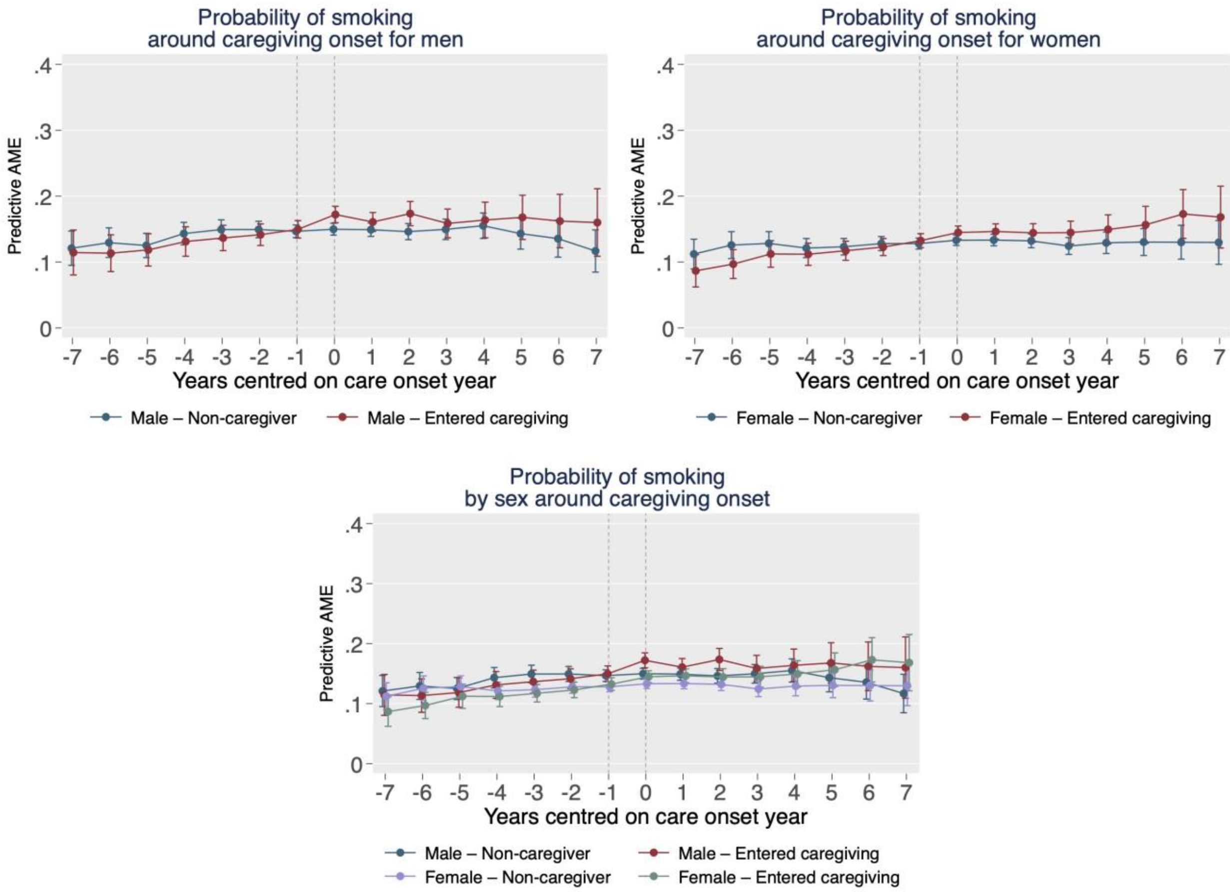


Figure 5.27 Trajectories of smoking by sex; Probability of smoking before and after caregiving onset across UKHLS waves 5 to 13, stratified by sex, based on a propensity score matched sample (n=25,976; 5,058 female caregivers, 3,601 male caregivers, 17,317 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

Age groups

In view of age groups, 16.6% (n=1,441) of those who transitioned into caregiving were between 16-29 years old while 35.6% (n=3,083) were between 30-49; 28.8% (n=2,497) between 50-64; and 18.9% (n=1,638) 65 years or older. **Figure 5.28** reveals that there an age gradient in the probability of smoking in participants in early adulthood have the highest probability of smoking and participants in late adulthood had the lowest probability of smoking. Besides, the association between transitioning into caregiving and smoking status differed by age groups. In caregivers in early adulthood (16-29), the probability of smoking increases when they transition into unpaid care while smoking probabilities remain relatively stable after the transition as shown in **Figure 5.28**. This association was even more pronounced in caregivers in early mid-adulthood (30-49) who showed a sharper increase in their probability of smoking that persisted in the years following the transition. For caregivers in late mid-adulthood (50-64) and late adulthood (65+), there are only small changes in their probability of smoking when they transitioned into caregiving, but smoking probabilities were generally comparable to non-caregivers. There were no significant association for middle-aged or older caregivers in late mid-adulthood and late adulthood while caregivers in early adulthood and caregivers in early mid-adulthood had a significant increase in the probability of smoking when they transitioned into caregiving compared to those who did not transition. The interaction term for the transition period was statistically significant (p=0.02). Post-transition, the probability of smoking increased continuously for caregivers in early mid-adulthood which was also statistically significant (p=0.05). These findings suggest that transitioning into caregiving before the age of 50 may be associated with an increased likelihood of smoking.

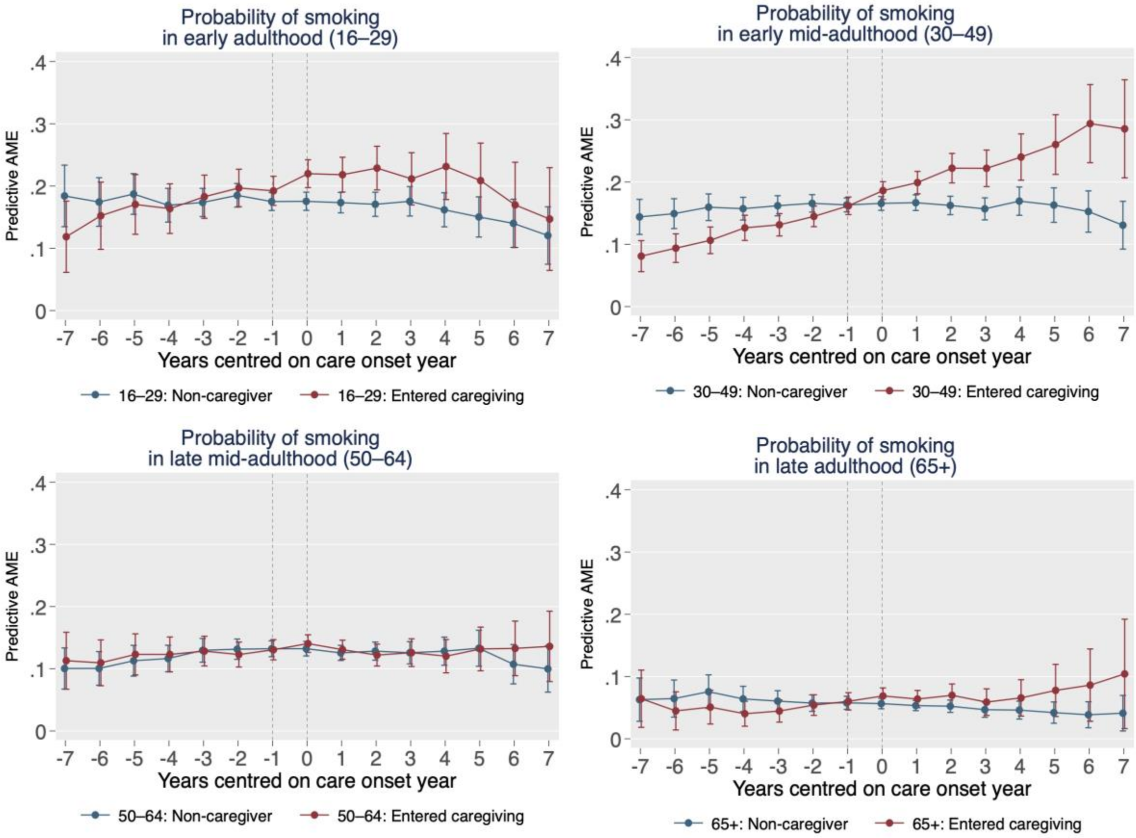


Figure 5.28 Trajectories of smoking by age group; Probability of smoking before and after caregiving onset across UKHLS waves 5 to 13, stratified by age at caregiving onset, based on a propensity score matched sample (n=25,976; 1,441 early adulthood [16–29], 3,083 early mid-adulthood [30–49], 2,497 late mid-adulthood [50–64], 1,638 late adulthood [65+], 17,317 controls). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

5.4.4.5 Summary

In the unadjusted analysis, it was found that smoking rates declined strongly across the sample and that caregivers had on average higher smoking rates compared to non-caregivers over the observation period. While caregivers who provided less than 20 hours of care closed the gap in smoking rates to similar levels as non-caregivers, caregivers who provided more than 20 hours of care had the highest smoking prevalence compared to non-caregivers and low intensity caregivers.

In the adjusted analysis using FE models, it was found that transitioning into caregiving was associated with higher odds of smoking regardless of care intensity. Sex and age group did not modify this association. These findings were confirmed by the trajectory analysis of the piecewise growth curve models. Transitioning into caregiving was associated with higher probability of smoking. Amongst smokers, transitioning into caregiving was associated with smoking an increased number of cigarettes only when more intense care was provided.

There was no evidence that sex modifies the relationship between transitioning into unpaid care and smoking while there was evidence that the association between transitioning into caregiving and smoking differed by age groups. There was an increase in the probability of smoking for caregivers in early adulthood and caregivers in early mid-adulthood under age 50 compared to their respective matched non-caregivers and the increase was sustained for caregivers in early mid-adulthood aged 30-49 only. This analysis suggests that caregiving, especially intensive caregiving is associated with higher smoking rates and increase in smoking behaviour over time and that transitioning into caregiving below the age of 50 is associated with an increase in smoking behaviour.

5.5 Discussion

This chapter aimed to investigate transitioning into caregiving and changes in health behaviours across the lifecourse in a large population-based longitudinal sample in the UK. For the analysis a dual approach was applied in which two methods were used to answer the research questions comparing FE models and piecewise growth curve models on a propensity score-matched sample. It was found that transitioning into caregiving was associated with a decrease in physical inactivity and an increase in the probability of smoking. Findings on problematic drinking were mixed. While FE models suggested an increase in problematic drinking following the transition into caregiving, this was not supported by the piecewise growth curve models which found no difference between those who transition into caregiving and those who do not. Lastly, there was no evidence for significant associations between transitioning into caregiving and changes in fruit and vegetable consumption.

An important consideration in interpreting the findings relates to how caregiving transitions were measured in the dataset. Participants were classified as entering caregiving based on self-reported responses to questions about providing regular help to a sick, disabled, or elderly person either inside or outside their household. However, this approach relies on self-identification and recognition of care tasks, which may not fully capture the gradual or informal nature of caregiving onset, particularly in the early life stages.[214] According to role theory,[24,25] individuals may engage in caregiving behaviours well before they adopt the caregiver identity. Tasks such as helping with transportation, emotional support, or occasional household management may not be immediately recognised as 'caregiving', especially when they evolve from existing family roles.[25] As a result, the measurement may underestimate or delay the observed transition into caregiving, particularly for lower-intensity or emerging caregiving roles. A previous study using piecewise growth curve models found that there was a decline in physical and mental health of participants prior to becoming a caregiver[17] which supports role theory of caregiving. This has implications for understanding the timing of changes in health behaviours, as some individuals may experience caregiving-related stress or role strain prior to formally reporting a caregiving role. It also raises broader questions about how caregiving is conceptualised and measured in population-level data and whether greater nuance is needed to capture early, hidden, or identity-neutral care work, particularly in policy-relevant research.

It must be noted that survey weights, that account for complex survey design, were not applied in the analysis, and this decision was methodologically justified given the modelling strategies employed**.** For the FE models, the focus was on estimating within-individual change over time. Since these models control for all time-invariant characteristics by design, and do not rely on population-level estimates, the application of survey weights is not necessary.[202,215] For the piecewise growth curve models, the analysis was conducted on a propensity score-matched sample, which purposefully alters the sample composition to balance covariates between treatment groups (those who transitioned into caregiving and those who remained non-caregivers). This matching process renders the resulting sample non-representative of the original population by design.[216–218] Hence, applying survey weights intended for the full population to a matched sample may not be necessary. The priority in this context was to ensure internal validity and comparability between groups, rather than generalisability to the broader population. Together, these methodological choices reflect a deliberate focus on causal inference and internal validity, aligning with the study's aim to understand the mechanisms of change in health behaviours following caregiving transitions.

One of the methodological challenges in this analysis was how to appropriately model cigarette consumption, given the distributional characteristics of the variable. Over 80% of respondents reported smoking zero cigarettes, resulting in excess zeroes and a strong right-skew in the data. In response, two-part models were selected as a pragmatic and theoretically sound approach. These models are well-suited for outcomes with a large proportion of zeroes and a continuous positive skew among non-zero responses. Their use is supported by previous studies that recommend two-part or zero-inflated models for similar behavioural health outcomes.[219–221] To further strengthen the analysis, a sensitivity analysis was conducted using a zero-inflated negative binomial (ZINB) model, which demonstrated superior fit in predicting the count distribution compared to other poison approaches, as reported in

Appendix 5.6. However, when comparing the predicted trajectories of cigarette consumption across caregiving transitions, both the ZINB and two-part models yielded identical trajectories in the piecewise growth curve framework. This result provides confidence that the two-part model not only offered a conceptually appropriate but also a robust and empirically justified modelling strategy for modelling the number of cigarettes people smoked over time.

The findings related to problematic drinking were inconsistent and appeared to vary by analytic approach**.** In the FE models, transitioning into caregiving was associated with increased odds of problematic drinking. In contrast, the piecewise growth curve models did not show a statistically significant association overall. The discrepancy between the fixed-effects models and the piecewise growth curve models may be explained by several factors. Firstly, in the FE models, only individuals who experienced a change in the outcome contributed to the estimation and as a result the sample for the fixed effect models and the sample for the piecewise growth curve model were different and had different sample sizes. Secondly, the two approaches answer subtly different questions. FE models estimate within-person changes, controlling for all time-invariant confounding, whereas the piecewise growth curve models compare trajectories between matched groups of caregivers and non-caregivers. Lastly, while the FE model suggested slightly higher odds of problematic drinking associated with caregiving, the magnitude of this association was relatively small.

Also, findings for problematic drinking varied by age group and caregiving intensity. Although the trajectories of problematic drinking were broadly similar across age groups, it seemed transitioning into caregiving in early adulthood (16-29) was associated with a decrease in problematic drinking compared to non-caregivers of the same age group. However, when stratifying for the intensity to which participants transition, it emerges that individuals providing high-intensity care (≥ 20 hours per week) consistently showed a lower probability of problematic drinking over time. This relationship appeared to reflect stable differences between groups rather than changes due to the caregiving transition itself. This may suggest that people who engage in more intensive caregiving may already have lower alcohol consumption levels, which could be explained with higher role responsibility or differing lifestyle patterns. These findings can be interpreted in a few ways. One possibility is that the onset of caregiving, particularly in mid- and later life, may initially lead to elevated stress, increasing the risk of maladaptive coping behaviours such as alcohol use.[89,94,134,142,159,222,223] Over time, however, individuals may adapt to caregiving demands, develop new coping mechanisms, or reduce drinking due to increased accountability and responsibility.[96,125,223,224] Another explanation is self-selection into caregiving roles, whereby individuals with lower-risk behaviours (such as drinking) may be more likely to take on intensive caregiving duties which would align with the 'healthy carer hypothesis'.[225,226] These patterns underscore the need to consider both the timing and intensity of caregiving when examining its impact on health behaviours and suggest that the relationship between caregiving and alcohol use may be shaped by a combination of role strain, adaptation, and selection mechanisms.

5.5.1 Limitations

One limitation of the analysis is that the employed fixed-effects logistic regression models used conditional maximum likelihood estimation, which excludes individuals whose outcome variable does not vary over time. While this method effectively controls for unobserved, time-invariant individual characteristics, it may reduce the sample size because participants without a change in outcome do not contribute to the estimates.[215,227,228] As alternative, fixed-effects Linear Probability Model (LPM) could have been considered.[227] The advantage of the LPM is that it retains all individuals in the sample, regardless of variation in the outcome[227] which may offer additional insights, particularly in studies where binary outcomes are rare (<25%). However, LPM also has limitations, including the possibility of predicted probabilities falling outside the [0,1] range.[229,230] Future work might benefit from comparing both modelling approaches to assess the robustness of results and better understand the implications of sample selection in fixed-effects analyses.

It must also be acknowledged that the presented analysis is constraint by the availability and timing of outcome data. Some health behaviours were only measured in alternate waves and were available for a maximum of four time points. While the analysis was designed to capture changes in health behaviours around key caregiving transitions, the infrequent measurement schedule introduces potential limitations. Specifically, the two-year gaps between data collection points may not adequately capture short-term or more immediate fluctuations in behaviour that occur in response to caregiving onset. As a result, the piecewise growth curve models may have missed more subtle or time-sensitive patterns of behavioural change, particularly if changes occurred soon after the transition but then stabilised by the time of the next survey wave. This limitation highlights the need for more frequent and precisely timed measurements in future research to better understand the temporal dynamics of caregiving-related health behaviour change.

5.6 Chapter conclusion

This chapter had the aim to investigate the relationship between transitioning into unpaid caregiving and changes in health behaviours across the lifecourse using longitudinal quantitative data from the largest household panel study in the UK. It was found that that transition into caregiving is associated with a decrease in physical inactivity and an increase in smoking behaviour. However, no changes in fruit and vegetable consumption could be observed and the relationship between transitioning into caregiving and problematic drinking was more complex. It was also found that there was no evidence that the association between caregiving transition is modified by sex while caregiving intensity and the lifecourse stage seem to be determinants of health behaviours during a transition into unpaid caregiving. While this chapter addressed key knowledge gaps in the relationship between transitioning into caregiving and health behaviours, it remains unknown how these behaviours change when individuals exit a caregiving role. The following chapter explores this next stage of the caregiving trajectory

6 Caregiving exit and changes in health behaviours

6.1 Introduction

In the previous chapter, the relationship between transitioning into caregiving and changes in health behaviours, such as physical inactivity, fruit and vegetable consumption, smoking and problematic drinking, was investigated. It was found that transitioning into caregiving was associated with a decrease in physical inactivity and increased smoking behaviour. However, transitioning into caregiving was not associated with a change in fruit and vegetable intake while the relationship between entering caregiving and problematic drinking was more complex.

While the impact of caregiving on health behaviours has been studied to some extent, there is a lack of evidence on how health behaviours change once caregiving ends. The scoping literature review from Chapter 2 did not identify any longitudinal studies that specifically examine the relationship between exiting caregiving and changes in physical inactivity, diet, alcohol consumption, smoking, or other health-related behaviours. This gap in the literature is unexpected, given that the cessation of caregiving represents a major life transition. It may bring a sense of relief from responsibilities, but also emotional challenges such as grief, guilt, or a disruption in personal identity. These factors could plausibly influence behavioural changes. This chapter addresses this gap by investigating whether, and to what extent, health behaviours change after caregiving ends.

6.1.1 Exit due to care recipient transition to institutional care

The transfer from unpaid and informal caregiving to a more formal setting or institutional caregiving may occur because the care needs of the care recipient exceed those that the caregiver can provide.[231–233] In other cases, a caregiver may not be able to continue with their role due to personal circumstances, such as ill health or moving into institutional care themselves. One might expect that this transfer to formal caregiving might be a relief for caregivers with a high subjective burden, but evidence suggests that there are more conflicting emotions at play if the care recipient is transferred to institutional caregiving settings. A study with 339 dementia caregivers found that feelings of guilt and embarrassment were inversely associated with the desire for institutionalisation.[234] This is supported by other studies which found that transitioning to institutional caregiving was associated with frustration and disappointment[235] among caregivers or the feeling that they have not adequately fulfilled their caregiving role and responsibilities.[236]

However, the increase in care needs of the care-recipient might not be the only reason why a transition to institutional caregiving becomes necessary. Some evidence has described how a decline in the physical and mental health of the caregiver may necessitate the use of formal care services.[237] Further, family dynamics and conflicts may influence decisions for institutional care. Family conflict is defined as tension, interpersonal struggles, or outright hostility among caregivers and other family members outside the caregiver–care recipient dyad. This can manifest as disagreement over particular care issues, such as the timing of placement, the choice of institution, or the perception that not enough was done to keep the relative at home, all of which can influence decisions regarding to transition to formal care settings.[238]

6.1.2 Exit due to death of the care recipient

Caregiving cessation often occurs due to the death of the care recipient which can also be conceptualised as a transition from caregiving to bereavement. This transition is associated with grief and depressive symptoms which may persist beyond the exit of caregiving. Research suggests, that that there is an increase in depressive symptoms in the period leading to the death due to the increased emotional burden.[239] This could be attributed to the anticipatory grief that caregivers may experience which has been shown to account for a significant variation in depressive symptoms among family caregivers of individuals with dementia.[240] This anticipatory grief can intensify emotional distress following the death of the care recipient, as caregivers may experience profound loss and sadness despite having had time to prepare or anticipate the death during their caregiving journey.[241]

Research also suggests that bereavement can exacerbate pre-existing depressive symptoms. For example, one study found that caregivers who had depressive symptoms prior to the death of the care recipient were more likely to suffer from complicated grief or depression after the death of the care recipient.[242] However, it might take one or two years until the difference between normal and prolonged grief emerges.[243] In contrast, some studies find that a higher care burden prior to the death of the care recipient was associated with fewer depressive symptoms after the death which supports the theory that exiting caregiving may provide some relief.[244]

However, these grief trajectories are not universal and some studies suggest that the emotional state of caregivers may fluctuate over time with some individuals experiencing a temporary relief in depressive symptoms shortly after the care recipient's death while others may experience more complicated grief trajectories that lead to sustained emotional distress.[245,246]

One study found found that bereavement after placing the care recipient into a long-term care facility intensified grief after the death of care recipient.[247]

6.1.3 Exit due to recovery of the care recipient

Research on caregiving dynamics often emphasises the cessation of caregiving due to increased care needs or the death of the care recipient, and scenarios where the care recipient's condition improves are less frequently studied. In fact, the cessation of caregiving due to recovery does not seem to be a common trajectory of caregiving cessation according to caregiving role theory.[24,25] Instead, many studies highlight that a higher caregiver burden and exhaustion are more frequently associated with the end of caregiving roles,[248] while improvements in the care recipient's condition can foster a more sustainable caregiving environment.[249]

Besides, studies have shown that the resilience of caregivers can be enhanced if care recipients experience more positive outcomes.[250] Other studies highlighted the importance of the reciprocal relationship between caregiver and recipient as they reported that a good quality of life of the caregiver was associated with more positive health outcomes of the care recipient.[251] Therefore, it may well be that an improvement of the care-recipient's health status generates more favourable conditions for the continuation of (less intense) caregiving rather than cessation.

In summary, the reasons why individuals exit caregiving may vary but are often accompanied by negative emotional experiences such as guilt, grief and depression. While cessation of caregiving with regards to mental health has been frequently studied,[32,252–254] it has remain unexplored how health behaviours change when individuals stop providing care. Although the objective burden of care is reduced, as caregiving tasks cease and time availability may increase, the emotional toll often persists. Feelings of grief, guilt, and a continued sense of responsibility may represent a legacy of caregiving that continues to act as a source of stress. On the other hand, an exit from caregiving may represent teachable moments. Such periods are disruptive and may prompt individuals to reflect on their health behaviours in light of changes to their role, identity, and emotional state. This chapter aims to close this gap in knowledge by investigating if and to what extent health behaviours of caregivers change when they transition out of caregiving.

6.2 Chapter aim & objectives

It is the aim of this chapter to address Objective 2 and Objective 5, namely, to investigate the relationship between exiting unpaid caregiving and changes in health behaviours across the adult life course in the UK. Chapter objectives include:

2a. To investigate whether exiting caregiving is associated with changes in health behaviours (physical inactivity, healthy fruit and vegetable consumption, smoking and problematic drinking).

2b. To compare trajectories of health behaviours between individuals who exit caregiving and those do not experience a cessation to caregiving as well as those who never provide care.

2c. To assess whether the intensity of caregiving or place of caregiving prior to exit is associated with the magnitude of change in health behaviours amongst those who exit caregiving.

2d. To examine whether the associations between exiting caregiving and health behaviours are modified by sex or life course stage of the caregiver.

6.3 Methodology

6.3.1 Data

As with the previous chapter, the data will come from UKHLS. Due to the availability of outcome measures, the study period for smoking was defined as the period between wave 5 and wave 13 whereas for physical inactivity, fruit and vegetable consumption, and problematic drinking, the study period was defined to be waves 7,9,11 and 13. This was described in detail in Chapter 4.

6.3.2 Measures

Outcomes

The outcomes of interest were physical inactivity, fruit and vegetable consumption, problematic drinking and smoking (smoking status and number of cigarettes) as defined in Chapter 4.4.

Exposure

The main exposure of interest was caregiving exit / cessation. For the purpose of modelling growth curves, a new binary variable was created that indicated whether participants experienced an exit from caregiving. Participants were classified as "Exiters" if they who were caregivers at baseline but reported not providing care in any subsequent wave. Participants who did not experience a transition and remained caregivers or non-caregivers in the two respective analyses were coded as "0". While this chapter focuses on the transition out of caregiving, it must be acknowledged that the reasons for the caregiving exit, such as institutionalisation or death of care recipient, cannot be explicitly characterised within the available data.

Additionally, variables that characterised the caregiving prior to exit were created for participants who exited. The first variable was caregiving intensity which related to the hours of caregiving that were self-reported in the wave prior to the exit of caregiving and the categories were either (1) low intensity, defined as providing less than 20 of caregiving per week; or (2) high intensity, defined as providing 20 hours of caregiving or more per week. The second variable was place of caregiving prior to exit which could be (1) caregiving provided outside the household; (2) caregiving provided inside the household; or (3) caregiving provided inside and outside the household (dual).

Covariates

As in the previous chapter, covariates were divided into time-invariant covariates such as sex, education, ethnicity, and time-varying covariates such as occupational class, employment status, de facto marital status, quintiles of household income, household size, number of children living in the household, general self-rated health and psychological distress. Time-varying covariates measured prior to caregiving exit were treated as potential confounders, as it was hypothesised in the DAGs (Chapter 4.5) that they were associated with both, the likelihood of caregiving transitions and health behaviours outcomes. In contrast, time-varying covariates measured after caregiving exit could act as mediators through which the experience of caregiving cessation affects health behaviours. Additionally, for the analysis of inactivity, physical limitations were measured through the physical component of the SF-12 questionnaire. All of these measures are described in detail in Chapter 4.4.

All covariates were included at baseline in the propensity score matching (PSM) models to ensure comparability between caregivers who exited and the comparison groups. However, none of these covariates were included in the fixed-effect models, as many were considered likely to lie on the causal pathway between exiting caregiving and changes in health behaviours. For example, exiting caregiving may affect employment status or stress levels, which could in turn influence behaviours such as smoking, drinking, or physical activity.

6.3.3 Statistical analysis

Similar to the analysis in the previous chapter (Chapter 5.3) a dual approach was seen as most suitable to answer the research question rigorously. For this, fixed effect models were used to estimate the association between caregiving exit and health behaviour. Afterwards, propensity score matching was performed between participants who experience a care exit and those you did not experience this transition. Trajectories were then estimated and compared for each of the groups using piecewise growth curve models.

6.3.3.1 Fixed-effect models

As described in the previous chapter, Fixed Effect (FE) models are a suitable method to answer the research question because they measure the within-individual variation over time by controlling for unobserved characteristics if they are constant over time. For this, the data set was reshaped from wide to long (with stacked multiple observations per individual) and a variable created that was coded "1" when an exit to caregiving occurred. When no exit to caregiving occurred, the variable was coded to "0". Hence when there was a change from "0" to "1", this change within an individual would indicate caregiving exit and through fixed-effect regression (FE), it would be possible to measure the association of this transition on the outcomes of interest.

6.3.3.2 Matching methods

For the analysis of the trajectories, propensity score matching was conducted based on the binary exit variable that was created. Participants who exited caregiving were matched to participants who did not experience this transition which were either participants who were caregivers in all waves or non-caregivers in all waves. For each of these control groups different propensity score models were estimated but included the same covariates that were previously identified. To account for possible statistical difference of covariates post-matching, an entropy balance estimation was performed as described in Chapter 5, and an entropy balance weight was created for the analysis later. This ensured that participants who experienced exit were similar to those without exit in view of their covariates.

6.3.3.3 Piecewise growth-curve models

The approach for the piecewise growth-curve models is similar to the approach used in the previous Chapter 5. Following propensity score matching, controls were assigned a 'wave of exit' based on the 'wave of exit' of their matched exiter. It is important to note that there were two control groups, and the workflow for the two analyses was conducted separately because it was not feasible to perform propensity score matching on three groups. After matching, only those successfully matched were included in the final analysis.

For the piecewise growth curve models, the data set was reshaped from wide to long-, and a-time variable was generated, centred around the caregiving exit year (coded 0). Negative values indicated the period before the exit, while positive values indicated the period after the exit. Logistic regression was performed for physical inactivity, smoking, and problematic drinking, while linear regression was used for fruit and vegetable consumption diet, and two-part models were used for the number of cigarettes smoked which was described in Chapter 5. In brief, the two-part models were suitable for semi-continuous outcomes like the number of cigarettes. In the two-part models, the first part modelled the probability of smoking (versus not smoking) using logistic regression, and the second part modelled the number of cigarettes smoked among smokers using linear regression.

To assess the statistical significance of differences in trajectories, spline regression was performed for comparisons between "exit caregiving vs. continue caregiving" and "exit caregiving vs. no caregiving." The spline regression included two key values of interest per analysis: (1) the p-value for the actual transition (from time point "-2" or "-1" to time point "0") where a p-value of ≤ 0.05 would indicate a significant difference in slope change between the trajectories of those who exited caregiving compared to matched controls; and (2) the post-transition p-values, where a p-value of ≤ 0.05 would indicate significant differences in slope changes following caregiving exit between those who exited caregiving and those who did not. To account for clustering at the household level, the VCE-cluster option in Stata was used, as in the previous analysis.

6.3.4 Analytical sample

As outlined in the previous chapter, a tailored analytical approach was adopted for each outcome to retain the maximum possible sample size. For the fixed effect models, participants were included in the analysis if caregiving status and health behaviour variables were was observe. Fixed effect models assess the level of change within individuals and hence participants who had to change in the outcome over time were dropped from the analysis by Stata.

For the piecewise growth curve models, the primary analysis had the aim to compare participants who exited caregiving compared to those who continued caregiving as control group. Hence, participants were included in this study when they were caregivers at baseline. Participants who exited caregiving were included if they had at least one observation prior to exit and one observation after caregiving exit. Controls were included in the propensity score models if caregiving status was observed across at least two waves. After propensity score matching, the final analysis was conducted on participants who were successfully matched.

Comparing caregivers who exited the role with those who continued caregiving would seem as an intuitive approach to compare trajectories of those exit care and those who continue to provide care. However, this chapter aimed to investigate the association of experiencing a caregiving exit compared to not experience this transition more broadly. In this context, non-caregivers, who never identified as a caregiver during the observation period, serve as a conceptually distinct and meaningful comparison group. Similar to continuing caregivers, they did not experience a transition out of caregiving and thus allow for exploration of whether the end of caregiving is associated with changes in health behaviours relative to those who do not experience this transition.

Nonetheless, this approach has limitations. Non-caregivers may differ in important ways from caregivers, for example in unobserved characteristics such as personality traits that are not possible to be matched by in the propensity score matching or entropy balancing. While matching on observable baseline characteristics can address observable differences, residual confounding remains a possibility. Additionally, as non-caregivers never assumed the caregiving role, they do not represent a direct reference group for participants who exit caregiving. These limitations should be kept in mind when interpreting the findings from this secondary analysis.

For this secondary part of the analysis, non-caregivers were included in this study if they were non-caregivers at baseline and never entered caregiving during the study period. The inclusion criteria for participants who exited caregiving was the same as in the approach above, hence sample size of those who exited caregiving was the same in both approaches. Sample size flow charts are provided for illustrative purpose for smoking while the sample size flow charts for the physical inactivity, fruit and vegetable consumption and problematic drinking can be found in Appendix 6.2.

Fixed effect models

For the fixed-effect models of the binary outcomes such as physical inactivity, smoking, and problematic drinking, most participants were excluded from the analysis. This was because conditional fixed-effect logistic regression in Stata only includes individuals who experienced a change in the outcome during the observation period. As fixed-effects (FE) models control for time-invariant confounders within individuals, no additional covariates were included, as time-varying confounders may lie on the causal pathway between caregiving exit and health behaviours. Therefore, no cases were excluded due to missing in covariate data. After applying these criteria, fixed-effect models were conducted on 18,262 participants for physical inactivity (**Figure 5.1**) 9,465 for problematic drinking (**Figure A5.2**) ;and 6,263 for smoking (**Figure A5.3**). In contrast, fruit and vegetable consumption was measured as a continuous outcome, which increases the likelihood of detecting change compared to binary outcomes. As with the binary outcomes, individuals who reported no change in fruit and vegetable consumption diet over time were excluded from the analysis.

This explains the larger sample size (N) for the fruit and vegetable consumption diet outcome, as continuous measures are more sensitive to changes in values over time. To address outliers, only observations within the 99th percentile were included, resulting in a final sample size of 35,779 for fixed-effect regression on fruit and vegetable consumption diet (**Figure A5.1**).

Piecewise growth curve models on propensity score matched sample

The process of sample selection differed for the piecewise growth curve models, as illustrated. **Figure 6.1**, which outlines the steps for smoking, using data from nine waves of observations. The right-hand branch of the flowchart represents the sample selection process comparing participants who exited caregiving with those who remained caregivers throughout the study ("long-term caregivers"). In contrast, the left-hand branch depicts the selection process for comparing participants who exited caregiving with those who were never caregivers during any of the observed waves. After applying the inclusion criteria, 5,385 participants who exited caregiving were matched with 1,467 long-term caregiving controls (right-hand branch) and 13,220 non-caregiving controls (left-hand branch). This is depicted in **Figure 6.1**.

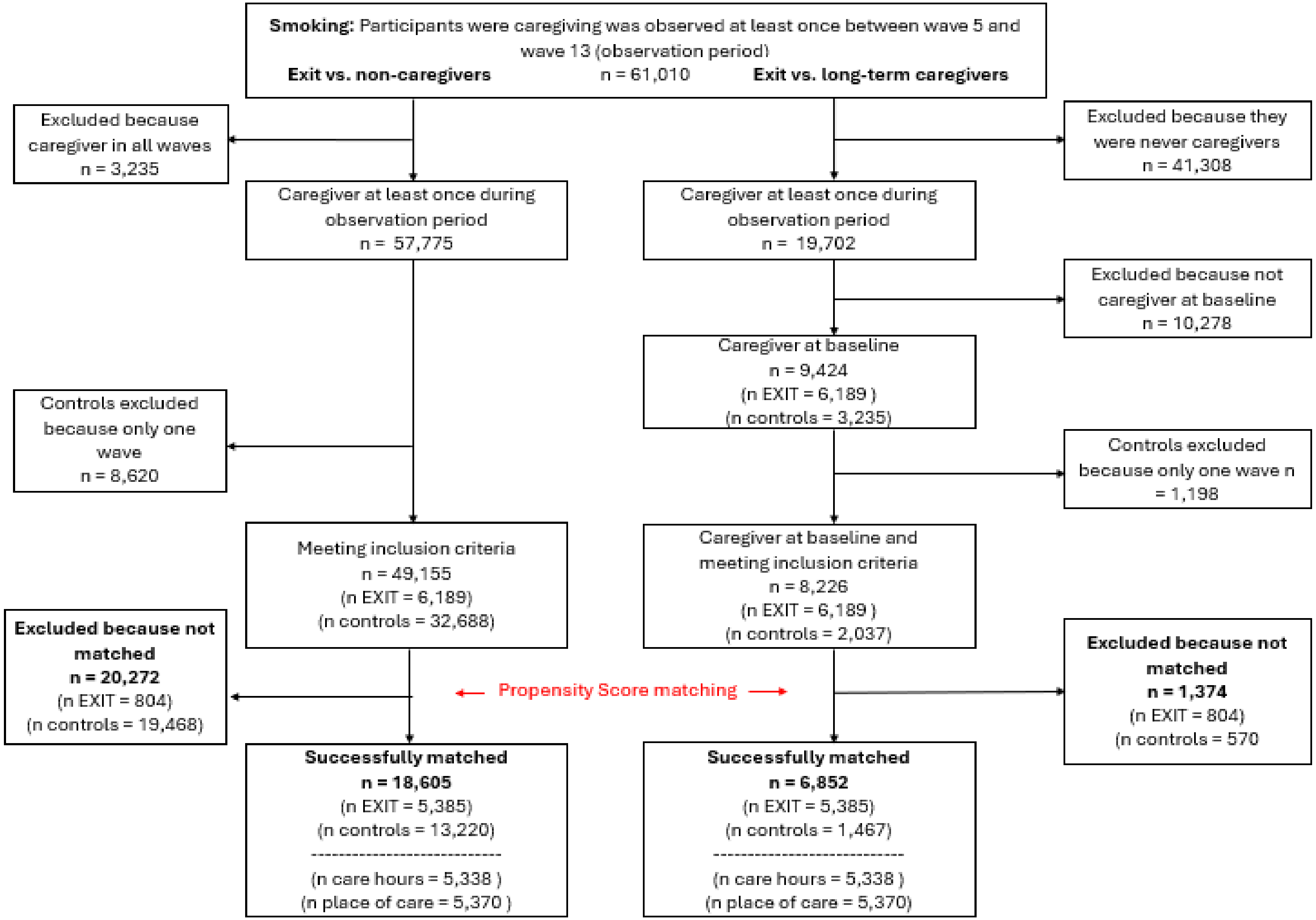


Figure 6.1 Sample size flow chart for smoking and caregiving exit, comparing exit vs non-caregivers and exit vs long-term caregivers.

Similarly, Appendix 6.2 outlines the sample selection process for physical inactivity, fruit and vegetable consumption diet, and problematic drinking, following the same structure as for smoking. In this flowchart, the right-hand branch represents comparisons between caregiving exiters and long-term caregivers, while the left-hand branch represents comparisons between caregiving exiters and non-caregivers. For physical inactivity, 3,340 participants who exited caregiving were successfully matched with 1,612 long-term caregivers and 6,108 non-caregivers (**Figure A6.2**). For fruit and vegetable consumption diet, 3,363 caregiving exiters were matched with 1,613 long-term caregivers and 6,135 non-caregivers (**Figure A6.3**). Lastly, for problematic drinking, 3,371 caregiving exiters were matched with 1,619 long-term caregivers and 6,154 non-caregivers (**Figure A6.4**).

6.4 Results

In this section, results are presented to investigate the relationship between caregiving exit and health behaviours. Each outcome is presented separately. For each outcome, fixed-effect models are presented as well as and piecewise growth curve models based on the propensity score matched sample. Results from the fixed-effect models are shown in tables, while the piecewise growth curve models are presented in graphical form. In addition, a table summarising the p-values for differences between exiters and non-transition groups during both the transition and post-transition periods in the piecewise regression models, along with references to the corresponding figures, is provided in Appendix 6.3.

6.4.1 Physical inactivity

6.4.1.1 Fixed effect models

Firstly, fixed effect models were estimated. as a first step in the analysis and these fixed-effect models were not adjusted for invariant confounding due to concerns that covariates were on the causal pathway between exit to caregiving and health behaviours. **Table 6.1** revealed that exiting from caregiving was associated with higher odds of physical inactivity after adjusting for wave (OR=1.09, 95%CI: 1.01/1.18). There was no evidence for an interaction between exit and sex (p=0.21) while there was evidence for an interaction between exit and age-groups (p=0.02). In the age-group-stratified analysis, it showed that only participants in late adulthood exiting caregiving had significantly higher odds of physical inactivity compared to participants from the same age-group who did not experience an exit from caregiving (**Table 6.2**). This suggests that exiting caregiving was associated with less physical activity, particularly for people aged 65+. However, from a public health perspective, the overlapping confidence intervals between age groups indicate little age differences.

Table 6.1 Fixed effect regression for caregiving exit and physical inactivity

Model	N		OR	95% CI	p
Model: Caregiving status + adjustment for wave	$N_{participants}$ = 18,262	No Exit	1.00	-	
	$N_{observations}$= 62,869	Exit	1.09	1.01/1.18	0.03
Interactions					
Caregiving-status*sex					0.21
Caregiving-status*age-group					0.02

Table 6.2 Fixed effect regression for caregiving exit and physical inactivity, stratified by age group.

Stratified results	**N=**		**OR**	**95% CI**	**p**
Caregiving exit and age groups					
Early adulthood 16-29)	$N_{participants}$ = 3.759	No Exit	1.00	-	0.56
	$N_{observations}$= 11.744	Exit	1.07	0.85/1.36	
Early mid-adulthood (30-49)	$N_{participants}$ = 6,277	No Exit	1.00	-	0.08
	$N_{observations}$= 21,680	Exit	1.14	0.99/1.31	
Late mid-adulthood (50-64)	$N_{participants}$ = 4,753	No Exit	1.00	-	0.89
	$N_{observations}$= 17,091	Exit	0.99	0.87/1.13	
Late adulthood (65+)	$N_{participants}$ = 3,473	No Exit	1.00	-	0.02
	$N_{observations}$= 12,354	Exit	1.21	1.04/1.42	

6.4.1.2 Trajectories of physical inactivity

Exit in relation to continuing caregiving

The trajectories of the predicted probability of physical inactivity in **Figure 6.2** illustrates that prior to the transition points, both those who exited caregiving and those who continued showed similar trends in the probability of physical inactivity. Negative values on the x-axis indicate the pre-transition period, the time point between”-2” and “0”, between the two dashed lines, indicates the transition period and the time points from “0” to the positive values on the x-axis indicate the post-transition period. Participants who exited caregiving exhibited an increasing trend in physical inactivity that began before the transition and continued throughout the post-transition period. This pattern suggests that exiting caregiving is associated with a higher likelihood of physical inactivity compared to matched controls who continued in the caregiving role. Despite this, the confidence intervals largely overlap at all time points, and the p-value for the transition was not significant (p=0.10).

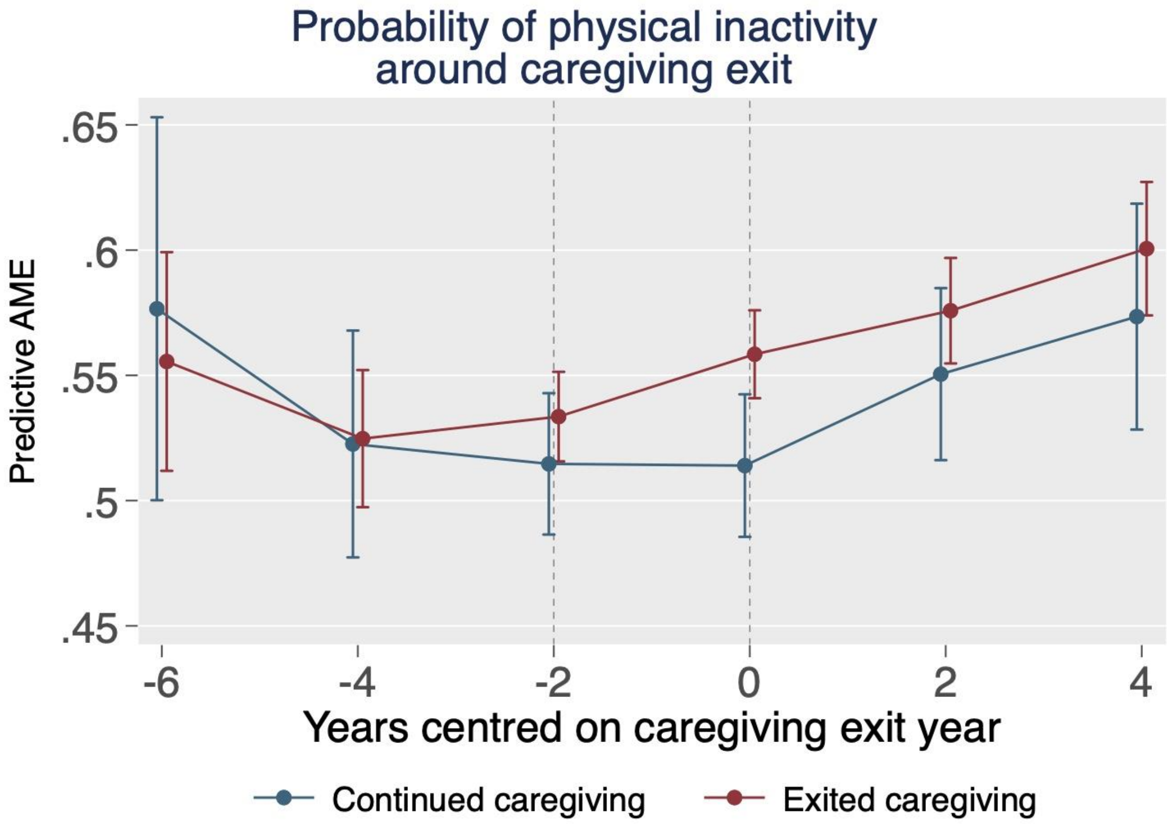


Figure 6.2 Physical inactivity: Exit care vs. Continued care; probability of physical inactivity before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, comparing participants who exited caregiving (n=3,340) with those who continued caregiving (n=1,612). Time is centred around caregiving exit, with dashed lines marking transition points. All participants were caregivers at baseline.

Exit in relation to non-caregivers

An additional piecewise growth model was created using a propensity score-matched sample of non-caregivers. **Figure 6.3** illustrates the predicted probabilities of this model, comparing the probability of physical inactivity for participants who exited caregiving against matched non-caregivers. The trajectories of physical inactivity were similar between the two groups before the transition period. However, around the transition point, the line representing the exit group began to diverge, showing a sharper increase in physical inactivity compared to non-caregivers, although this increase was only marginally non-significant (p=0.06). In the post-transition period, the exit group continued to exhibit a more pronounced increase in physical inactivity relative to the non-caregiver group, though this difference was marginally non-significant (p=0.06). This trend suggests that while exiting caregiving was associated with a greater likelihood of physical inactivity, the observed association remained statistically inconclusive.

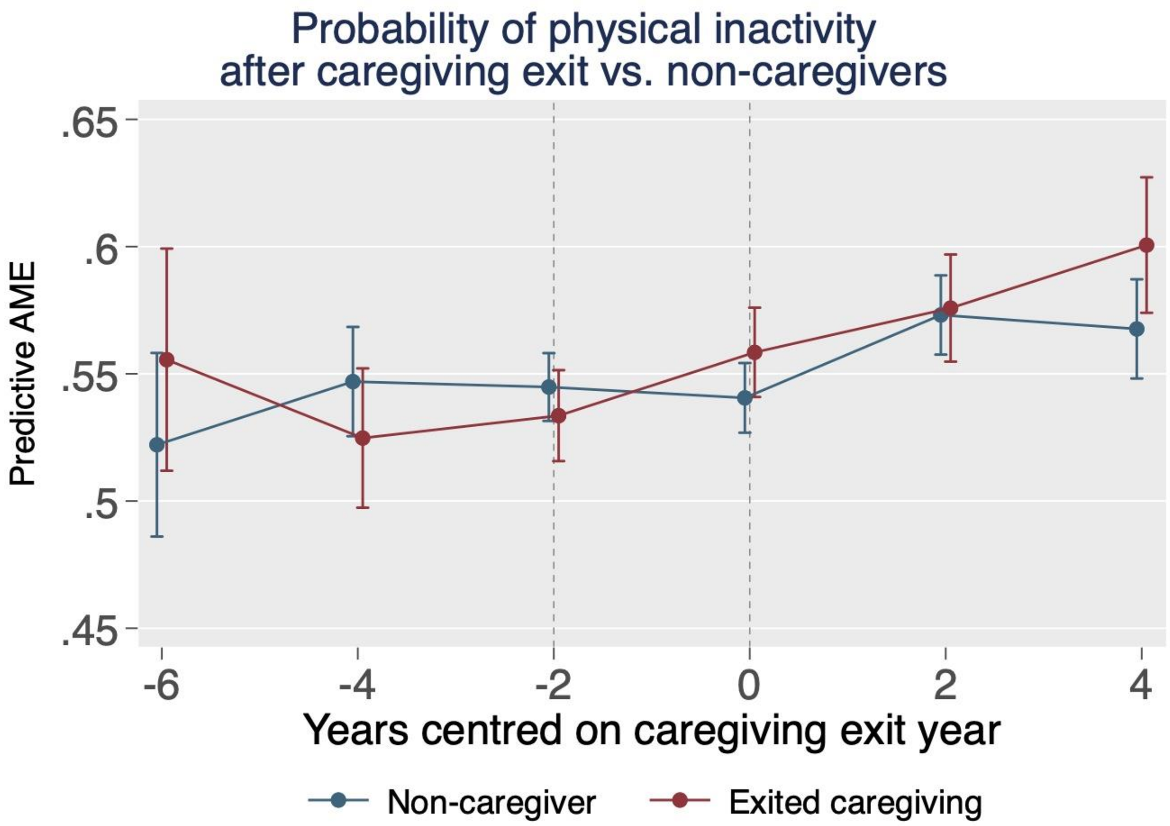


Figure 6.3 Physical inactivity: Exit care vs. no care; probability of physical inactivity before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, comparing participants who exited caregiving (n=3,340) with non-caregivers (n=6,108). Time is centred around caregiving exit, with dashed lines marking transition points.

To facilitate comparison between the two models (one with continued caregivers as the comparison group and the other with non-caregivers), the graphs from both analyses were superimposed, as shown in **Figure 6.4**. In the left panel, all four trajectories are displayed, revealing that the trajectories for the exit group are identical across both models, as expected. To streamline the visualisation, only one trajectory line for the exit group was retained. The graph demonstrates that participants who exited caregiving showed an increase in physical inactivity compared to both those who continued caregiving and non-caregivers. Given the consistency of the exit caregiving trajectories across models, only a single exit trajectory (right graph of **Figure 6.4**) will be presented in future superimposed graphs in this chapter for clarity and ease of interpretation.

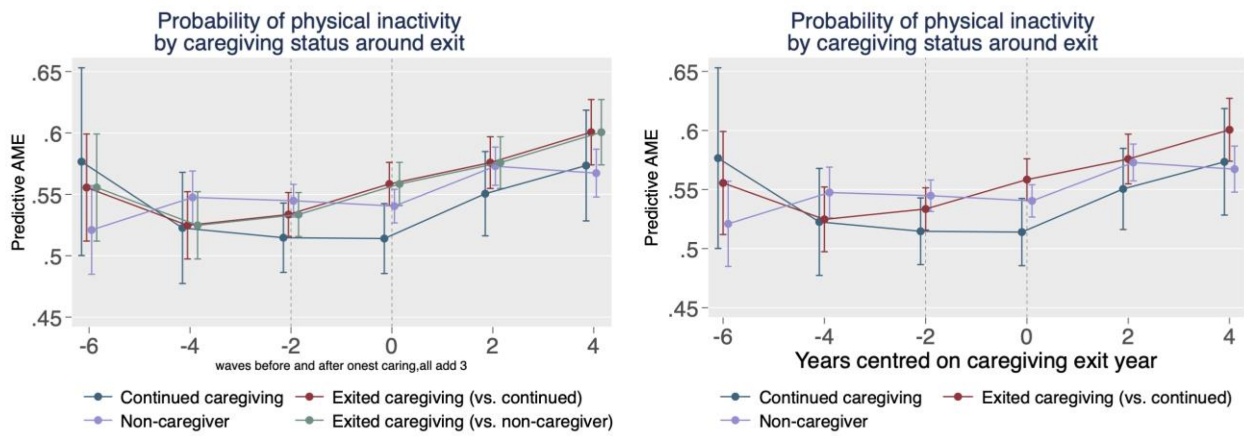


Figure 6.4 Physical inactivity and exit - superimposed graphs, probability of physical inactivity before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, comparing participants who exited caregiving with those who continued caregiving (n=3,340 vs 1,612) and with non-caregivers (n=3,340 vs 6,108). Time is centred around caregiving exit, with dashed lines marking transition points. All participants were caregivers or non-caregivers at baseline.

Caregiving hours prior to exit

Next, the trajectories of physical inactivity were stratified by caregiving intensity prior to exit. Among the 3,331 participants who exited caregiving, 81.8% (n = 2,704) had been engaged in low-intensity caregiving (<20 hrs per week), while 18.2% (n = 603) provided high-intensity caregiving before exit. **Figure 6.6** shows a marked difference between these two groups: exiting high-intensity caregiving (time point -2 to 0) was associated with a significant increase in physical inactivity compared to matched participants who continued caregiving (p=0.01) as well as non-caregivers (p=0.009). Moreover, in the post-transition period (time point 0 to 4), physical inactivity for those who exited high-intensity caregiving appeared to plateau in the wave following exit and increasing again between the final two waves. The interaction term for these slope changes were statistically significant for, continuing caregivers (p=0.01) and non-caregivers (p=0.02). It is also worth noting that matched continuing caregivers and matched non-caregivers exhibited very similar trajectories while low-intensity caregivers only had a small increase in physical inactivity. This suggests that the hours of caregiving provided had the strongest impact on physical inactivity levels when participants exited caregiving and that participants became less physically active when they exited high-intensity caregiving.

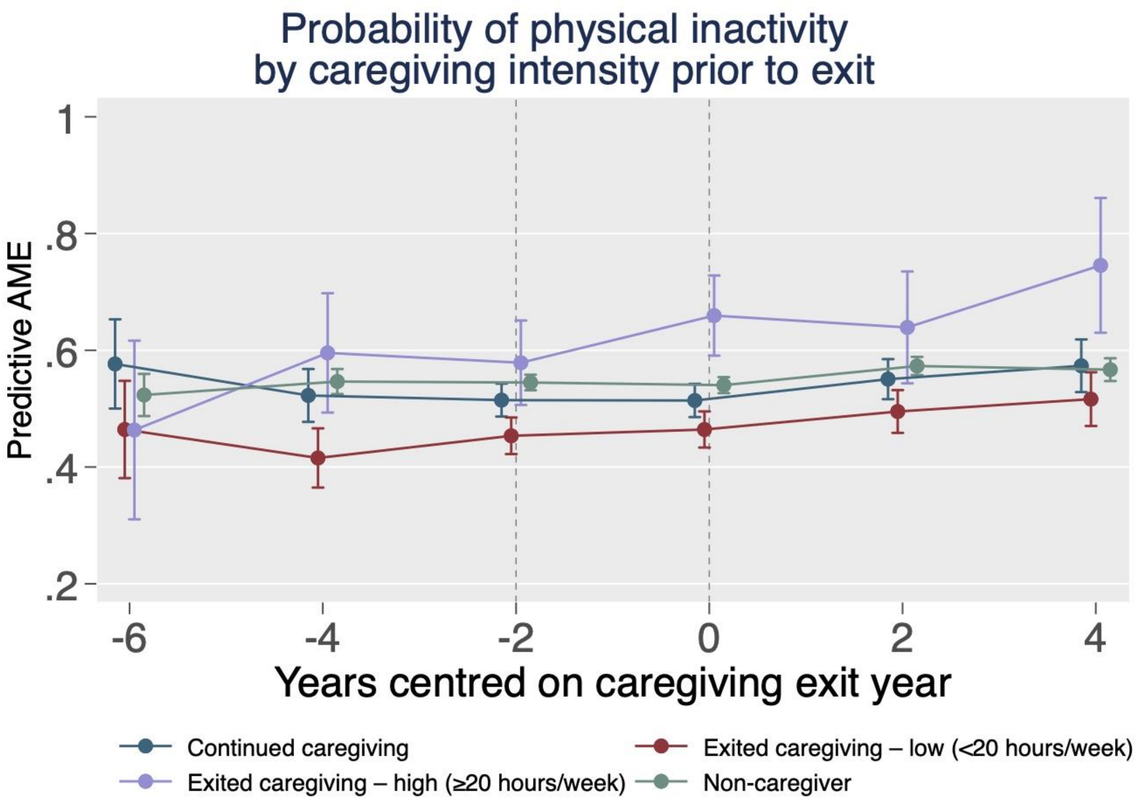


Figure 6.5 Physical inactivity and exit by care intensity; probability of physical inactivity before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, stratified by caregiving intensity prior to exit among participants who exited caregiving (n=3,307; 2,704 low-intensity, 603 high-intensity), alongside continuing caregivers (n=1,612) and non-caregivers (n=6,108). Time is centred around caregiving exit, with dashed lines marking transition points.

Place of caregiving prior to exit

Regarding the place of caregiving prior to exit, 3,331 participants had valid observations and 69.8% (n=2,325) exited caregiving that took place outside the household while 25.9% (n=861 participants) exited caregiving that took place inside the household and 4.2% (n=144) exited caregiving from both inside and outside the household (dual). While participants who provided caregiving inside the household and dual caregivers prior to exit had the highest probability of physical inactivity, there was no statistically significant difference in slope changes during the transition period between the groups (p=0.32 for comparison with continuing caregiver and p=0.11 for comparison with non-caregivers) as shown in **Figure 6.6**. In the post-transition period, dual caregivers seemed to have the sharpest increase in physical inactivity, but the confidence intervals were wide due to a small sample and post-transitions slope changes were not significant (p=0.09 for models matched against continuing caregivers and p=0.15 for models matched against non-caregivers). This suggests that while caregivers inside the household and dual caregivers might have had a higher level of physical inactivity, exiting caregiving was less influential on the trajectories after exit from caregiving.

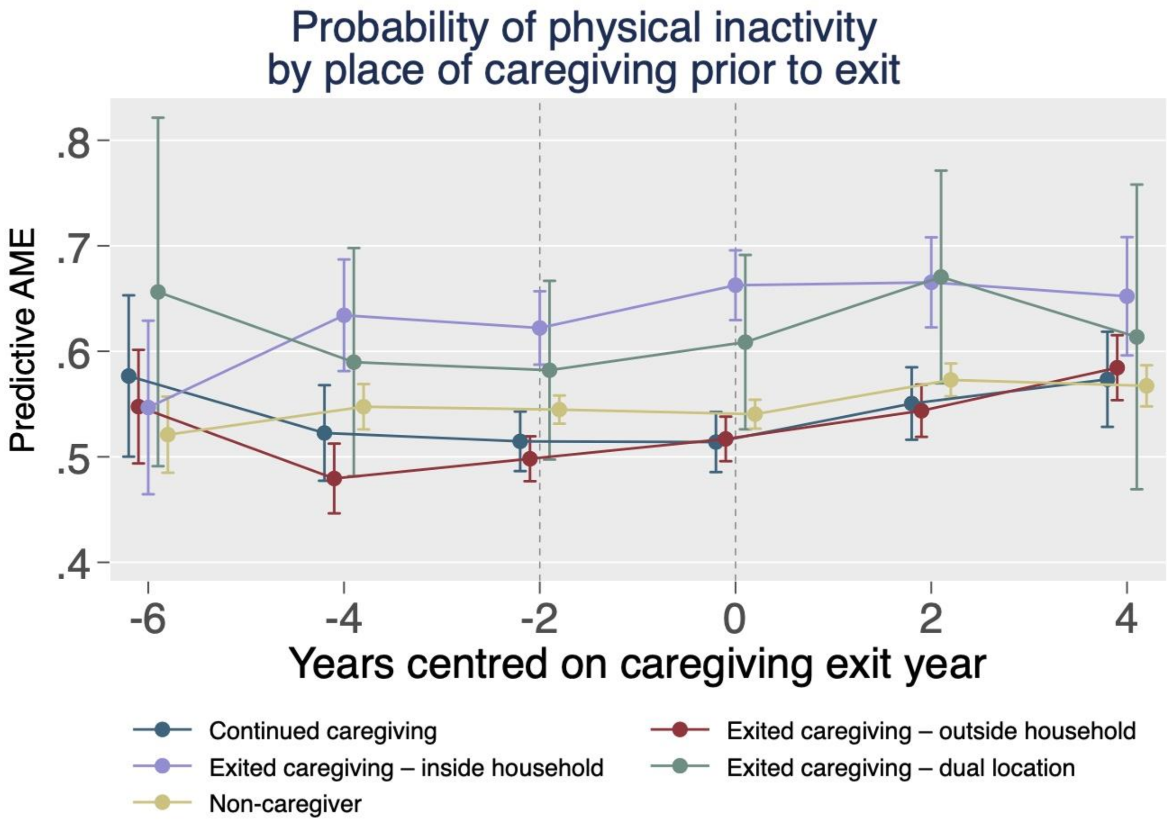


Figure 6.6 Physical inactivity and exit by place of care; probability of physical inactivity before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, stratified by place of care prior to exit among participants who exited caregiving (n=3,330; 2,325 outside household, 861 inside household, 144 both inside and outside), alongside continuing caregivers (n=1,612) and non-caregivers (n=6,108). Time is centred around caregiving exit, with dashed lines marking transition points. Place of care was only measured for participants who exited caregiving.

Sex

Regarding sex, out of the 3,340 participants who exited caregiving, 62.7% (n=2,093) were female and 37.3% (n=1,247) were male. The interaction-term for sex was statistically not-significant for the comparison with continuing caregivers (p=0.75) or non-caregivers (p=0.23) which indicates that sex did not modify the relationship between caregiving exit and physical inactivity. **Figure 6.7** shows the superimposed trajectories by sex and shows that the trajectories for male and female participants who exited caregiving were quite parallel although female exiters had a significant increase in physical inactivity compared to continuing female caregivers which was statistically significant for the transition period (p=0.002) as well as post-transition period (p=0.001).

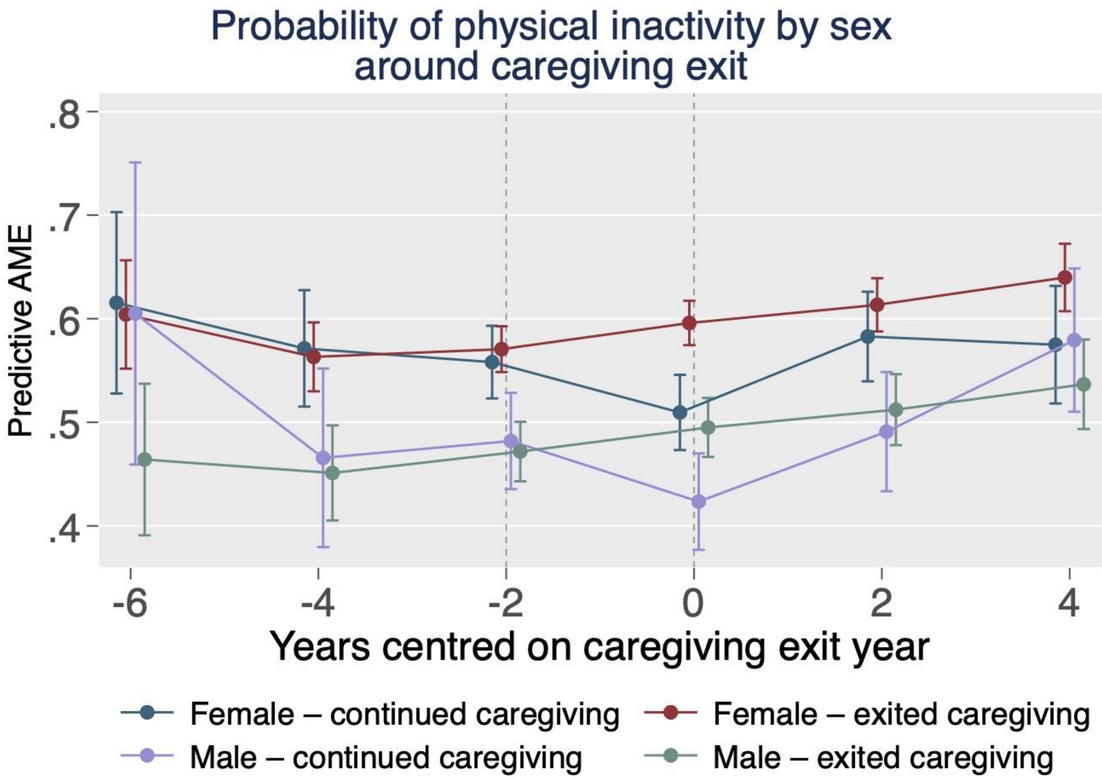


Figure 6.7 Physical inactivity and exit by sex; probability of physical inactivity before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, stratified by sex among participants who exited caregiving (n=3,340; 2,093 female, 1,247 male), alongside continuing caregivers (n=1,612). Time is centred around caregiving exit, with dashed lines marking transition points. Sex was stratified for participants who exited caregiving.

In contrast, exiting caregiving was not associated in males compared to continuing caregivers (p=0.94) or non-caregivers (p=0.11). Although trajectories between male and female exiters are quite parallel, the confidence interval between males who exit caregiving and those who continue caregiving overlaps (**Figure 6.7**) whereas the differences in trajectories are more pronounced for women. These findings suggest an increase in physical inactivity following caregiving cessation in both males and females, with a somewhat stronger association observed among females that was statistically not significant.

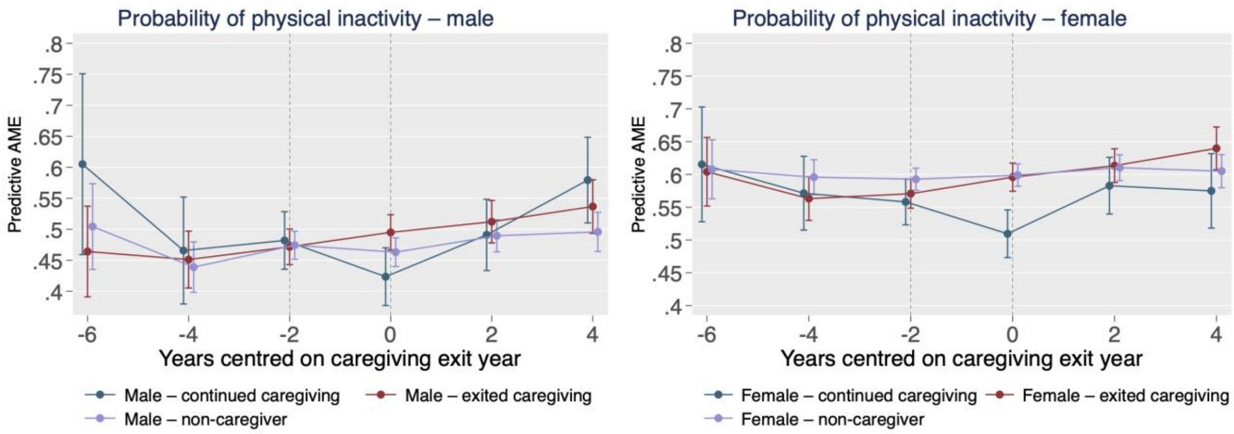


Figure 6.8 Physical inactivity and caregiving exit by sex, superimposed graphs; probability of physical inactivity before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, stratified by sex, comparing participants who exited caregiving (n=1,247 males; n=2,093 females) with continuing caregivers and non-caregivers. Time is centred around caregiving exit, with dashed lines marking transition points.

Age groups

In terms of age groups, 8.6% (n = 287) of participants who exited caregiving were early adulthood caregivers prior to exit; 26.2% (n = 874) were in early mid-adulthood; 35.7% (n = 1,191) were in late-mid-adulthood; and 29.6% (n = 988) were in late adulthood. Overall, physical inactivity increased with the caregiver's age, as illustrated in **Figure 6.9**. Visual inspection suggests that physical inactivity levels among those who exited caregiving remained relatively stable during the transition period, while inactivity decreased among matched continuing caregivers which resulted in a widening gap between the two groups, particularly in late adulthood and, to a lesser extent, early mid-adulthood. However, the interaction term for the transition part of the piecewise trajectory and age groups for this association was not statistically significant (p=0.45). In the post-exit period, early adulthood caregivers appeared to show the steepest increase in physical inactivity, though the interaction term for these post-exit trajectories was also statistically non-significant (p=0.82).

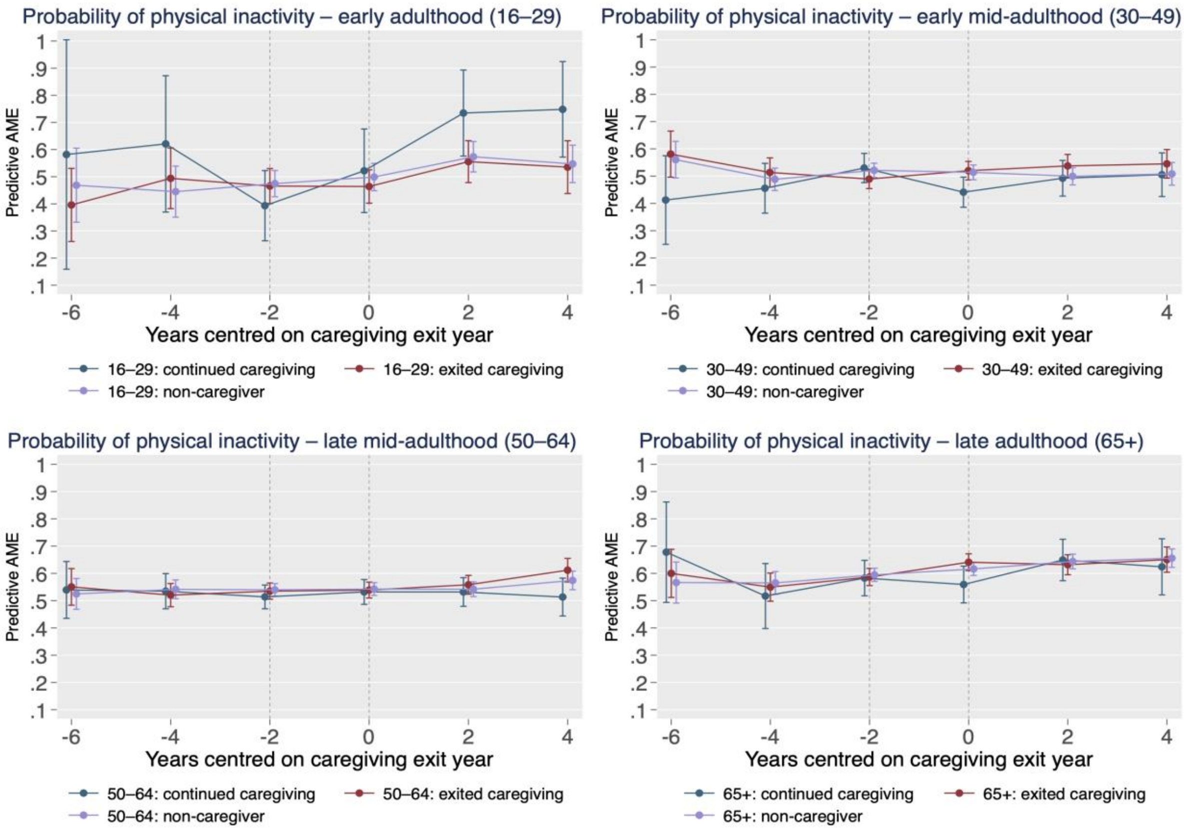


Figure 6.9 Physical inactivity and exit by age-group; probability of physical inactivity before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, stratified by age at caregiving exit, comparing participants who exited caregiving (n=3,340; 287 early adulthood [16–29], 874 early mid-adulthood [30–49], 1,191 late mid-adulthood [50–64], 988 late adulthood [65+]) with continuing caregivers (n=1,612) and non-caregivers (n=6,108). Time is centred around caregiving exit, with dashed lines marking transition points.

6.4.1.3 Summary

In the fixed-effect models, exiting caregiving was associated with higher odds of physical inactivity particularly among older adults which was in agreement with the growth-curve models. Propensity-matched growth-curve models revealed that, compared to continuing caregivers and non-caregivers, those who exited caregiving showed a gradual rise in physical inactivity. Particularly, high-intensity caregivers experienced a sharper increase in inactivity post-exit compared to lower-intensity caregivers and non-caregivers. Place of caregiving also influenced inactivity, with household-based and dual-location caregivers showing higher baseline inactivity, but this was not attributable to the exit to caregiving. There was no evidence that sex modifies the relationship between caregiving exit and physical activity while there was some evidence that there was a stronger increase in physical inactivity in people who exit caregiving in early mid-adulthood (30-49) and late adulthood (65+).

6.4.2 Fruit and vegetable consumption

6.4.2.1 Fixed effect models

In a first step of the analysis, fixed effect models were estimated based on 46,446 participants as shown in **Table 6.3**. Exiting caregiving was not associated with change in daily fruit and vegetable consumption (Coeff.=0.00; 95%CI: -0.01/0.02, p=0.41). There was no evidence that sex or age-group of participants modified the association between exiting caregiving and daily fruit and vegetable consumption. Hence, results from fixed effect modelling suggest that there was no evidence for a relationship between exiting caregiving and change in daily fruit and vegetable consumption.

Table 6.3 Fixed effect regression for caregiving exit and fruit and vegetable consumption, measured in daily average portions of fruits and vegetables

Model	Sample		Coeff.	95% CI	p
Model: Caregiving status + adjustment for wave	$N_{participants}$ = 46,446 $N_{observations}$= 129,303	No Exit Exit	Ref. 0.00	- -0.01/0.02	 0.41
Interactions					
Caregiving-status*sex					0.25
Caregiving-status*age-group					0.71

6.4.2.2 Trajectories of physical inactivity

Exit caregiving in relation to continued caregiving

In total 3,363 participants exited caregiving and were matched against 1,613 participants who continued caregiving. The trajectories of the predicted number of daily fruits and vegetables in **Figure 6.10** illustrated that participants who exited caregiving and those who continued caregiving had similar trajectories before, during and after the exit of caregiving. The p-value for the slope change during the transition and post-transition were both not significant (p=0.51 and p=0.29 respectively).

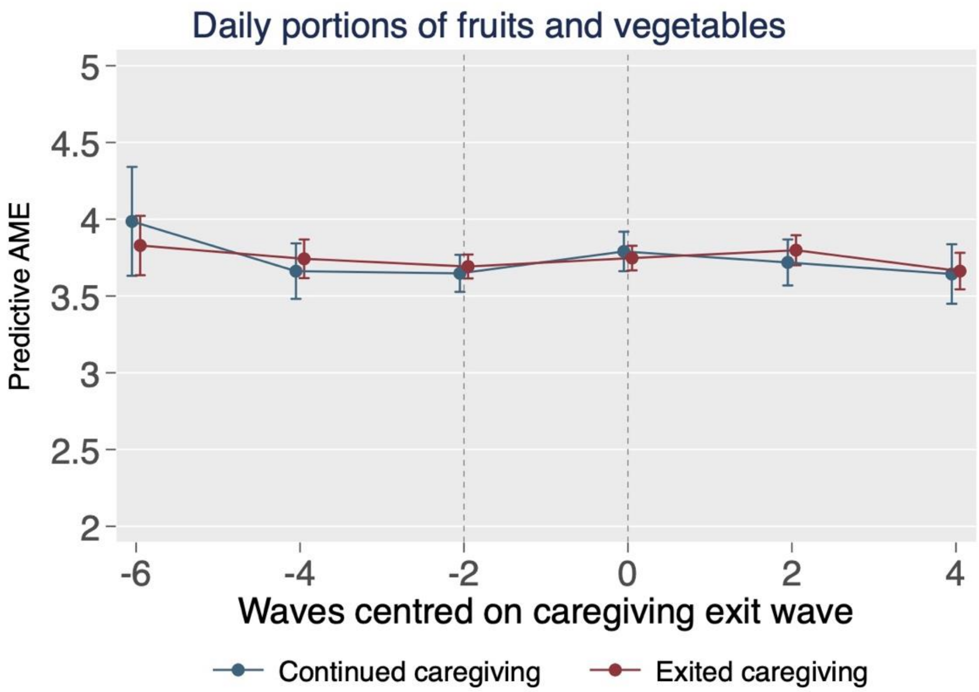


Figure 6.10 Healthy diet - exit care vs. continue care, average daily portions of fruit and vegetables before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, comparing participants who exited caregiving (n=3,363) with those who continued caregiving (n=1,613). Time is centred around caregiving exit, with dashed lines marking transition points. All participants were caregivers at baseline.

Exit caregiving in relation to non-caregiving

A second model was created in which participants who exited caregiving were compared to participants who were non-caregivers throughout the study period. In this approach, the 3,362 caregivers who exited caregiving were matched with 6,133 non-caregivers. **Figure 6.11** depicts the trajectories of fruit and vegetable consumption which were quite similar, and confidence intervals overlapped at all observations. The interaction term for the transition and post-transition was statistically not significant (p=0.29 and p=0.92 respectively).

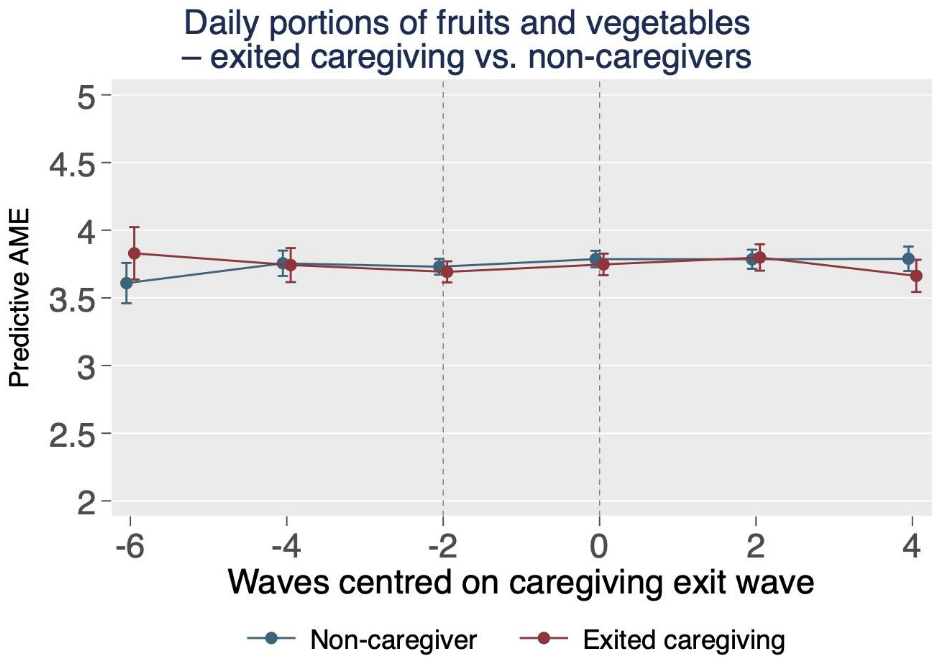


Figure 6.11 Fruit and vegetable consumption - exit care vs. no care; average daily portions of fruit and vegetables before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, comparing participants who exited caregiving (n=3,363) with non-caregivers (n=6,135). Time is centred around caregiving exit, with dashed lines marking transition points.

To facilitate comparison, the graphs from the two previous models were superimposed in **Figure 6.12**. The left panel illustrates that the trajectories of the exit group are identical in both analyses, as expected. Consequently, the right panel displays only a single graph for the exit group, simplifying the visualisation. The similar trajectories and estimates indicate no apparent relationship between caregiving exit and daily fruit and vegetable consumption.

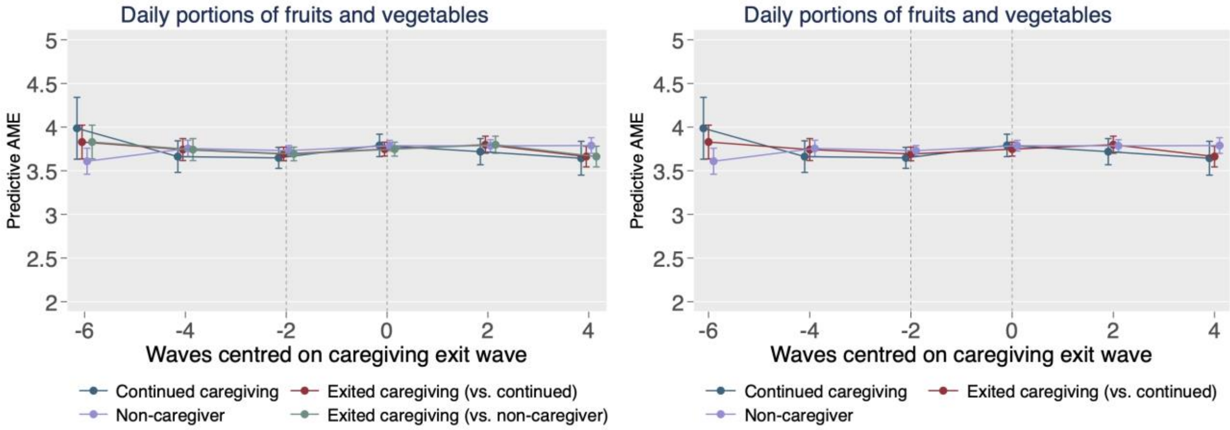


Figure 6.12 Healthy diet and exit care - superimposed graphs, average daily portions of fruit and vegetables before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, comparing participants who exited caregiving with those who continued caregiving (n=3,363 vs 1,613) and with non-caregivers (n=3,363 vs 6,135). Time is centred around caregiving exit, with dashed lines marking transition points. All participants were caregivers or non-caregivers at baseline.

Caregiving hours prior to exit

The analysis was then stratified by caregiving hours, previously conceptualised as caregiving intensity. In total, 81.2% (n=2724) participants exited caregiving from lower intensity while 18.2% (n=607) exited caregiving from higher intensity caregiving. **Figure 6.13** shows that participants who were high-intensity caregivers prior to exit had the lowest daily fruit and vegetable consumption compared to low-intensity caregivers, continuous caregivers, and non-caregivers. However, during the transition period, there was no significant difference in fruit and vegetable consumption between caregivers who exited care and those who continued caregiving (p=0.72) or those who were not caregiving (p=0.82), suggesting that exiting care was not associated with a change in the slope of consumption during this time. After the exit from caregiving, trajectories remained stable as well and no significant relationships were found.

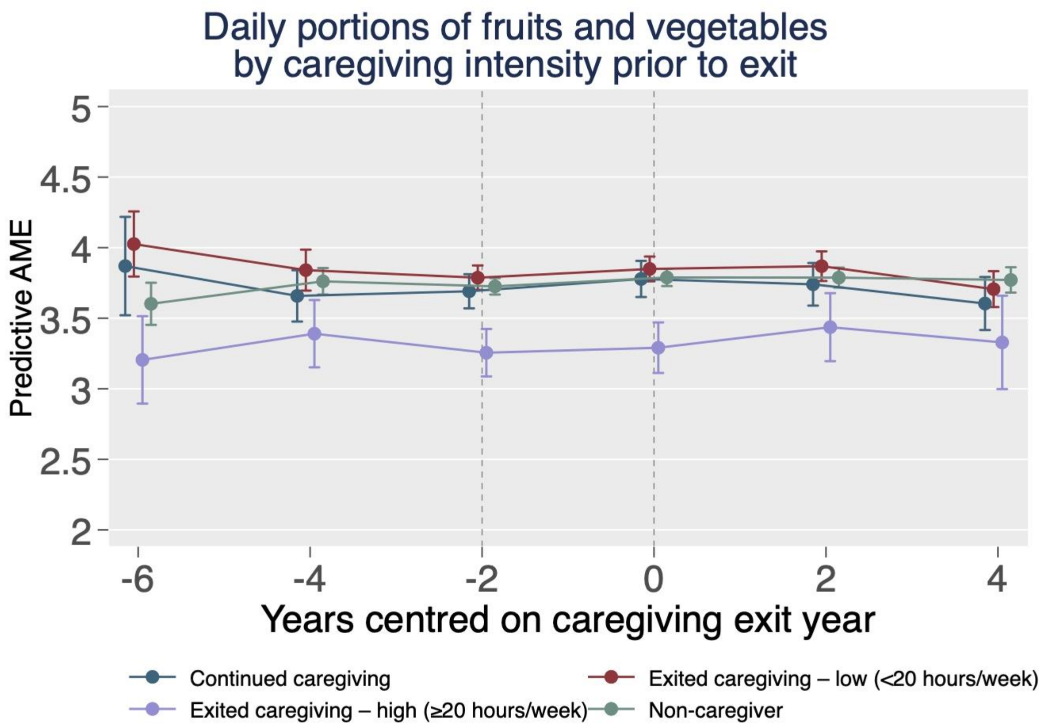


Figure 6.13 Fruit and vegetable consumption and exit by care intensity; average daily portions of fruit and vegetables before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, stratified by caregiving intensity prior to exit among participants who exited caregiving (n=3,331; 2,724 low-intensity, 607 high-intensity), alongside continuing caregivers (n=1,613) and non-caregivers (n=6,135). Time is centred around caregiving exit, with dashed lines marking transition points.

Place of caregiving prior to exit

In terms of place of care, 69.6% (n=2,336) provided caregiving outside the household before exiting caregiving, while 25.9% (n=869) provided caregiving within the household, and 4.4% (n=149) provided dual caregiving (both outside and inside the household). **Figure 6.14** illustrates the trajectories of daily fruit and vegetable consumption by place of caregiving prior to exit, compared to matched continuous caregivers and non-caregivers. Participants who provided caregiving within the household consistently had the lowest daily fruit and vegetable consumption across the pre, during, and post-exit periods. For all groups, trajectories remained largely stable throughout the transition, except for dual caregivers, who showed a small but noticeable decrease in fruit and vegetable consumption. However, as this is a very small group with large confidence intervals, the interaction terms for the transition and post-transition periods were statistically non-significant (p=0.95 and p=0.13, respectively).

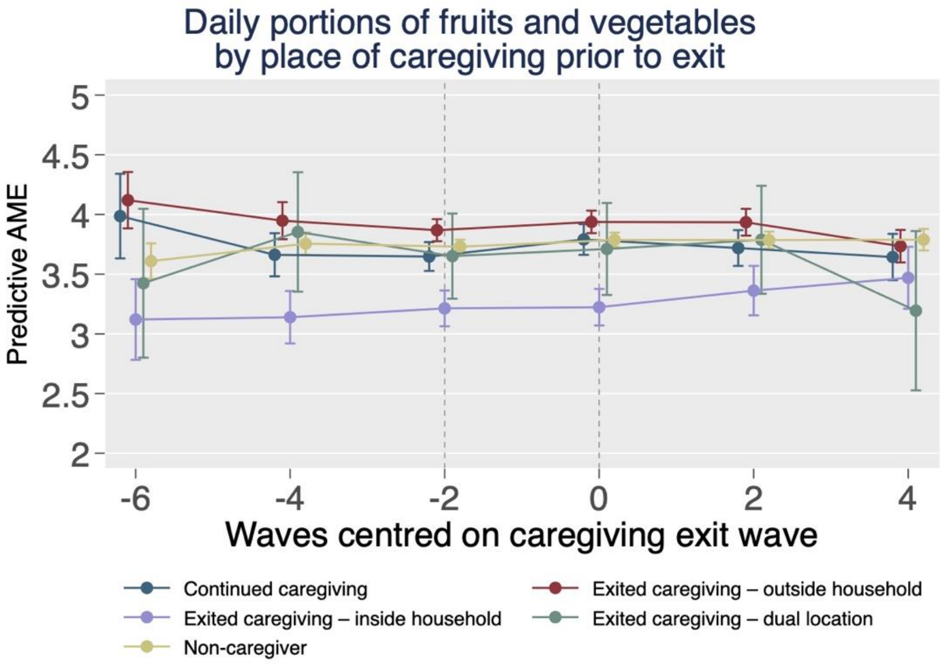


Figure 6.14 Healthy diet and exit by place of care, average daily portions of fruit and vegetables before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, stratified by place of care prior to exit among participants who exited caregiving (n=3,354; 2,336 outside household, 869 inside household, 149 both inside and outside), alongside continuing caregivers (n=1,613) and non-caregivers (n=6,135). Time is centred around caregiving exit, with dashed lines marking transition points.

6.4.2.3 The role of sex and age

Sex

In view of sex, 37.3% (n=1,256) of all exiters were male and 62.7% (n=2,107) were female. **Figure 6.15** depicts the trajectories of fruit and vegetable consumption stratified by sex. Female participants had generally higher daily fruit and vegetable consumption compared to male, but trajectories did not differ and the interaction term for the transition and post-transition were statistically not significant (p=0.84 and p=0.79 compared to continuing caregivers respectively). This suggests that there is no evidence that sex modified the relationship between caregiving exit and daily fruit and vegetable consumption.

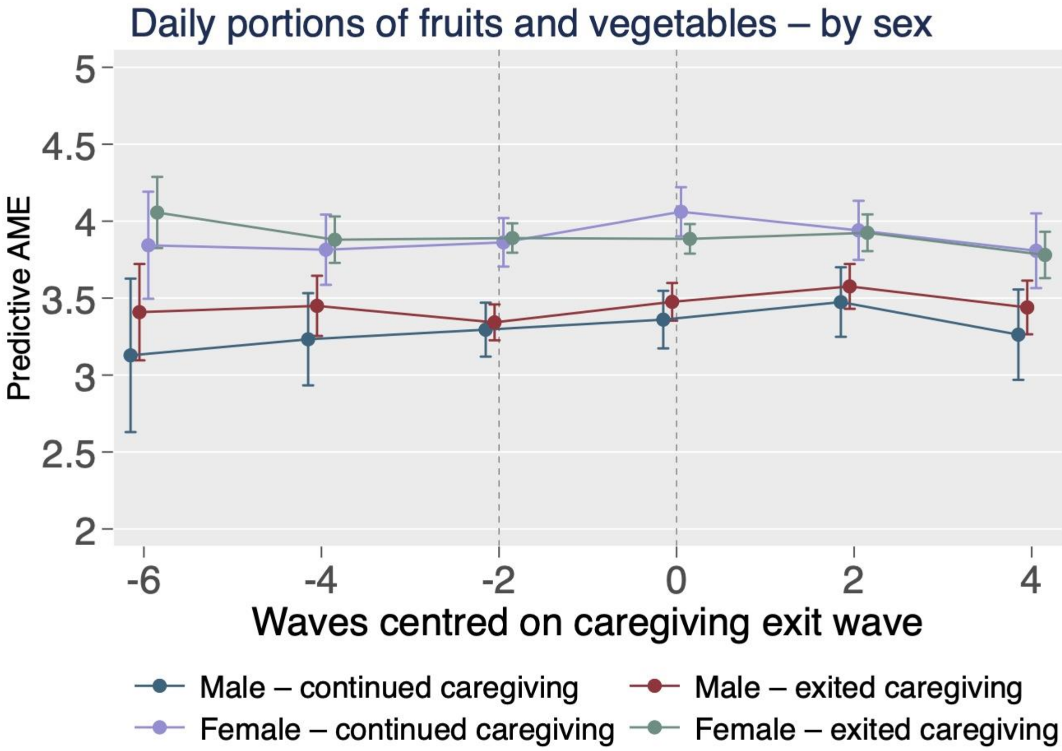


Figure 6.15 Fruit and vegetable consumption and exit by sex; average daily portions of fruit and vegetables before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, stratified by sex, comparing participants who exited caregiving (n=3,363; 2,107 females, 1,256 males) with continuing caregivers (n=1,613). Time is centred around caregiving exit, with dashed lines marking transition points. All participants were caregivers at baseline.

However, in a further sub-group analysis by sex in **Figure 6.16**, it emerged that, in females, caregiving exit was associated with fewer daily fruit and vegetables consumed compared to matched female participants who continued caregiving (p=0.01) Given that the magnitude of the association is small and is mainly driven by the fact that continued caregivers had an increase of fruit and vegetable consumption during this period, this may merely reflect normal variation rather than a meaningful relationship. There was no significant association for male participants.

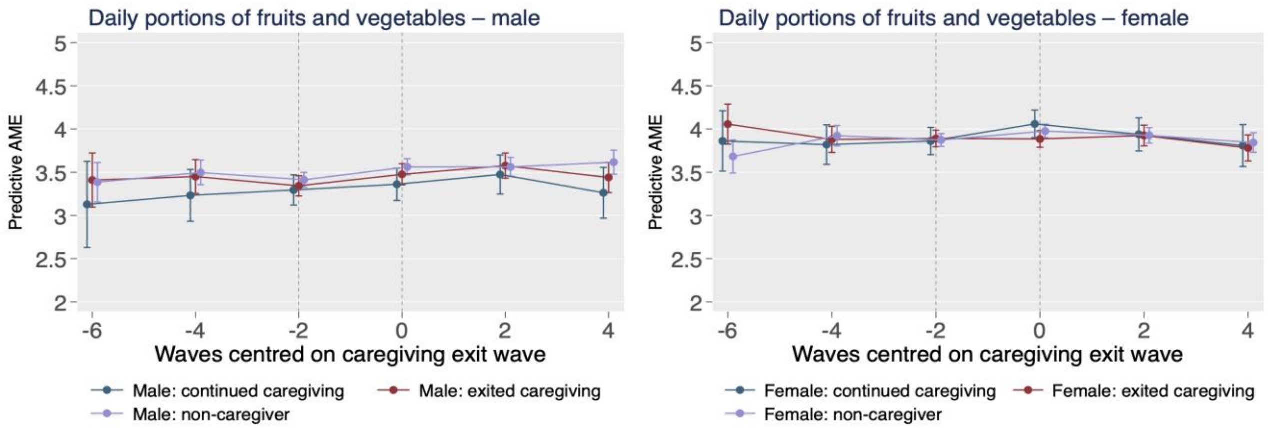


Figure 6.16 Healthy diet and exit, stratified by sex; average daily portions of fruit and vegetables before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, stratified by sex, comparing participants who exited caregiving (n=3,363; 2,107 females, 1,256 males) with continuing caregivers (n=1,613) and non-caregivers (n=6,135). Time is centred around caregiving exit, with dashed lines marking transition points. All participants were caregivers or non-caregivers at baseline.

Age groups

In view of age groups, 8.5% (n=287) exiters were in early adulthood; 26.1% (n=879) were in early mid-adulthood; 35.6% (n=1,197) were in late mid-adulthood; and 29.7% (n=1,000) were in late adulthood. **Figure 6.17** shows the trajectories of fruit and vegetable consumption for all groups who exited caregiving. Exiters in early adulthood had the overall lowest fruit and vegetable consumption while exiters above the age of 50 had the overall highest daily fruit and vegetable consumption. Despite this, there was no evidence of a significant interaction between age groups and caregiving exit (p=0.58). In view of age-stratified results, confidence intervals for most strata overlap and there was a marginally significant association for late-mid-adulthood exiters were participants who continued caregiving had a sharper increase in fruit and vegetable consumption compared to participants who exited caregiving (p=0.04). Further, it was observed that in late adulthood, exit to caregiving seemed to be associated with an increase in fruit and vegetable consumption in the post-exit period but this association was statistically not significant (p=0.30).

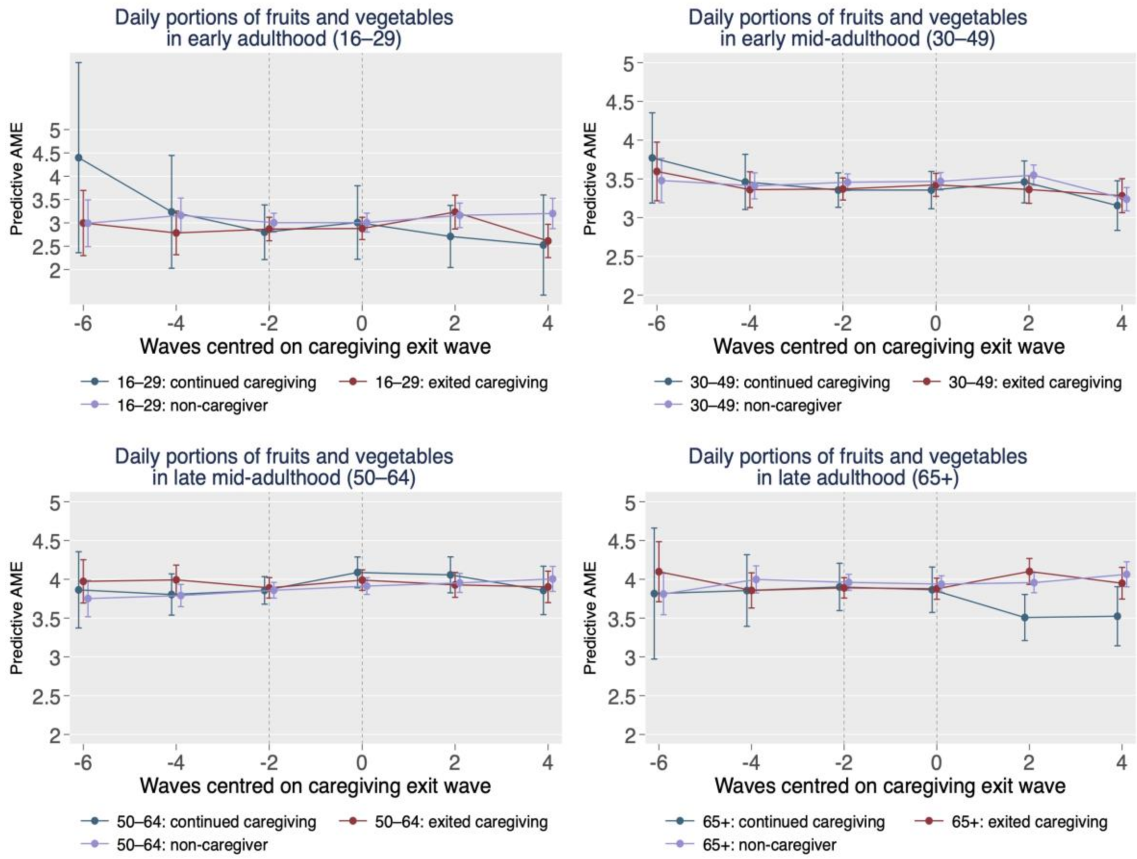


Figure 6.17 Healthy diet and exit, stratified by age groups; average daily portions of fruit and vegetables before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, stratified by age at caregiving exit, comparing participants who exited caregiving (n=3,363; 287 early adulthood [16–29], 879 early mid-adulthood [30–49], 1,197 late mid-adulthood [50–64], 1,000 late adulthood [65+]) with continuing caregivers (n=1,613) and non-caregivers (n=6,135). Time is centred around caregiving exit, with dashed lines marking transition points.

6.4.2.4 Summary

The fixed effect models and the piecewise-growth models agreed that there was no significant association between caregiving exit and change in daily fruit and vegetable consumption. There was no evidence that sex and age groups modified the relationship between caregiving exit and daily fruit and vegetable consumption. The marginal significant associations that were found in the sub-group analysis may be due to multiple tests and might not reflect a true underlying moderation effect.

6.4.3 Problematic drinking

6.4.3.1 Fixed effect models

In a first step of the analysis, fixed effect models were estimated based on 9,465 participants as shown in **Table 6.4**, it can be seen that exiting caregiving was not associated with change in problematic drinking (OR=0.96, 95%CI: 0.86/1.08, p=0.53). There was no evidence that sex or age-group of participants modified the association between exiting caregiving and problematic drinking. Hence, results from fixed effect models suggest that there was no evidence for a relationship between exiting caregiving and problematic drinking.

Table 6.4 Fixed effect regression for caregiving exit and problematic drinking

Model	**N=**		**OR**	**95% CI**	**p**
Model: Caregiving status + adjustment for wave	$N_{participants}$ = 9,465 $N_{observations}$= 32,528	No Exit Exit	1.00 0.96	- 0.86/1.08	0.53
Interactions					
Caregiving-status*sex					0.77
Caregiving-status*age-group					0.11

6.4.3.2 Trajectories of problematic drinking

Exit caregiving in relation to continued caregiving

In total 3,371 participants exited caregiving and were matched against 1,619 participants who continued caregiving. The predicted trajectories of the probably of problematic drinking in **Figure 6.18** illustrated that participants who continued caregiving had a more pronounced decline in problematic drinking compared to participants who exited caregiving. While this association was small, it was statistically significant (p=0.04). In the post-exit period, however, trajectories of exiters and continued caregivers intersected again (p=0.05).

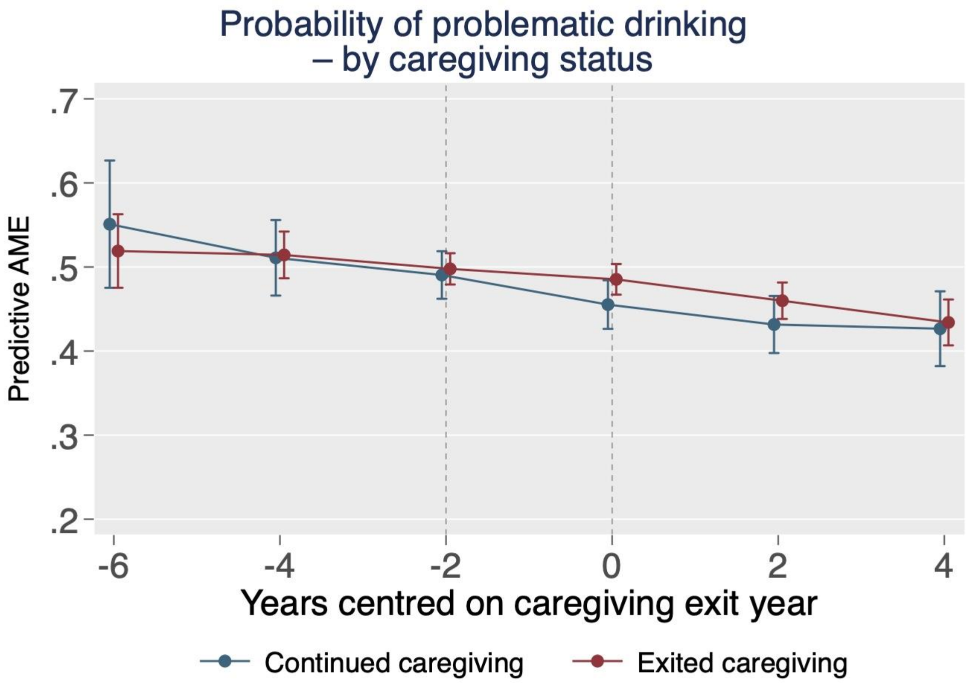


Figure 6.18 Problematic drinking - exit vs. continued care; probability of problematic drinking before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, comparing participants who exited caregiving (n=3,371) with those who continued caregiving (n=1,619). Time is centred around caregiving exit, with dashed lines marking transition points. All participants were caregivers at baseline.

Exit caregiving in relation to non-caregiving

In a second model, exiters were compared to 6,156 participants who were non-caregivers at all observation points as illustrated in **Figure 6.19**. In this model, participants who exited caregiving had almost identical trajectories of problematic drinking compared to participants who were non-caregivers. The interactions terms were not significant for the transition period (p=0.80) and the post-transition period (p=0.88).

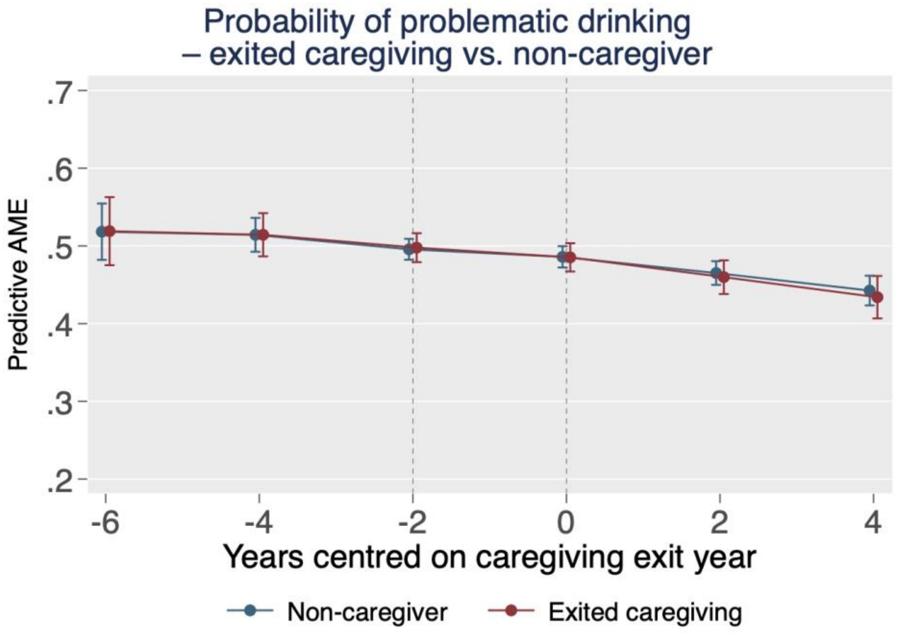


Figure 6.19 Problematic drinking - exit vs. no care; probability of problematic drinking before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, comparing participants who exited caregiving (n=3,371) with non-caregivers (n=6,154). Time is centred around caregiving exit, with dashed lines marking transition points. All participants were non-caregivers or caregivers at baseline.

To compare the two previous models visually, trajectories were superimposed as shown in **Figure 6.20**. In the left-hand panel, trajectories for participants who exit caregiving are identical as expected as this was the same sample in both models. To ease interpretation, only one trajectory for caregiving exit was retained.

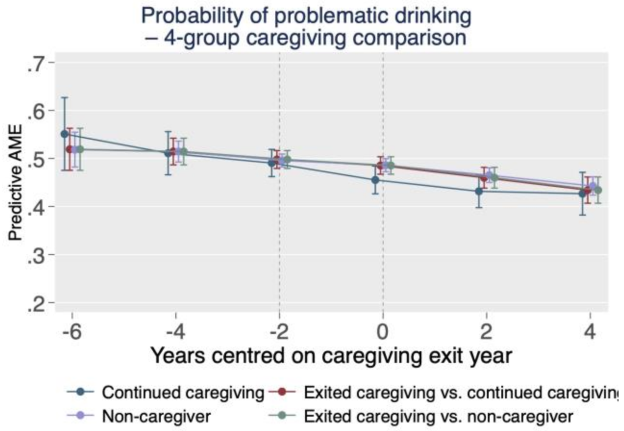


Figure 6.20 Problematic drinking and exit - superimposed graphs; probability of problematic drinking before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, comparing participants who exited caregiving with those who continued caregiving (n=3,371 vs 1,619) and with non-caregivers (n=3,371 vs 6,154). Time is centred around caregiving exit, with dashed lines marking transition points.

Caregiving hours prior exit

Prior to caregiving exit, 81.8% (n=2,729) of participants provided less than 20 hours of caregiving per week, while 18.2% (n=608) provided more than 20 hours. **Figure 6.21** shows the trajectories of problematic drinking by caregiving intensity, revealing that individuals with higher caregiving intensity before exit had the lowest probability of problematic drinking compared to low-intensity caregivers, matched continuing caregivers, and matched non-caregivers. This trend was consistent across the pre-transition, transition, and post-transition periods. Despite these associations, the trajectories remained nearly parallel, and none of the interaction terms reached statistical significance (Appendix 6.3). This suggests that high-intensity caregivers generally hav a lower likelihood of problematic drinking, but caregiving exit had minimal impact on changes in problematic drinking.

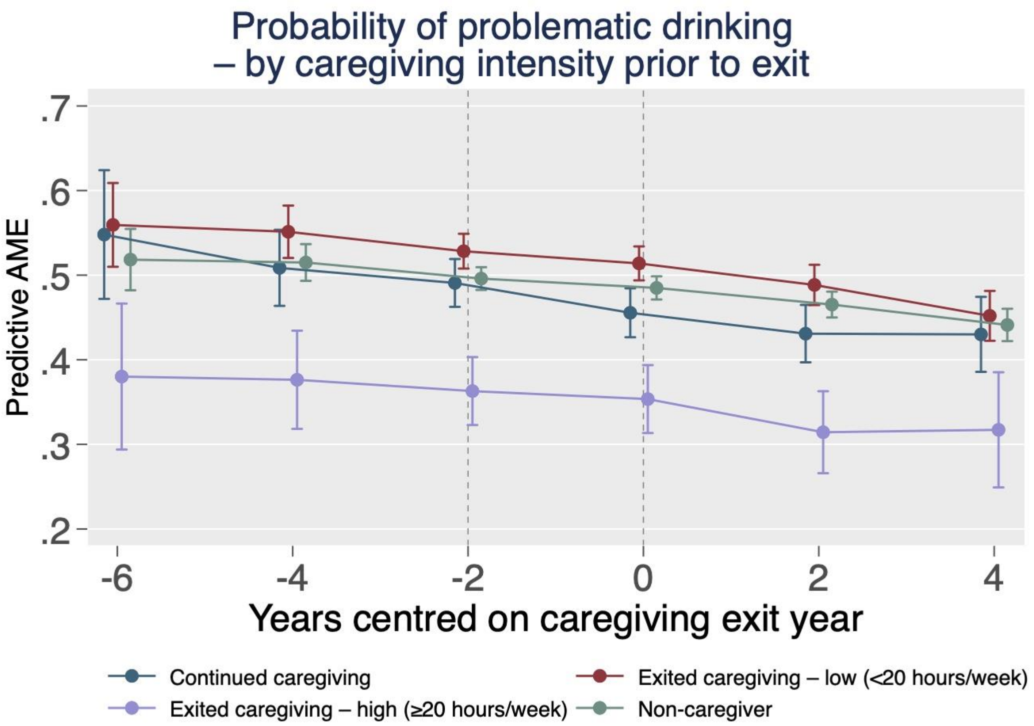


Figure 6.21 Problematic drinking and exit by care intensity; probability of problematic drinking before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, stratified by caregiving intensity prior to exit among participants who exited caregiving (n=3,337; 2,729 low-intensity, 608 high-intensity), alongside continuing caregivers (n=1,619) and non-caregivers (n=6,154). Time is centred around caregiving exit, with dashed lines marking transition points.

Place of caregiving prior to exit

Regarding place of caregiving prior to exit, 69.8% (n=2,347) were caregivers outside the household, 25.9% (n=869) provided caregiving inside the household, and 4.3% (n=145) were dual caregivers. There was a clear distinction between those who provided caregiving outside versus inside the household (**Figure 6.22**). Participants who provided caregiving outside the household had the highest probability of problematic drinking at nearly all time points, while those caring inside the household had the lowest probability. However, the trajectories were similarly shaped, with none of the interaction terms reaching statistical significance (Appendix 6.3). This suggests that while caregivers outside the household generally had a higher probability of problematic drinking and those inside had a lower probability, the exit from caregiving had minimal impact on these trajectories.

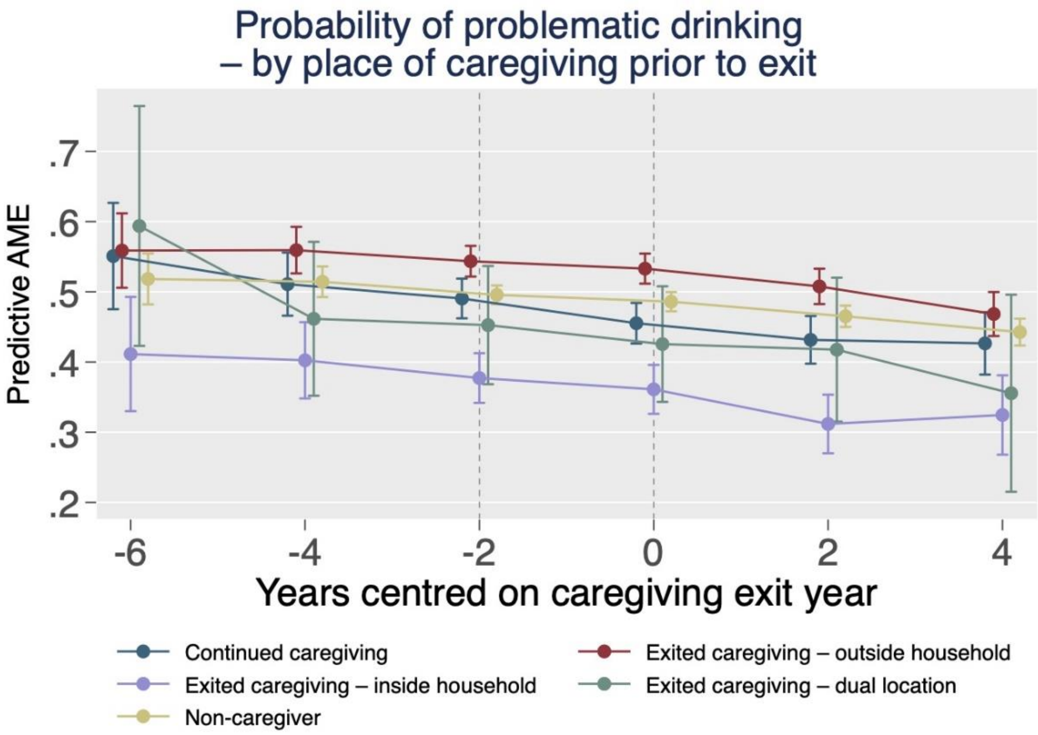


Figure 6.22 Problematic drinking and exit by place of care; Probability of problematic drinking before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, stratified by place of care prior to exit among participants who exited caregiving (n=3,361; 2,347 outside household, 869 inside household, 145 both inside and outside), alongside continuing caregivers (n=1,619) and non-caregivers (n=6,154). Time is centred around caregiving exit, with dashed lines marking transition points.

6.4.3.3 The role of sex and age on trajectories

Sex

Of all individuals who exited caregiving, 37.4% (n=1,259) were male, and 62.7% (n=2,112) were female. The estimates and trajectories for problematic drinking were similar between males and females, with no statistically significant interactions observed during the transition or post-transition periods (p=0.38 and p=0.19, respectively; **Figure 6.23**).

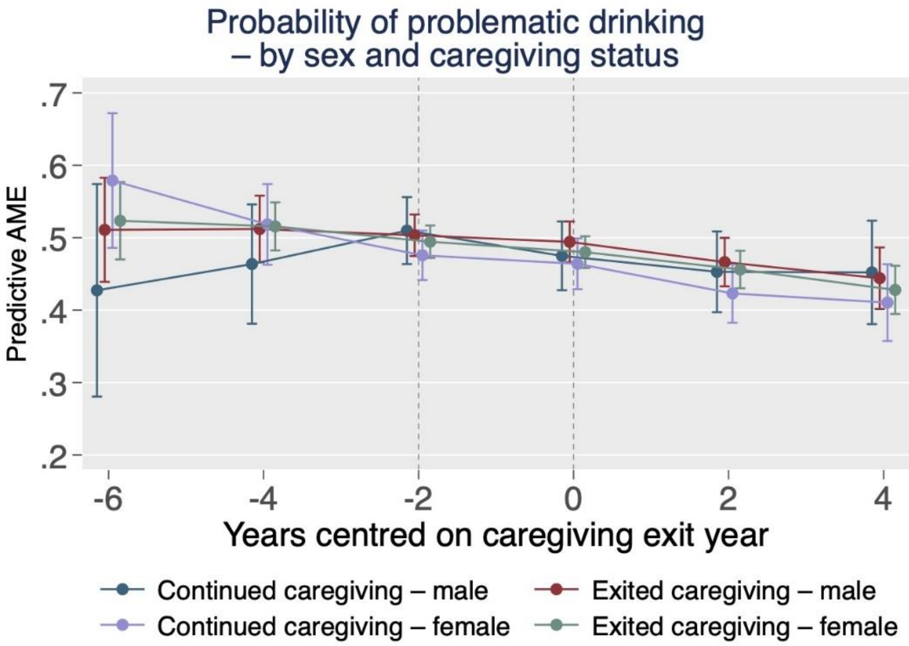


Figure 6.23 Problematic drinking and exit by sex; probability of problematic drinking before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, stratified by place of care prior to exit among participants who exited caregiving (n=3,361; 2,347 outside household, 869 inside household, 145 both inside and outside), alongside continuing caregivers (n=1,619) and non-caregivers (n=6,154). Time is centred around caregiving exit, with dashed lines marking transition points.

This lack of association is further supported by examining trajectories separately by sex (**Figure 6.24**): the trajectories for matched non-caregivers and participants who exited caregiving were similar across both sexes. This consistency suggests no significant interaction effect of sex on the relationship between caregiving exit and problematic drinking.

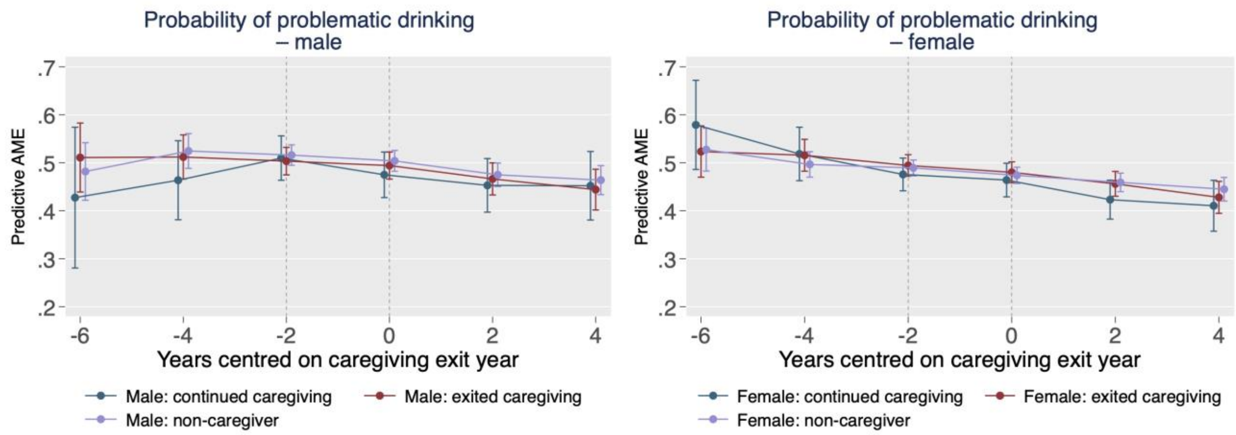


Figure 6.24 Problematic drinking and exit, stratified by sex; probability of problematic drinking before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, stratified by sex, comparing participants who exited caregiving (n=3,371; 2,112 females, 1,259 males) with continuing caregivers (n=1,619) and non-caregivers (n=6,154). Time is centred around caregiving exit, with dashed lines marking transition points.

Age groups

Among those who exited caregiving, 8.5% (n=288) were in early adulthood, 26.2% (n=882) in early mid-adulthood, 35.6% (n=1,199) in late mid-adulthood, and 29.7% (n=1,002) in late adulthood. When comparing trajectories for exiters alone (**Figure 6.25**), the probability of problematic drinking decreased in early adulthood and late adulthood but remained stable in early and late mid-adulthood. However, these differences were not statistically significant (p=0.42). Examining the age strata separately suggested that exiters in early mid-adulthood (aged 30–49) maintained stable levels of problematic drinking, whereas matched continuing caregivers in this age group showed a gradual decline, resulting in a visible divergence in trajectories over time., although the interaction term was not statistically significant (p=0.09), likely due to overlapping confidence intervals (**Figure 6.25**). These findings suggest that the life stage at the time of caregiving exit may somewhat influence the relationship between caregiving exit and problematic drinking, though this evidence should be interpreted with caution.

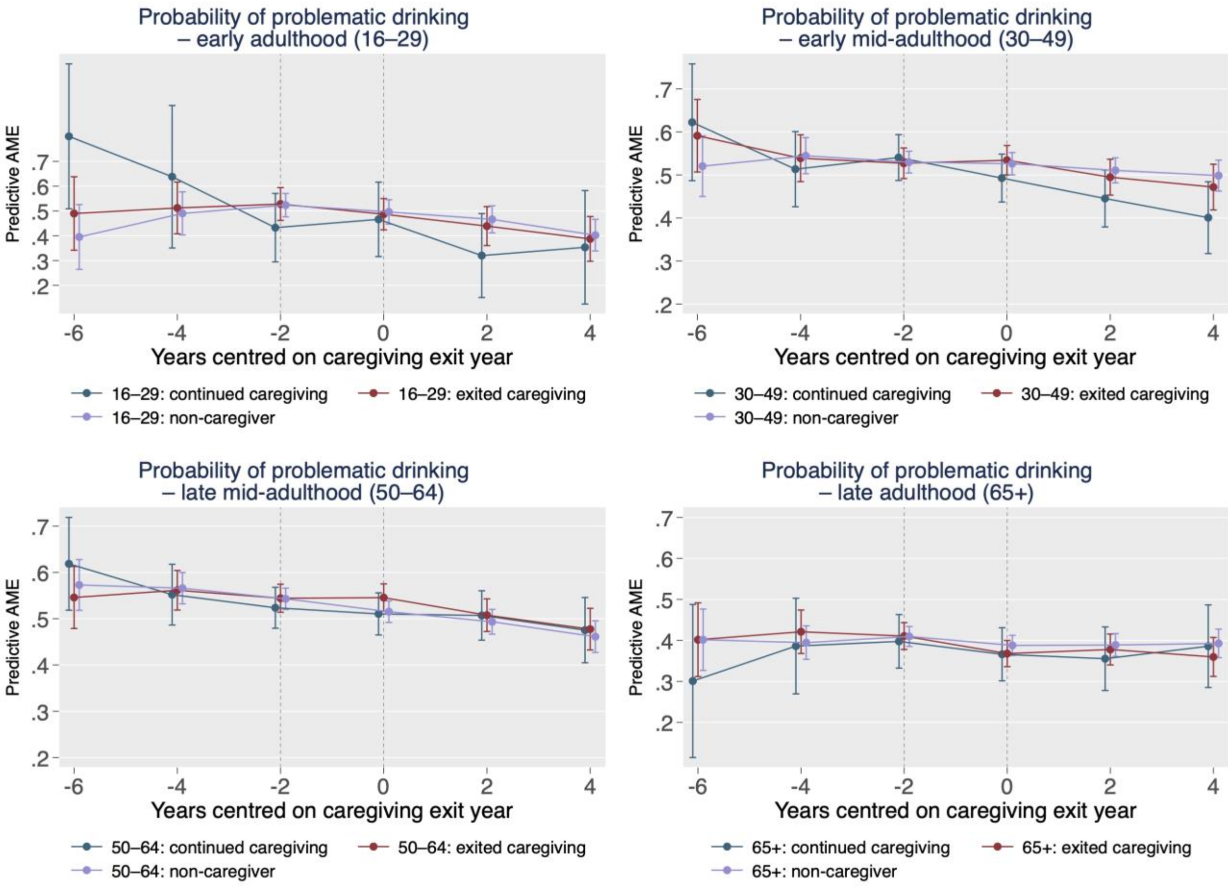


Figure 6.25 Problematic drinking and exit, stratified by age group; probability of problematic drinking before and after caregiving exit across UKHLS waves 7, 9, 11, and 13, stratified by age at caregiving exit, comparing participants who exited caregiving (n=3,371; 288 early adulthood [16–29], 882 early mid-adulthood [30–49], 1,199 late mid-adulthood [50–64], 1,002 late adulthood [65+]) with continuing caregivers (n=1,619) and non-caregivers (n=6,154). Time is centred around caregiving exit, with dashed lines marking transition points.

6.4.3.4

6.4.3.5 Summary

FE models indicated no significant association between exiting caregiving and problematic drinking, with no evidence that sex or age influenced this relationship. These results were confirmed in piecewise growth curve models, which similarly showed no significant association between caregiving exit and problematic drinking. Additional analysis revealed that low-intensity caregivers and caregivers outside of the household had a higher probability of problematic drinking, while high-intensity or in-household caregivers had a lower probability of problematic drinking, but this was not related to the exit of caregiving. Besides, there was no evidence that sex modified the relationship between caregiving exit and problematic drinking, though weak evidence suggested that the life-course stage at which participants exited caregiving may have mildly altered drinking trajectories for those in mid-adulthood.

6.4.4 Smoking

6.4.4.1 Fixed effect models

In a first step of the analysis, fixed effect models were estimated based on 6,266 participants as shown in **Table 6.5**. It can be seen the exiting caregiving was not associated with change in smoking (OR=0.96, 95%CI: 0.86/1.07, p=0.49). There was no evidence that sex or age-group of participants modified the association between exiting caregiving and smoking. Hence, results from fixed effect models suggest that there is no evidence for a relationship between exiting caregiving and smoking.

Table 6.5 Fixed effect regression for caregiving exit and smoking status

Model	Sample		OR	95% CI	p
Model: Caregiving status + adjustment for wave	$N_{participants}$ = 6,266 $N_{observations}$= 40,084	No Exit Exit	1.00 0.96	- 0.86/1.07	0.49
Interactions					
Caregiving-status*sex					0.50
Caregiving-status*age-group					0.38

6.4.4.2 Trajectories of physical inactivity

Exit caregiving in relation to continue caregiving

During the nine waves of observation period, 5,385 participants exited caregiving and were matched with 1,467 participants who continued caregiving throughout the study. The predicted trajectories of the probability of smoking were estimated for up to seven years prior to and post exit as represented in **Figure 6.26**. Trajectories of exiters and their matched continuing caregivers were close and parallel (p=0.72) while in the post-exit period, matched participants who continued caregiving seemed to have a slight increase in the probability of smoking in the long-term, but confidence intervals were wide and the p-value for the post-transition period were statistically not significant (p=0.88).

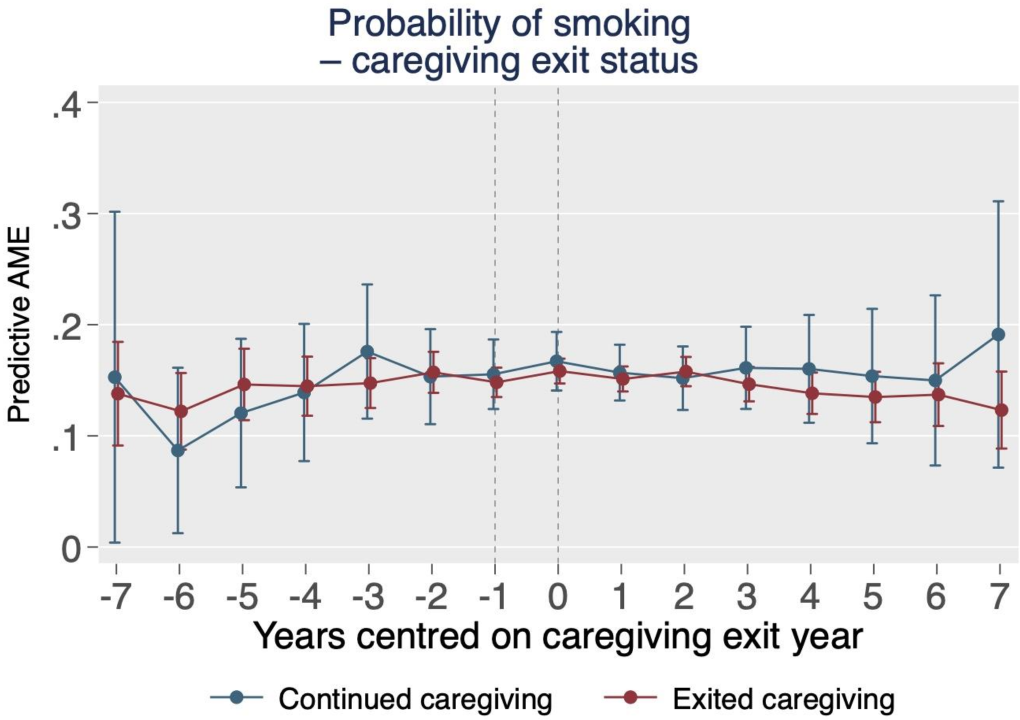


Figure 6.26 Smoking - exit vs. continued care; probability of smoking before and after caregiving exit across UKHLS waves 5 to 13, comparing participants who exited caregiving (n=5,385) with those who continued caregiving (n=1,467). Time is centred around caregiving exit, with dashed lines marking transition points. All participants were caregivers at baseline.

Exit caregiving in relation to non-caregivers

A second piecewise growth curve model was estimated with 13,219 matched non-caregivers as comparison group. **Figure 6.27** illustrates the predicted probability of smoking between those who exited caregiving and non-caregivers which shows that there was no significant slope changes between exiters and matched non-caregivers (p=0.08). During the post-transition period trajectories reversed and exiters had a slight decline in the probability of smoking relative to the trajectories of matched non-caregivers which was marginally significant (p=0.04).

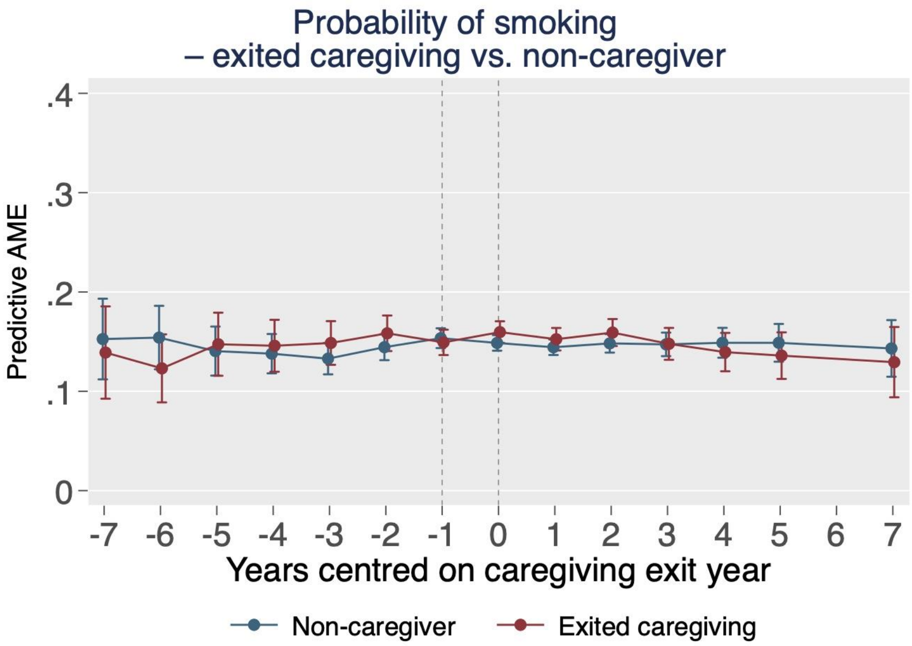


Figure 6.27 Smoking - exit vs. non-caregivers; probability of smoking before and after caregiving exit across UKHLS waves 5 to 13, comparing participants who exited caregiving (n=5,385) with non-caregivers (n=13,220). Time is centred around caregiving exit, with dashed lines marking transition points.

To allow a better comparison of both models, a graph with superimposed trajectories was created as shown in **Figure 6.28**. The left-hand panel illustrates the trajectories for both models and both groups and shows that both exit trajectories are identical as expected because it is the same group. For this reason, only one of the exit trajectories was depicted in the right-hand side panel which shows the trajectories of those who exit caregiving and those who continue caregiving diverge but only by a small margin.

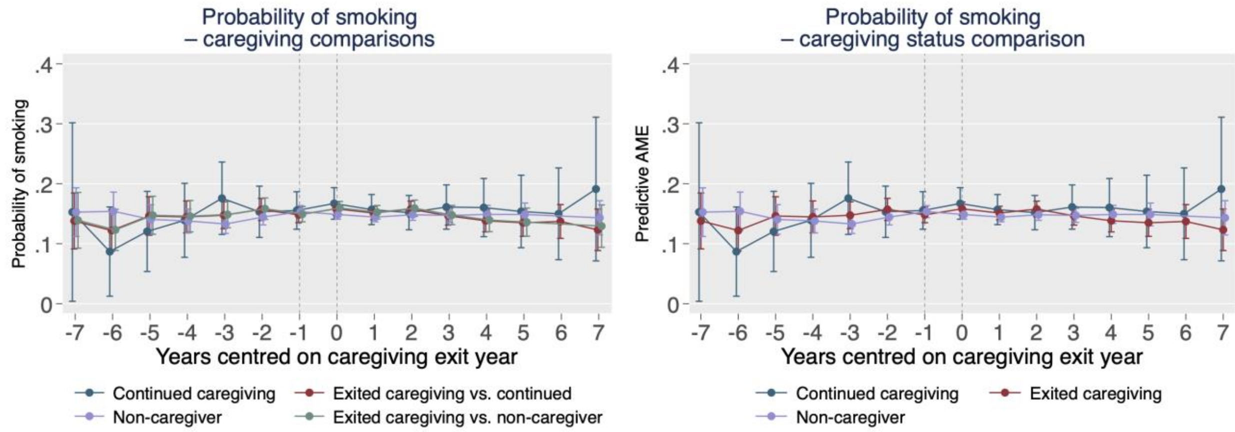


Figure 6.28 Smoking and exit - superimposed graph; probability of smoking before and after caregiving exit across UKHLS waves 5 to 13, comparing participants who exited caregiving with those who continued caregiving (n=5,385 vs 1,467) and with non-caregivers (n=5,385 vs 13,220). Time is centred around caregiving exit, with dashed lines marking transition points

Number of cigarettes amongst smokers

As a next step, a sub-group analysis was performed on the number of cigarettes participants smoked for participants who were smokers at baseline. In total, 996 exiters were smokers at baseline and they were matched against continuing caregivers and non-caregivers as shown in **Figure 6.29**. It shows that exit of caregiving was not associated with a change in the number of cigarettes they smoked compared to non-caregivers (transition p=0.77). Similarly, there was no evidence for an interaction between exiting caregiving and the number of cigarettes compared to continuing caregivers (p=0.15). Participants who exited care seemed to have a decrease in the number of cigarettes smoked relative to matched continuing caregivers in the post transition period, but this was not statistically significant (p=0.11).

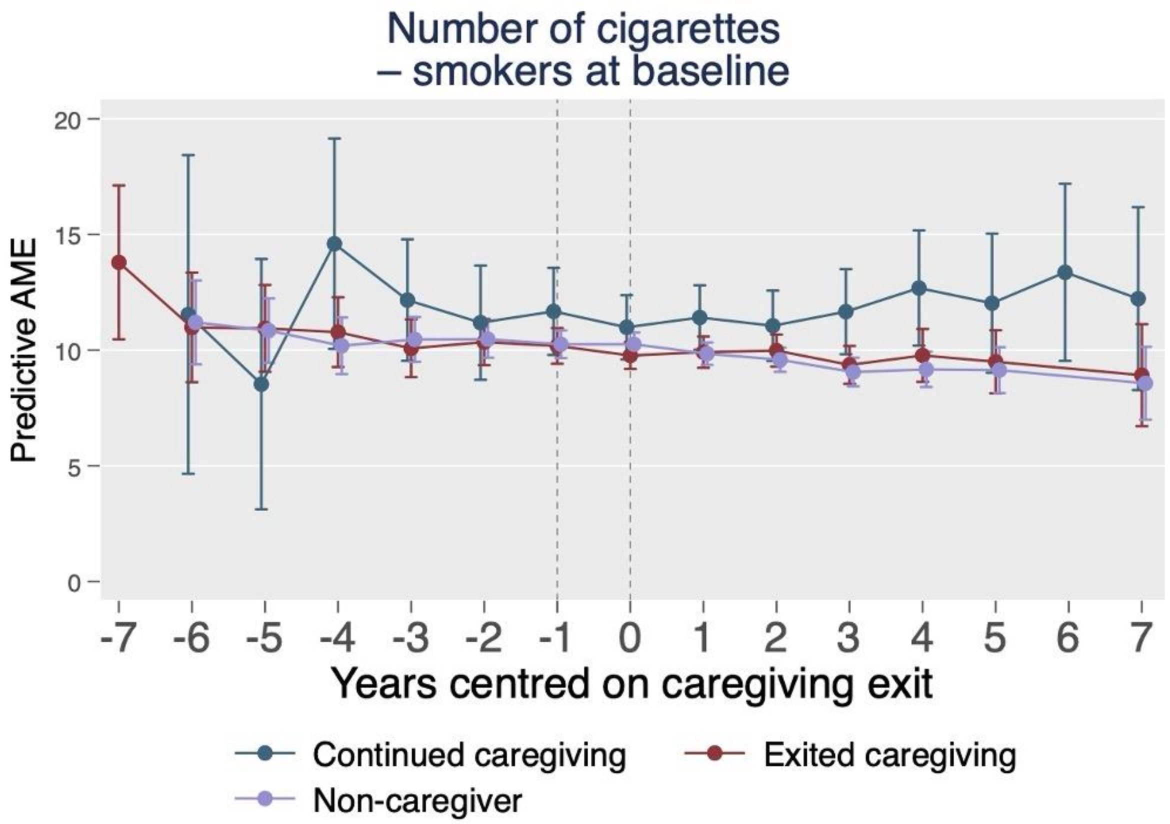


Figure 6.29 Number of cigarettes and exit - smoker at baseline; average number of cigarettes smoked before and after caregiving exit across UKHLS waves 5 to 13 among participants who were smokers at baseline, comparing those who exited caregiving (n=996) with those who continued caregiving (n=306) and with non-caregivers (n=2,074). Time is centred around caregiving exit, with dashed lines marking transition points. All participants were smokers at baseline.

Caregiving hours prior to exit

Next, the analysis was stratified by the number of caregiving hours provided prior to exit from caregiving. In total, 81.2% (n=4,334) provided less than 20 hours of caregiving per week while 18.8% (1,004) provided 20 hours of caregiving per week or more. **Figure 6.30** represents the predicted trajectories of the probability of smoking in the different intensity-strata compared to matched continuing caregivers as well as non-caregivers. Although there appears to be an increase in the slope for the probability of smoking in the post-transition period among those who exited higher-intensity caregiving, compared to non-caregivers, this was not statistically significant (p=0.77 for the exit period; p=0.66 for the post-exit period), probably due to the very large confidence intervals.

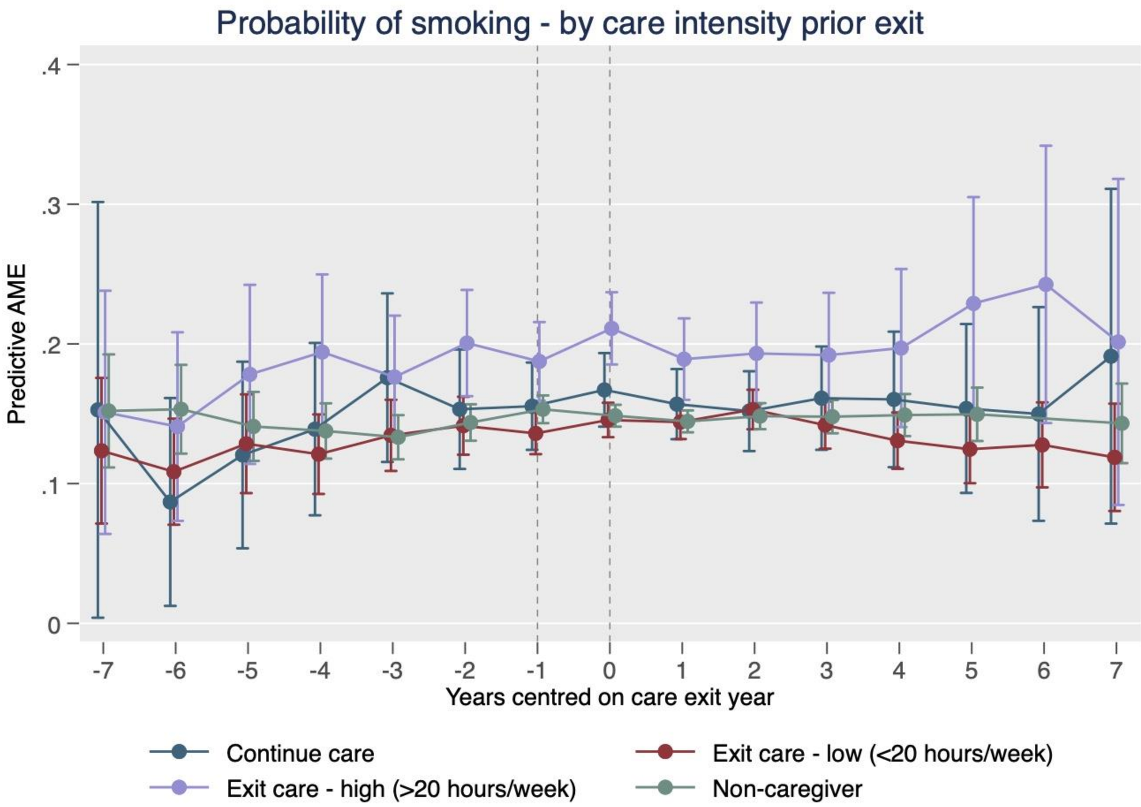


Figure 6.30 Smoking and exit by care intensity; probability of smoking before and after caregiving exit across UKHLS waves 5 to 13, stratified by caregiving intensity prior to exit among participants who exited caregiving (n=5,338; 4,334 low-intensity, 1,004 high-intensity), alongside continuing caregivers (n=1,467) and non-caregivers (n=13,220). Time is centred around caregiving exit, with dashed lines marking transition points.

Place of caregiving prior to exit

Regarding the place of caregiving prior exit, 67.0% (n=3,540) provided caregiving outside the household prior to exit; 28.5% (n=1,506) provided caregiving inside the household prior to exit; and 4.5% (n=239) provided dual caregiving prior to exit (inside and outside the household). For the piecewise growth curve model stratified by place of caregiving prior to exit, in **Figure 6.31**, shows that exiters who were provided caregiving inside the household had high probability of smoking compared to matched controls while caregivers who provided caregiving outside the household had the lowest probabilities of smoking compared to the matched controls. Despite these differences, there were no significant differences in the trajectories during exit or in the post-exit period (p=0.69 and p=0.48). This suggest that there is no evidence for a significant relationship between place of caregiving prior to exit and smoking.

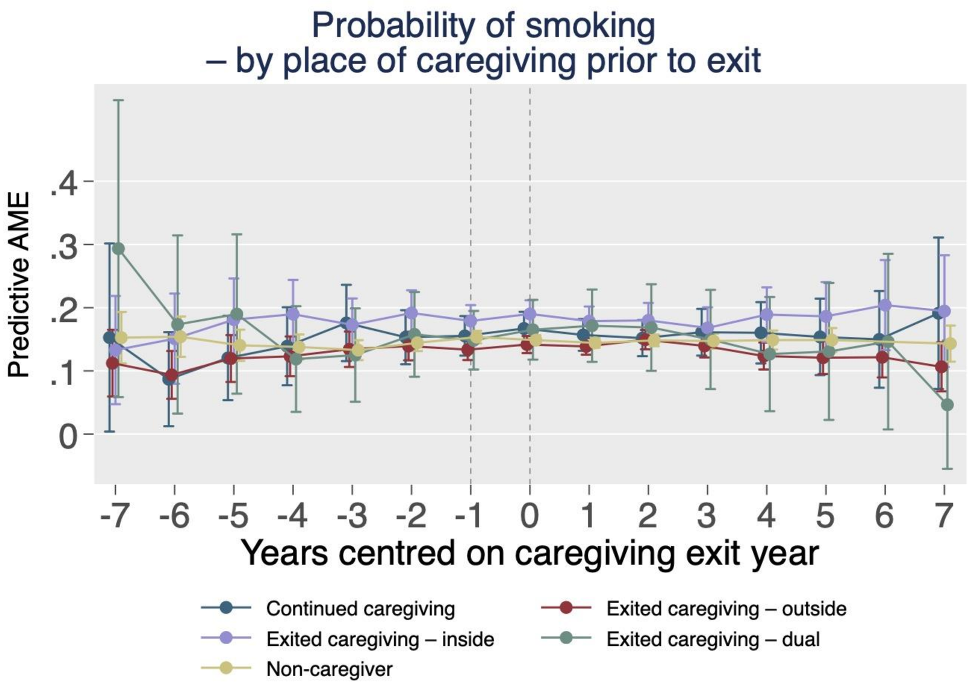


Figure 6.31 Smoking and exit by place of care; probability of smoking before and after caregiving exit across UKHLS waves 5 to 13, stratified by place of care prior to exit among participants who exited caregiving (n=5,285; 3,540 outside household, 1,506 inside household, 239 both inside and outside), alongside continuing caregivers (n=1,467) and non-caregivers (n=13,220). Time is centred around caregiving exit, with dashed lines marking transition points. Place of care was only measured for participants who exited caregiving.

6.4.4.3 The role of sex and age

Sex

Out of all exiters, 39.9% (n=2,146) were male and 60.1% (n=3.239) were female. **Figure 6.32** represents the predicted trajectories of the probability of smoking that was stratified by sex. It appears that most of the trajectories were quite similar and confidence intervals largely overlapped and there was no evidence for an interaction during the transition period (p=0.43) or post-transition (p=0.53) although matched female participants who continued caregiving seemed to have an increase of smoking in the long term.

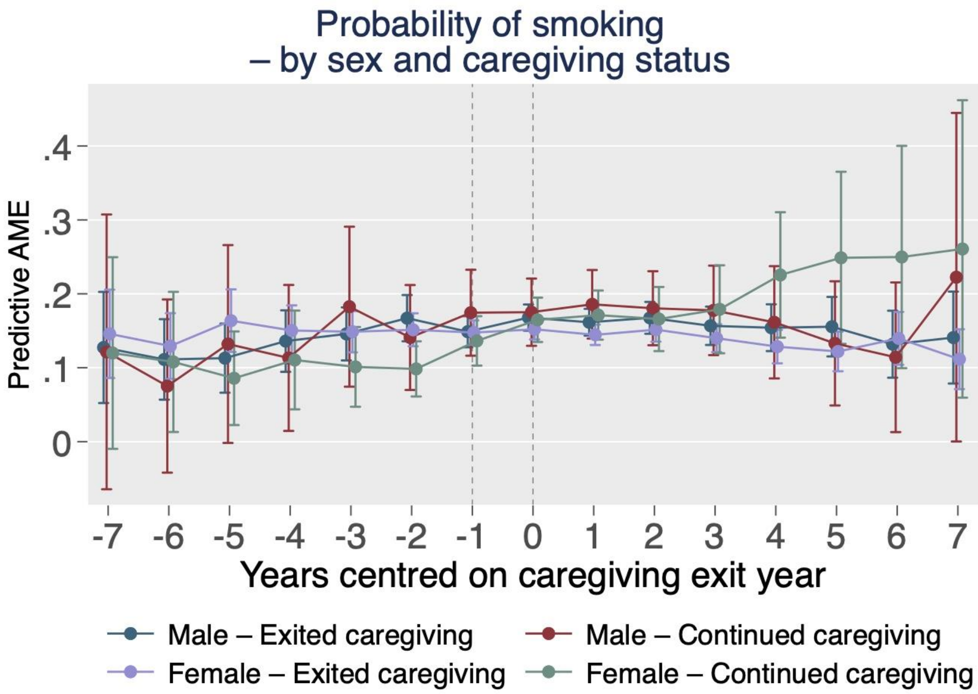


Figure 6.32 Smoking and exit by sex; probability of smoking before and after caregiving exit across UKHLS waves 5 to 13, stratified by sex, comparing participants who exited caregiving (n=5,385; 3,239 females, 2,146 males) with those who continued caregiving (n=1,467). Time is centred around caregiving exit, with dashed lines marking transition points. All participants were caregivers at baseline.

Hence, sex-strata were depicted separately, and the trajectories of the second control group (non-caregivers) were added as shown in **Figure 6.33**. In the analysis for women, exiting caregiving was associated with slope changes in the probability of smoking compared to matched females who continued caregiving during the transition period (p=0.02). This association appeared to be driven by an increase in smoking among continuing caregivers, while the smoking probability among exiters remained relatively stable. In the post-transition period, this divergence seemed to increase over time but remained only marginally significant (p=0.06) probably due to the large confidence intervals that are the result of a small sample who continued caregiving. For male exiters, however, there was no significant association in males for the transition period (p=0.50) and post-transition (p=0.47).

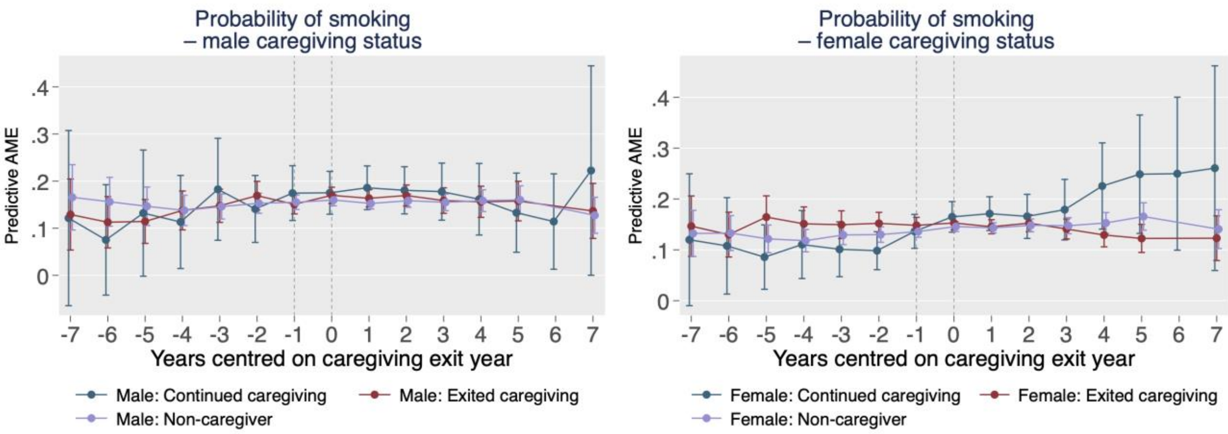


Figure 6.33 Smoking and exit, stratified by sex; probability of smoking before and after caregiving exit across UKHLS waves 5 to 13, stratified by sex, comparing participants who exited caregiving (n=5,385; 3,239 females, 2,146 males) with continuing caregivers (n=1,467) and non-caregivers (n=13,220). Time is centred around caregiving exit, with dashed lines marking transition points.

Age groups

In view of age groups, 16.1% (n=866) of exiters were in early adulthood; 29.2% (n=1,570) were in early mid-adulthood; 33.0% (n=1,776) were in late mid-adulthood; and 21.8% (n=1173) in late adulthood. Due to the limited sample size, most trajectories could only be modelled from up to four years prior the exit of caregiving as shown in **Figure 6.34** which depicts trajectories of exiters by age group. This figure shows that exiters in early adult life had the most volatile trajectories with decrease of smoking around the exit followed by an increase of smoking in the post-exit period. In contrast, trajectories in other age groups were more stable and exiters in late adulthood and late mid-adulthood had the lowest probability of smoking. Despite this, the interaction term for the transition period or post-transition were statistically non-significant (Appendix 6.3).

Next, age-strata were analysed separately and the trajectory for the comparison-group of non-caregivers was superimposed as shown in **Figure 6.34**. It was noted that the only significant association was in early mid-adulthood in which participants between 30-49 who exited caregiving had an increase in the probability of smoking relative to matched non-caregivers in the transition period (p=0.01) and post-transition (p=0.004) but the magnitude of the association is very small.

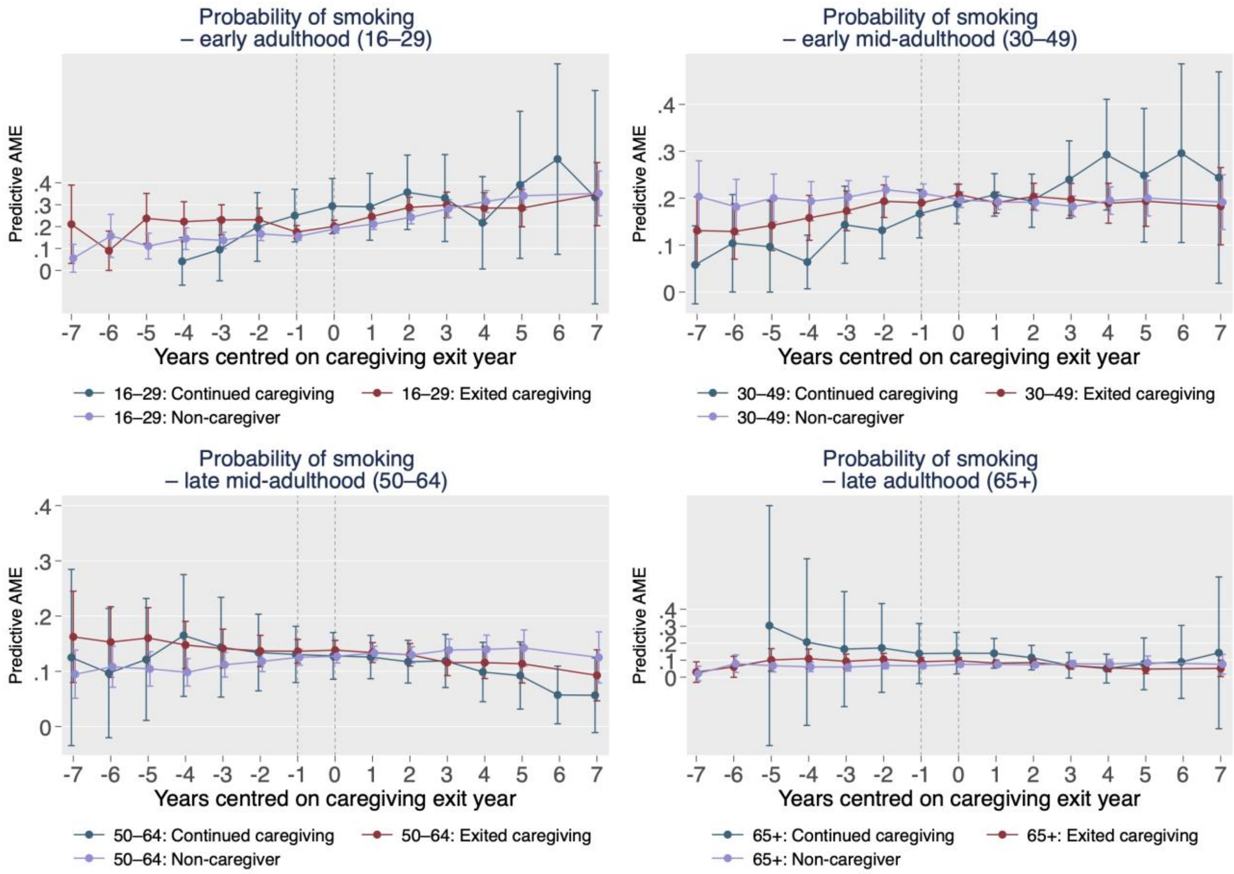


Figure 6.34 Smoking and exit, stratified by age group; probability of smoking before and after caregiving exit across UKHLS waves 5 to 13, stratified by age at caregiving exit, comparing participants who exited caregiving (n=5,385; 866 early adulthood [16–29], 1,570 early mid-adulthood [30–49], 1,776 late mid-adulthood [50–64], 1,173 late adulthood [65+]) with continuing caregivers (n=1,467) and non-caregivers (n=13,220). Time is centred around caregiving exit, with dashed lines marking transition points.

6.4.4.4 Summary

Fixed effect models revealed that there was no significant association between exiting caregiving and smoking and that sex and age did not modify this relationship. This was largely replicated by the piecewise growth curve models which did not find any significant associations between caregiving exit and changes in the probability of smoking. Although exiters from higher intensity caregiving and caregivers inside the household showed consistently higher probability of smoking, this was not related to the exit from caregiving. There was some evidence that sex modified the relationship to a small degree, because exiting caregiving was associated with a small but significant decrease probability of smoking compared to those who continued caregiving but only for female participants. There was no evidence for a modifying effect of age on this relationship.

6.5 Discussion

This chapter had the aim to investigate the relationship between exit from caregiving and health behaviours across the lifecourse using a population-based longitudinal sample from the UK. It was found that caregiving cessation was associated with an increase in physical inactivity but there were no associations found for fruit and vegetable consumption, problematic drinking and smoking. While these findings will be discussed in detail alongside findings from the other chapters in Chapter 9: Discussion, the following section focuses on interpreting the findings specific to this chapter.

First, the analyses consistently showed that exiting caregiving is associated with increased physical inactivity, particularly among older adults and high-intensity caregivers, who experienced sharper increases in physical inactivity following caregiving exit. The role of age as a potential modifier was marginal and exiting caregiving in later life showed the largest increase in physical inactivity in the fixed effect models, but this association was marginally not significant in the piecewise regression. In contrast, no significant interaction with sex was found.

The finding that physical inactivity decreased following the onset of caregiving (Chapter 5), whereas it increased after caregiving cessation, suggests that changes in caregiving status are temporally aligned with changes in physical activity levels. One possible explanation is that the responsibilities associated with providing care may increase overall movement and activity in daily life, either through physically assisting the care recipient or engaging in additional household tasks.[114,255,256] When caregiving ends, these activity-promoting tasks are no longer part of the daily routine. Individuals may then revert to pre-caregiving activity levels, or in some cases become less active if their caregiving role had previously structured their day and provided a source of regular movement. An alternative explanation is that individuals in poorer health, or those with fewer opportunities for physical activity, may be more likely to stop providing care, and their inactivity levels may rise for reasons unrelated to the caregiving role itself.[225,257,258]

In terms of fruit and vegetable consumption, neither fixed-effect nor piecewise growth-curve models identified a significant association between caregiving exit and change in daily fruit and vegetable consumption. Although minor associations emerged in subgroup analyses, these were not robust and may be attributable to statistical variance rather than true moderation effects, indicating a stable fruit and vegetable consumption pattern post-caregiving exit. The absence of notable change in fruit and vegetable consumption following caregiving exit may reflect the stability of dietary habits, which are generally less responsive to short-term changes in daily routine than physical activity.[88,167,259] Fruit and vegetable consumption may also be more strongly influenced by broader socioeconomic and cultural factors, including income, food availability, and long-standing health beliefs.[260–263]

The analysis of problematic drinking mirrored these findings, showing no significant association with caregiving exit. A mild interaction effect between caregiving exit timing and drinking patterns was observed in mid-adulthood, although there was no significant moderation by sex or age overall. Caregiving exit can often be a stressful period, particularly when it follows the death or institutionalisation of the care recipient, or when it involves adjusting to the loss of a central daily role.[240,264,265] However, the absence of an association in these analyses may indicate that individuals do not generally respond to this stress through changes in alcohol consumption. It is also possible that drinking patterns are often shaped by long-standing habits, cultural norms,[266] and social contexts,[267] which may be less susceptible to short-term fluctuations related to caregiving exit.

Finally, both fixed-effect and growth-curve models indicated no substantial link between caregiving exit and smoking behaviour. This was in contrast with analysis from Chapter 5 which found that transitioning into caregiving was linked with an increased likelihood of smoking, which may reflect the use of smoking as a coping strategy during periods of heightened stress.[94,96,99] The absence of change in smoking following caregiving cessation suggests that once established, such patterns may persist beyond the caregiving period. This persistence could indicate that the behaviour becomes embedded in daily routines, creating a lasting legacy of the caregiving experience.[268,269]

A potential interaction effect with sex was observed, particularly among females, where exiting caregiving was associated with a slight decrease in the probability of smoking compared with females who continued caregiving, although the magnitude of this association was small. One possible explanation for this small sex-specific pattern is that women often carry a greater share of caregiving responsibilities, which can involve sustained emotional, physical, and social demands.[44,46,59,223] If smoking is used as a coping strategy during this period, the removal of the caregiving role may alleviate a key source of stress, making it easier to stop smoking. However, evidence suggests that women are generally less likely than men to successfully quit smoking after major life changes or stressful events.[270–272] These contrasting possibilities highlight the need to interpret the observed pattern with caution and to explore in future research how the end of caregiving interacts with gendered coping strategies and smoking cessation behaviours

6.5.1 Limitations

One important caveat to the findings of this chapter is the lack of information on reasons for caregiving cessation. UKHLS does not collect data on why caregiving ends, particularly in cases where care is provided outside the household. While it would be possible to perform dyadic analyses for caregivers who cohabit with the care recipient, this was not feasible for caregivers providing care outside the household. As discussed in the introduction to this chapter, caregiving cessation is often accompanied by adverse life events such as the institutionalisation or death of the care recipient, or a decline in the caregiver's own capacity to provide care.[231–233] This implies that exit from caregiving is rarely neutral, but often a negative and stressful experience. Therefore, understanding how caregiving cessation relates to changes in health behaviours provides important insights for supporting former caregivers during this vulnerable period even though the specific reasons for caregiving exit are unknown.

Further, it is important to consider whether it was appropriate to match participants on baseline characteristics rather than on characteristics from the wave immediately prior to caregiving cessation. A longitudinal population-based study by Pennington and colleagues,[273] also using UKHLS data, compared trajectories of health-related quality of life between bereaved caregiver dyads and bereaved non-caregivers dyads. Their findings showed that health-related quality of life had already begun to decline in caregivers prior to the bereavement event, while no such decline was observed in non-caregivers. This suggests that caregiving burden may intensify in the period prior to cessation, with cumulative and anticipatory stress potentially affecting caregiver's wellbeing even before the role ends. Therefore, matching on baseline characteristics, prior to a caregiving cessation, may be more appropriate to capture the long-term effects of caregiving cessation on health behaviours.

It must also be highlighted that FE models were not adjusted for time-varying confounders, as outlined in the directed acyclic graph (DAG) presented in Chapter 4.5. There is reason to believe that these time-varying variables lie on the causal pathway between caregiving cessation and health behaviours, rather than acting as confounders. For example, if the care recipient was the caregiver's spouse and caregiving ceased due to their death, the caregiver's marital status would change. In this case, marital status is not a confounder but a mediator on the causal pathway between caregiving cessation and subsequent changes in health behaviours. Adjusting for such variables could lead to over-adjustment bias and obscure the true effect of caregiving cessation.

Conceptually, the aim of this chapter was to compare participants who experienced caregiving cessation to those who did not undergo this transition, in order to isolate the impact of exiting the caregiving role on health behaviours. The most intuitive comparison group for this purpose would be individuals who continued to provide care, as they represent a group that did not transition out of caregiving. However, in practice, the number of participants who continued caregiving across waves was relatively small, limiting statistical power and representativeness. Consequently, a second comparison group was introduced: participants who were non-caregivers across all waves. While these individuals were not exposed to caregiving at any point, they also did not experience an exit from caregiving, making them a conceptually valid reference group for exploring the consequences of role cessation. This approach allowed for a broader and more robust analysis of the impact of caregiving exit, while still maintaining a focus on the transition out of the caregiving role as the exposure of interest.

Nevertheless, this approach has limitations. Non-caregivers may differ systematically from caregivers in ways that are not fully captured by observed baseline characteristics that were used for the propensity score matching, such as unmeasured social or psychological factors. As such, comparisons between caregivers exiting care and lifelong non-caregivers may introduce selection bias or residual confounding. Furthermore, because the non-caregiving group never assumed a caregiving role, they may not represent a realistic counterfactual for caregivers whose lives have been shaped by the caregiving experience. These limitations should be considered when interpreting the results.

6.6 Chapter conclusion

This chapter explored the associations between caregiving exit and a range of health behaviours, including physical inactivity, fruit and vegetable consumption, alcohol consumption, and smoking, using fixed-effect and growth-curve models on a propensity score matched sample. The findings reveal complex and context-dependent relationships, with notable variations based on caregiving intensity, place of caregiving, and age. While it was found that exiting caregiving was associated with an increase in physical inactivity, there was no evidence that exiting caregiving was associated with changes in fruit and vegetable consumption, problematic drinking or smoking.

7 Changes in Caregiving Intensity and Health Behaviours

7.1 Introduction

In the previous chapters, transitions into and out of caregiving were examined in relation to health behaviour changes using fixed-effects and piecewise growth curve models applied to a propensity score-matched sample. It was found that transitioning into unpaid caregiving was associated with reduced odds of physical inactivity and increased odds of smoking. Further, transitioning into caregiving was associated with increased odds of problematic drinking, whereas longer-term trajectories suggested that higher-intensity caregiving was associated with a lower probability of problematic drinking over time. In contrast, transitioning out of caregiving was associated with increased physical inactivity but showed no significant association with other health behaviour changes.

In the previous analysis, transitions into caregiving most commonly involved low-intensity care provided outside the household. Although the majority of caregiving exits also occurred from low-intensity and outside-household caregiving, a higher proportion of those who exited caregiving had provided higher-intensity care within the household compared to those who had newly entered caregiving. This pattern suggests that some individuals may move from lower- to higher-intensity caregiving during a caregiving episode. However, a significant limitation of the approach used in the previous chapters is its focus on a single transition, either the onset of caregiving or its cessation. It did not account for changes in caregiving intensity that may occur during the caregiving period.

However, the transitions between different caregiving intensities may have important implications for health behaviour trajectories, yet the existing literature, as identified in the previous literature review section, lacks population-based longitudinal studies examining how changes in caregiving intensity relate to health behaviours over time. While some studies have explored cross-sectional associations between indicators of caregiving intensity and health behaviours[84–96,99,100,102,103,105] or longitudinal studies that focused on intensity when transitioning into caregiving,[101,104,114] no prior research has examined trajectories of caregiving intensity alongside health behaviour changes. This chapter seeks to address this knowledge gap by employing a novel approach to examine caregiving intensity trajectories and their potential influence on health behaviour outcomes.

7.1.1 Defining caregiving intensity

Caregiving intensity can be conceptualised as a multidimensional construct that encompasses time, effort and emotional investment that caregivers dedicate to the role. Studies often consider the hours of care provided as an indicator for caregiving intensity,[17,274,275] while other studies consider the task performed by caregivers as an indicator[258,276–278] or even the quality of the relationship between caregiver rand care recipient.[279,280]

In UKHLS, information on the hours of care provided is available for caregiving inside and outside the household. However, data on the care tasks is not available in UKHLS. This raises the question of whether 'place of caregiving' might serve as a proxy for caregiving intensity in the absence of direct measures on caregiving tasks. Research suggests that the location of caregiving, either within or outside the household, significantly influences caregiving burden, with individuals who provide care within the household experiencing a greater burden.[71] This is supported by other studies which found that caregiving within the household tends to be more intense than caregiving outside the household, whether measured in hours of care provided or the type and frequency of tasks.[281] This might be because caregiving outside the household often involves less direct involvement in daily care tasks and may offer greater flexibility to take breaks or step away from caregiving responsibilities when needed,[282] while caregivers inside the household often face continuous demands.[283] Furthermore, some literature suggests that caregiving within the household is more intense due to the heightened emotional involvement associated with caring for someone in close proximity[284] whereas caregiving outside household have more flexibility and less emotional weight associated with caregiving role.[285]

It can be concluded that caregiving intensity can be conceptualised as a multifaceted construct which is influenced by the time and complexity of the care tasks. Caregiving hours can reflect the amount of the time demand of caregiving, while the place of care (whether inside or outside the household) can offer additional contextual information. The combination of caregiving hours and place of care is, therefore, considered to provide a meaningful approximation of caregiving intensity which captures both, the time demands of caregiving as well as the nature of the caregiving setting, given the data available in UKHLS.

7.1.2 Conceptual considerations

As discussed in Chapter 1 Background section, theorists have conceptualised that caregiving occurs in five phases.[24,25] The first phase of caregiving involves the initial onset, during which the caregiver may begin providing support in ways that are not typically part of their previous relationship with the care recipient. At this stage, caregivers might not yet identify as 'caregivers'. In the second phase, caregivers begin to recognise their new role and start identifying as caregiver. In the third phase, the boundaries of the normative relationship between the caregiver and care recipient start to shift and caregiving becomes increasingly the dominant aspect for the relationship between caregiver and recipient. The fourth phase, where it occurs, is characterised by a sustained period of caregiving until the care needs of the care recipient exceed what the caregiver can provide. Finally, the fifth phase marks the end of caregiving, either due to recovery, transition to institutional care, or the passing of the care recipient. However, it must be acknowledged that while the caregiving role theory is a useful framework, it has been criticised for being too simplistic and may not capture the nuanced realities faced by caregivers in various contexts.[27,30]

Despite this criticism, the conceptualisation of caregiving role theory has several implications: (1) caregivers might initiate their role with lower intensity and then increase intensity; (2) caregivers might experience a stable caregiving intensity over a longer period of time; and (3) decreasing caregiving intensity due to the recovery of the care-recipient is not a very common transition, rather, caregivers transition out of the role of a caregiver. While there have been some attempts to study role acceptance[31] and other concepts such as role captivity,[35] no literature could be found which tested the phases of caregiving role theory empirically. This study aims to close this gap by identifying trajectories of caregiving intensity and investigating how these trajectories are related to health behaviour outcomes.

7.2 Chapter aim & objectives

It is the overarching aim of this chapter to address Objective 3, namely, to investigate if and to what extend the trajectories of caregiving intensity influence health behaviours amongst caregivers. Chapter objectives include:

3a. To characterise different trajectories of caregiving intensity and examine their characteristics.

3b. To assess whether these trajectories are associated with changes in health behaviour outcomes.

3d. To examine if the association between caregiving intensity and health behaviours are modified by sex or life course stage of the caregiver.

7.3 Methods

7.3.1 Study design

This study is a secondary longitudinal data analysis using data from UKHLS as described in previous chapter: General Methods.

7.3.2 Data

UKHLS collects data on caregiving hours and place of caregiving in all 13 waves. However, information on health behaviours is only available in waves 2, 5, 7, 9, 11, and 13. Moreover, the health behaviour questions were revised in wave 7 and remained consistent in waves 9, 11, and 13 as outlined in Chapter 4 . As a result, caregiving data from waves 2 to 13 will be used in this study, while health behaviour measures will be limited to the available waves. Baseline health behaviour measures for covariate adjustment will be taken from waves 2 or 5, and outcome measures from waves 7, 9, 11, or 13.

7.3.3 Measures

7.3.3.1 Exposure: Caregiving intensity

A new variable was created for wave 2 to wave 13 which encompassed the hours of care and place of care as more comprehensive measure of caregiving intensity. Firstly, a variable of care hours was derived which was based on the questions *"Now thinking about everyone who you look after or provide help for both those living with you and not living with you - in total, how many hours do you spend each week looking after or helping (him/her/them)?".* The original categories were: (1) 0-4 hours; (2) 5-9 hours; (3) 10-19 hours; (4) 20-34 hours; (5) 35-49 hours;

(6) 50-99 hours; (7) 100 or more hours / continuous care; (8) varies under 20 hours; and (9) varies over 20 hours.

To simplify analysis and ensure adequate group size of each category, the original nine caregiving hours categories were recoded into four meaningful intensity groups: low (0–9 hours), medium (10–19 hours), high (20–34 hours), and very high (35+ hours) of care per week. Respondents who reported varying hours under 20 were grouped with the medium category (10-19 hours), and those reporting varying hours over 20 were grouped with the very high category (35+ hours) to reflect likely patterns of more substantial caregiving commitment. These "varying" groups comprised approximately 2.0–3.5% and 3.0–5.6%, respectively, of those who reported care hours in each wave.

Secondly, groups were created based on this hour variable combined with a variable with three categories which contained information about the place of care which could be (1) outside the household; (2) inside the household; or (3) inside and outside the household (dual). As a result, the new grouping variable had 12 categories ranging from low care hours outside to very high care hours inside the household as shown in **Table 7.1**,

Table 7.1 Caregiving intensity variable

New caregiving intensity categories
Low (0-9 hours) outside
Low (0-9 hours) inside
Low (0-9 hours) dual
Medium (10-19 hours) inside
Medium (10-19 hours) outside
Medium (10-19 hours) dual
High (20-35 hours) inside
High (20-35 hours) outside
High (20-35 hours) dual
Very high (35+ hours) inside
Very high (35+ hours) outside
Very high (35+ hours) dual

7.3.3.2 Outcomes and covariates:

The outcomes of interest were physical inactivity (inactive/active), number of daily fruit and vegetable, problematic drinking (problematic drinking/no problematic drinking and smoking (current smoker / no current smoker) as defined in Chapter 4.4.

7.3.3.3 Health behaviours at baseline

The analytical plan involved adjusting for baseline health behaviours. However, the health behaviour module's questions changed from wave 7 onwards, and the questions from waves 2 and 5 differed from these. Consequently, it was not possible to fully harmonise the variables across waves. Instead, similar variables were created to serve as proxies for baseline health behaviours for adjustment purposes. Baseline health behaviours were assigned based on the timing of the first observed caregiving. For participants whose caregiving was first observed at UKHLS Wave 2, 3, or 4, baseline health behaviours were drawn from Wave 2. For those who first reported caregiving at Wave 5 or later, baseline measures were taken from Wave 5. This approach ensured that health behaviours were measured prior to any change in caregiving intensity. All chosen baseline variables are defined below and were used to predict the outcomes. Further details can be found in Appendix 7.6.

Physical activity at baseline

The physical activity module in wave 2 and 5 of UKHLS was limited to questions about walking. Participants were asked the question: "*On how many days in the last four weeks did you spend 30 minutes or more walking? This could be made up of more than one walk."* Based on the responses, a variable was created that measured the number of days in the past four weeks participants were walking for at least 30 minutes. This variable contained five categories: (1) none; (2) 1-2 days; (3) 3-4 days; (4) 5-6 days; and (5) every day.

An alternative variable was considered that measured how often participants engaged in a number of selected sport activities, but this variable had 38% missingness (Appendix 7.5). While walking at baseline may not fully capture overall physical activity, it was significantly associated with subsequent physical inactivity and was therefore used in preference to the sports-based measure with substantial missingness.

Fruit and vegetable consumption at baseline

In waves 2 and 5 of UKHLS, participants were asked three questions: (1) on how many days they eat fruit ("*Including tinned, frozen, dried and fresh fruit, on how many days in a usual week do you eat fruit?*"; (2) on how many days they eat vegetables ("*Including tinned, frozen and fresh vegetables, on how many days in a usual week do you eat vegetables? Do not include potatoes, crisps or chips*."); and (3) how many portions of fruit and vegetables they consume on a typical day ("*On a day when you eat fruit or vegetables, how many portions of fruit and vegetables in total do you usually eat? The showcard has some pictures that may give you an* *idea of what a portion looks like*."). Based on the responses from these three questions, a categorical variable was created which contained the average daily portions of fruits and vegetables with the following categories: (1) zero portions; (2) one to three portions; (3) four portions; and (4) five or more portions.

Number of drinks at baseline

The Audit-C measure was not available in wave 2 and wave 5 of UKHLS to measure problematic drinking at baseline. As a proxy for alcohol consumption, a new variable was generated that was based on two questions: (1) whether they ever had an alcoholic drink ("*Excluding non-alcoholic and low alcohol drinks but including shandy, have you ever had an alcoholic drink, that is, a whole drink not just a sip?").;* and (2) how often they had an alcoholic drink in the last year *("Thinking now about all kinds of drinks, how often have you had an alcoholic drink of any kind during the last 12 months?").*

The new variable measured the number of drinks in the last 12 months and had four categories: (1) no drinks: (2) monthly but less than weekly drinks; (3) one to four drinks per week; and (4) 5 or more drinks per week. These cut offs were chosen based on the possible responses and it must be acknowledged that they do not perfectly align with the same cut-offs from the Audit-C question on the number of drinks, however, the variable predicted problematic drink at the outcome wave (Appendix 7.6).

Smoking status at baseline

A variable was generated which was based on two questions from the questionnaire: (1) whether they ever smoked (*"Have you ever smoked a cigarette, a cigar or a pipe?);* and (2) whether they smoked currently *("Do you smoke cigarettes at all nowadays?").* Based on the responses, participants were categorised as either (1) non-smoker; (2) ex-smoker; or (3) current smoker. This variable strongly predicted smoking status at outcome as seen in Appendix 7.6.

7.3.3.4 Covariates

The same covariates as defined in previous chapters were used including sex (male/female); age groups (early adulthood:16-29; early mid-adulthood: 30-49; late mid-adulthood: 50-64; and late adulthood: 65 and older), cohabiting status (single, widowed, separated / married or cohabiting), highest education attainment (no qualification / A-levels, GCSE, other qualifications / degree or other higher qualification), ethnicity (white / black / Indian / Pakistani / Bangladeshi / other Asian or other), occupational class (not employed / management and professional/intermediate/routine), income quintiles (from 1 [lowest] to 5 [highest], employment status (not employed/full-time employed/part-time employed), number of children living in the household, household size, self-rated general health (excellent, very good or good / fair or poor), psychological distress (GHQ score) and physical limitations (SF12 score).

Additionally, for each of the outcomes, a variable was created to indicate in which waves the outcomes were observed, as this observation period spans over eight years. This variable was used in the adjusted models to account for changes in outcomes over time or possible period effects.

7.3.4 Statistical analysis

Several approaches were considered to of identify the different trajectories of caregiving intensity and their characteristics. Group-based trajectory modelling (GBTM) was initially considered as a method for identifying distinct patterns of caregiving intensity over time. One way to implement this approach is through the *traj* command in Stata, which fits finite mixture models to longitudinal data.[286] However, this command does not support the modelling of ordinal categorical outcomes, which limits its applicability for analysing caregiving intensity transitions in this study. Hence, Latent Class Analysis (LCA) was considered a suitable alternative to model the trajectories of the ordered categorical variable of care intensity. In Stata, there were convergence issues with these models and the analysis was moved to R and the Latent Class Analysis was performed using the poLCA package in R.[287] Some visual tools from sequence analysis have been used to describe latent classes using the R package TraMiner.[288]

7.3.4.1 Latent Class Analysis (LCA)

For the LCA, the guidelines by Sinha et al., [289] and Weller et al.[290] was followed which provide a structured approach and best practice guidance for LCA. In brief, after generating the intensity variable from Waves 2 to 13 of UKHLS, latent class models were estimated starting with one class (Model 1) and with each model the number of classes were increased by one up to eight classes (Model 8). The choice to estimate up to eight classes was pragmatic, aiming to capture a range of plausible caregiving intensity classes, including both stable patterns at different intensity levels and distinct types of change over time, without overfitting the model or compromising interpretability. These different latent class solutions were compared using the Information Criterion (IC) Bayesian Information Criteria (BIC), sample size adjusted BIC (aBIC) and constant Akaike Information criterion (cAIC). Lower ICs indicate better model fit. Additionally, an elbow plot of fit statistic was generated to assess in which models the fit visually changes.

Afterwards, the potential class solutions were examined using visual tools from sequence analysis to analyse the characteristics and composition of each class. This step also involved assessing whether the emerging classes made theoretical and conceptual sense. After determining the most suitable number of classes, classification diagnostics were performed. For this, relative entropy was assessed, which is a diagnostic statistic that measures how accurately a model defines classes. Ideally, an entropy value close to 1 is preferred, and values above 0.8 are acceptable. While there is no universally agreed-upon cut-off for entropy, values below 0.6 may hinder publication as the resulting solution suggests a 'fuzzy' classification with poorly defined and overlapping classes.[290] Although entropy serves as a measure for class separation, it should not be used as indicator for the selection of the number of classes because the highest entropy does not always indicate the best fit, as overfit models may have higher entropy. However, low entropy can signal poor class separation, necessitating closer inspection of the models and the quality of the indicators used.[289]

Further, average posterior probabilities were computed in a matrix where the diagonal values represent average likelihood that an individual belongs to a particular class, based on their scores on the indicators used to define these classes. According to Weller and colleagues,[290] values closer to 1.0 are desired for the diagonal values while values above 0.80 are also seen as acceptable.[291] The off-diagonal element in the posterior probability matrix represents the likelihood of cases being misclassified, meaning that individuals belong to one class assigned to a different class in the current solution. Ideally, these off-diagonal values should be low and closer to 0, indicating minimal misclassification.[290]

It must be noted that some researchers argue that the theoretical soundness of identified classes in latent class analysis is more important than fit statistics.[292,293] They emphasise that classes should be conceptually meaningful and align with existing theoretical frameworks even if the fit statistics are not optimal because theoretically grounded classes are less likely to be artefacts of the specific sample or model used.[294,295] Therefore, it is the aim of the analysis to consider fit statistics, classification statistics as well as theoretical considerations to determine the number of latent classes for further analysis.

7.3.4.2 Regression analysis

Following LCA, a class variable was generated that contained the most likely class for each individual based on the posterior probabilities of class membership. Then regression modelling was performed to assess associations between the derived trajectories of intensity and health behaviours: linear regression for fruit and vegetable consumption and logistic regression for physical inactivity, problematic drinking and smoking. For each outcome, three models were estimated: (1) Model 1 which was an unadjusted model of the outcome containing only the class variable; (2) Model 2 was the partially adjusted model which contained the latent class variable and was adjusted for the corresponding health behaviour at baseline. The main purpose of this model was to assess whether the baseline health behaviour predicted the outcome and to assess to what extent the baseline health behaviour attenuated the relationship between latent class membership and health behaviour outcome; and (3) which was the model adjusted for all selected covariates which accounted for the health behaviour at baseline and the covariates including sex, age group, education, ethnicity, occupational class, income quintiles, employment status, household size, number of children living in the household, cohabiting status, self-rated general health, psychological distress, Additionally, the model adjusted for all selected covariates for physical inactivity were adjusted for baseline physical health (SF-12).

Lastly, interactions were tested for sex and age group at baseline for each model. For this, in each model adjusted for all selected covariates an interaction term was introduced between class membership and sex, and in a separate model between class membership and age group at baseline (which acted as a proxy for the lifecourse stage of participant). Then, an overall p-value for this interaction term was computed using the Wald test. If the p-value was 0.05 or smaller, the null-hypothesis was rejected that models with interaction term was similar to the model without interaction term stratified results were produced.

7.3.5 Bias reduction

7.3.5.1 Survey design

To reduce bias in the analysis that may be due to the complex survey design of UKHLS, the survey package in R[296] was used for the descriptive analysis and all the regression models. This package was employed to account for the complex survey design of UKHLS, ensuring that the survey's stratified, clustered, and weighted design was appropriately incorporated into the analysis. By using the survey package, adjusted estimates and standard errors could be produced that accounted for probability to be selected and respond to the survey.

The baseline weight [indscub_xw] was chosen which represents an adult cross-sectional weight for the full interview with self-completion questionnaire from wave 2 onwards. This weight was preferred over a longitudinal weight because the inclusion criteria require participants to have been present for at least two waves, not necessarily all 13. Since the outcome is measured only at the end of the study, baseline weights appropriately reflect the study's complex survey design. In contrast, longitudinal weights in UKHLS address monotone attrition and are, therefore, restricted to individuals who participated in all 13 waves. Their use would exclude participants with incomplete wave participation, significantly reducing the sample size and potentially introducing bias due to selective attrition. While the use of baseline weights is a pragmatic choice for the analysis, it is acknowledged that attrition cannot be fully accounted for. To mitigate this, participants with valid outcome measures in earlier waves (7, 9, and 11) were included, rather than restricting the analysis solely to those with completed outcome measures at wave 13.

7.3.5.2 Multiple imputation

To account for item non-response, multiple imputation (MI) was performed using the 'mice' package in R.[297] MI is a popular method to address item non-response or missingness in epidemiological studies. It has the advantage that it fills missing values based on a statistical model method called 'multiple imputation by chained equation' which means that each imputed variable has its own separate prediction model.[91] It accounts for the uncertainty associated with the missing data by generating multiple imputed datasets. The results from the multiple imputed datasets are then pooled to produce final estimates, which are generally more robust and less biased than those obtained from single imputation methods.[298] The main assumption of MI is that missingness is at random (MAR) meaning that the likelihood of data being missing is unrelated to the missing data itself, conditional on the data that is observed.[299]

To determine the number of required imputed data sets, the approach from von Hippel[300] was applied which is a formula based on the Fraction of Missing Information (FMI), *'alpha'* which is the significance level of the conservative FMI and the coefficient of variation (CV). The conservative FMI refers to the upper bound of the FMI across key variables or models, selected to ensure that the number of imputations is adequate even for the variables with the highest missing information, thereby reducing the risk of underestimating standard errors.[300] For this, a pilot analysis was performed with 20 imputations and based on this imputation, the FMI was calculated and the number of needed imputation calculated using the R package 'howManyImputations'.[301] It must be noted that FMI differed across each outcome due to the varying amount of missingness. This resulted in different recommended numbers of imputations for each outcome. Additionally, the formula depends on coefficient of variation which is roughly the percentage by which changes in standard error (SE) are acceptable if an imputation was performed again. For example, a CV of 0.10 means that a change of the SE estimate by 10% would be acceptable if the data was imputed again.[300]

In the models adjusted for all selected covariates, the analysis of FMI and the application of von Hippel's formula[300,301] revealed that 2 to 5 imputation would be required if CV was set to 0.10 and 4 to 17 imputations would be required if CV was set to 0.05. However, it must also be considered that a large number of imputations might be computationally demanding and time-consuming without adding precision to the analysis.[302] Therefore, it was decided to impute 10 datasets. This choice was justified as it balanced the need for precision with practical considerations of computational feasibility. Additionally, a complete case analysis was conducted, and the results compared to ensure the robustness of the findings.

In addition to determining the number of imputations, another important consideration was how to handle missingness in the outcome variable. Generally, it is recommended to include the outcome in the imputation model because this enhances the prediction of the missing covariates.[303] However, there is no consensus on whether responses that contain an imputed outcome should be included in the analysis or deleted after imputation. Von Hippel[304] advocates for a deletion of the imputed outcomes after imputation, which is an approach called "Multiple Imputation, then Deletion' (MID). However, one simulation study found that MID produced biased results when the auxiliary variables were associated with missingness of the outcome.[305] Besides, the same researchers also recommended to retain the imputed outcome when estimating relative risk based on another simulation study.[306]

This issue was further investigated by Kontopantelis and colleagues[307] who compared seven different multiple imputation approaches under different scenarios such as varying sample size and fraction of missingness. The authors of this study concluded that MID and regular imputation (with including the imputed outcome in the analysis) performed equally well, as long as the outcome was included in the imputation model.[307] Given the potential concerns of the MID approach and the low proportion of missingness in the outcomes (<3%), it was decided to include the outcome in the imputation model, to impute the missing outcome and to retain the imputed outcome in the final pooled analysis.

After making the above analytical decisions, the imputation process was commenced by setting the seed to "12345" to enable reproducibility of the imputations. In total, 10 separate data sets were imputed, and the algorithm ran for a maximum of 10 iterations. All variables that were part of the substantive model were also used in the imputation model. There were no additional auxiliary variables identified for the imputation model because the substantive model already contained demographic and socioeconomic variables that are usually associated with missingness and the outcome.[308] An analysis of missingness in this sample (Appendix 7.8) revealed that missingness was associated with health behaviours at baseline and outcome. Besides, most covariates were associated with missingness apart from sex and cohabiting status.

Then, Multiple Imputation by Chained Equation was performed, and imputation methods were specified to match the variable type by generating a predictor matrix and assigning each variable with the appropriate method. Ordinal regression was specified for education, income quintiles, household size, number of children living in the household, fruit and vegetable consumption at baseline, walking frequency at baseline and drinks frequency at baseline.

Binary logistic regression was specified for physical inactivity (outcome), smoking status (outcome), problematic drinking (outcome), cohabiting status, sex and self-rated general health. Multinominal regression was performed for class, ethnicity, occupational class, employment status and baseline smoking status. Lastly, linear regression with predictive mean matching was performed to avoid implausible values[309] for the continuous variables age at baseline, GHQ at baseline, SF12 at baseline and fruit and vegetable consumption (outcome). As a final step, the imputation results were inspected by examining the imputed variables and counting the number of imputed values for each variable.

7.3.6 Analytical sample

Participants will be included in this study if:

- They had valid observations of baseline health behaviour at wave 2 (or wave 5 if they entered the study later) to allow for adjustment of baseline health behaviour.
- They had valid observations at the outcome at wave 13 or earlier waves (11, 9, or 7) if they exited the study earlier, to reduce potential biases related to participant attrition.
- Between the baseline and outcome measures of health behaviour, they had care hours and place of care observed in at least two waves to capture transitions in caregiving intensity.
- They had at least two consecutive observations of caregiving intensity to detect trends and transitions without larger gaps, which may indicate exit and re-transition into caregiving rather than a transition in intensity within caregiving.
- Among caregivers who met the inclusion criteria, caregiving intensity was coded as missing at a time point if they were non-caregivers at that time point. This aimed to isolate the trajectories of caregiving intensity among participants without focusing on entering or exiting caregiving, which was not the focus of this study.

The latter inclusion criterion might seem controversial because it created a high amount of missing data, which may introduce uncertainty into the analysis. For this reason, two alternative approaches were considered: (1) restricting the analysis to participants who were caregivers at every wave of observation, which would have allowed a focus on transitions within caregiving without the interference of transitioning into and out of caregiving. However, this would have eliminated most of the sample and generated a very selective sample of long-term caregivers. (2) Coding caregiving intensity as zero if participants were non-caregivers at a particular point in time. However, this would have resulted in models that emphasise the transition into and out of caregiving.

Sample Size

Latent Class Analysis was performed on 8,556 participants who met inclusion criteria. This sample was drawn from participants in the UK Household Longitudinal Study (UKHLS) who had information on caregiving status across Waves 2 to 13 (n=87,966). Participants who were non-caregivers in all observed waves were excluded (n=61,686), leaving 26,280 individuals who were identified as caregivers in at least one wave. Of these, participants who were caregivers in only a single wave were excluded (n=10,110), resulting in 16,170 individuals who were caregivers in at least one wave. A further 537 participants were excluded due to missing information on caregiving intensity, leaving 15,633 participants who were caregivers for at least two waves between Wave 2 and Wave 13. Next, participants with no observed health outcomes or corresponding baseline health behaviour data were excluded (n=5,433), reducing the sample to 10,200 participants. Finally, individuals for whom caregiving intensity was not observed consecutively were excluded (n=1,644). The final analytical sample consisted of 8,556 participants, on whom latent class analysis (LCA) was performed based on caregiving intensity over consecutive waves.

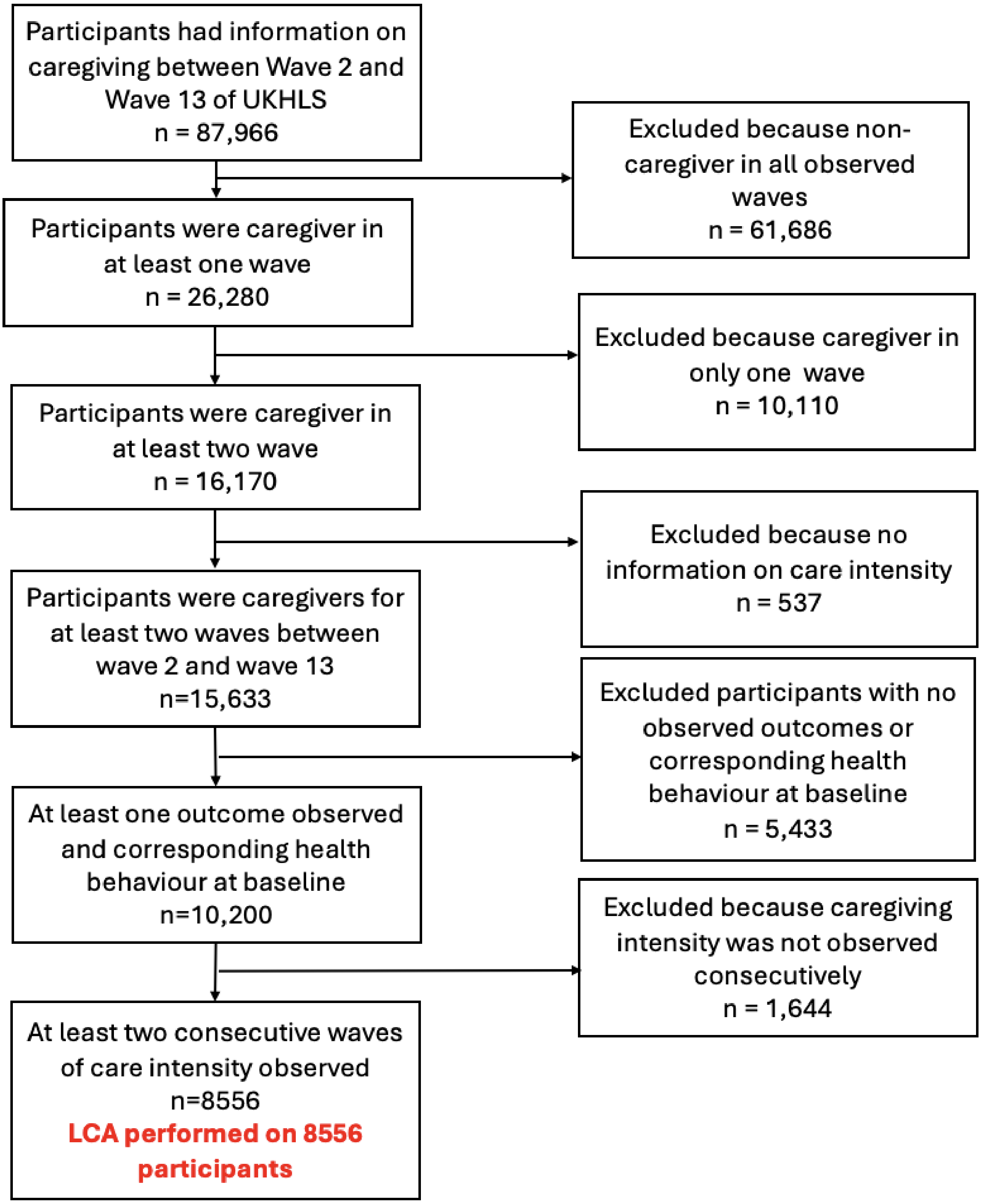


Figure 7.1 Sample Size flow chart for LCA on caregiving intensity.

The analytical sample for each health behaviour outcome (physical inactivity, fruit and vegetable consumption, problematic drinking, and smoking) was drawn from 8,556 eligible participants in the UK Household Longitudinal Study (UKHLS). Across all outcomes, multiple imputation was employed to address missing covariates and outcomes, ensuring a consistent sample size of 8,556 participants for the substantive analyses. The sample size flow for physical inactivity is below while the sample size flow charts for fruit and vegetable consumption, problematic drinking and smoking can be found in Appendix 7.1.

For physical inactivity**,** out of the 8,556 eligible participants, 185 participants had missing data on the physical inactivity outcome, while a further 8 had missing values for walking at baseline. Additionally, 1,052 participants had missingness in at least one covariate including education (n=22), ethnicity (n=2), occupational class (n=99), income quintiles (n=25), working status (n=7), cohabiting status (n=5), GHQ (n=638), self-rated health (n = 579), and SF12 (n=882). This resulted in 8,363 participants (97.7%) with outcome and walking at baseline observed while 7,311 participants (85.4%) had no missingness in any of the covariates or outcome (**Figure 7.2**).

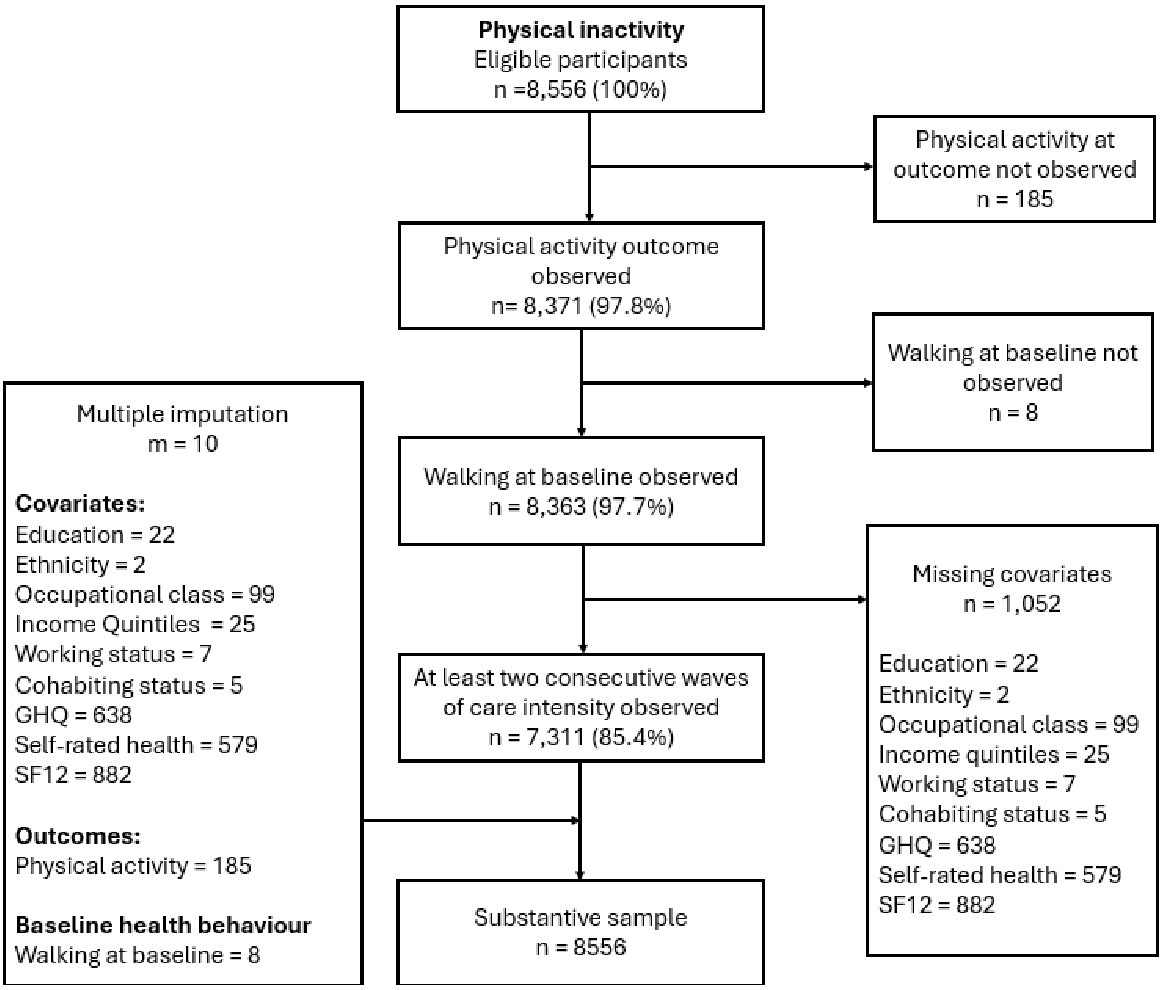


Figure 7.2 Sample size flow chart for physical inactivity of eligible participants following LCA of caregiving intensity between wave 2 and wave 13 of UKHLS.

For fruit and vegetable consumption**,** 109 participants had missing data on the fruit and vegetable consumption outcome, while an additional 16 had missing data for fruit and vegetable consumption at baseline. Furthermore, 790 participants had missingness in the covariates, including education (n=23), ethnicity (n=2), occupational class (n=106), income quintiles (n=26), working status (n=5), cohabiting status (n=5), GHQ (n=587) and self-rated health (n 593). Consequently, 8,431 (98.5%) participants had fruit and vegetable consumption observed at outcome and baseline while 7,641 (89.3%) had no missingness in any of the covariates or outcome (**Figure A7.1**).

For problematic drinking**,** 191 participants had missing data on the problematic drinking outcome, while 764 had missing data on drinking frequency at baseline. A further 302 had missingness in the covariates, including education (n=20), ethnicity (n=2), occupational class (n=97), income quintiles (n=24), working status (n=6), relationship status (n=3), GHQ (n=161) and self-rated health (n=110). This left 7,601 (88.8%) with drinking frequency at baseline and problematic drinking observed at outcome while in total, 7,299 (85.3%) participants had no missingness in covariates and outcome (**Figure A7.2**).

For smoking, only four participants had missing data on the smoking outcome, and one participant had missing data on smoking at baseline. Additionally, 801 participants had missing covariates, including education (n=23), ethnicity (n=2), occupational class (n=107), income quintiles (n=26), working status (n=7), cohabiting status (n=5), GHQ (n=653) and self-rated health (n=592). As a result, 8,551 (99.94%) participants had smoking observed at baseline and outcome while 7,750 (90.6%) participants had no missingness in covariates or outcome (**Figure A7.3**).

7.4 Results

7.4.1 Latent class analysis

7.4.1.1 Caregiving intensity variable

As outlined in the previous section, a caregiving variable was created with 12 groups ranging from low care hours (0-9 hours) outside the household to very high care hours (35+ hours) inside the household. An arbitrary example of this variable and its categories from wave 7, can be seen below in **Table 7.2**. This table shows that some of the groups had a very small sample size. However, for the further analytical approach, which will consist of Latent Class Analysis (LCA), it is recommended to perform the analysis with groups of at least 5%.[290] Hence, some of the smaller categories were collapsed into larger categories. Dual caregivers (inside and outside the household) were moved to caregiving inside the household because it is the conceptually more intense caregiving category. Further, caregivers who provided more than 20 hours of care per week outside the household were collapsed into one group. As a result of this, the final care intensity variable consisted of seven groups in each wave of observation.

Table 7.2 Frequency, proportion, and recoding of the caregiving intensity variable, based on eligible participants (n=8,556) with at least two consecutive waves of caregiving intensity observed and at least one baseline health behaviour outcome recorded.

Category	**Frequency (n=8,556)***	**Proportion**
Low (0-9 hours) outside	1,907	46.7%
Low (0-9 hours) inside	403	9.9%
Low (0-9 hours) dual	105	2.6 %
Medium (10-19 hours) inside	355	6.7 %
Medium (10-19 hours) outside	216	5.3 %
Medium (10-19 hours) dual	48	1.2 %
High (20-35 hours) inside	137	3.4 %
High (20-35 hours) outside	254	6.2 %
High (20-35 hours) dual	35	0.9 %
Very high (35+ hours) inside	484	1.9 %
Very high (35+ hours) outside	77	11.9 %
Very high (35+ hours) dual	63	1.5 %
Re-categorised	**Frequency** (n=8,556)*	**Proportion**
Low (0-9 hours) outside	1,907	46.7%
Low (0-9 hours) inside	508	12.4%
Medium (10-19 hours) outside	355	8.7%
Medium (10-19 hours) inside	264	6.5%
High/very high (>=20 hours) outside	214	5.2%
High (20-34 hours) inside	289	7.1%
Very high (35+ hours) inside	547	13.4%

*after inclusion criteria were applied to the sample

7.4.1.2 Preliminary analysis

As a first analytical step, the newly created caregiving intensity variable was graphically displayed over time with the State Distribution Plot in **Figure 7.3**. It illustrates the state distribution of caregiving intensity across 12 waves of UKHLS. This variable is censored to the right which was expected because outcomes could only be measured until participants exited the study or were lost to follow up. The distribution of caregiving intensity was quite consistent across waves with low care hours outside was most frequently observed followed very high care hours inside the household, followed by low care hours inside the household. This was followed by medium care hours outside, then high care hours inside the household and medium hours inside the household while high care hours outside the household was least frequently observed.

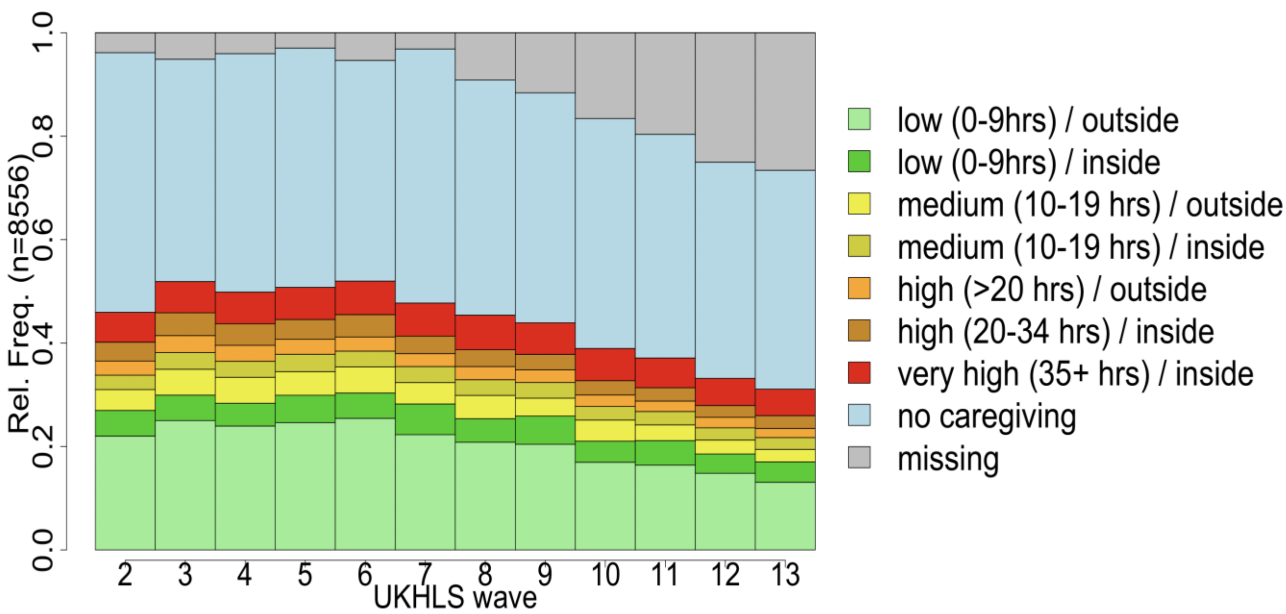


Figure 7.3 State Distribution Plot of Caregiving Intensity; distribution of caregiving intensity over time across UKHLS waves 2 to 13 among eligible participants (n=8,556) with at least two consecutive waves of caregiving intensity and one recorded baseline health behaviour outcome. Caregiving intensity is stratified by hours per week and place of care (inside vs outside the household). 'No caregiving' indicates participants not providing care at the wave; 'missing' indicates unavailable caregiving information.

Next, a sequence index plot was depicted in **Figure 7.4** which is a detailed visualisation of individual caregiving intensity trajectories over 12 waves of UKHLS. Each horizontal line represents an individual's caregiving pathway, with colours corresponding to different caregiving intensity levels. The sequence index plot highlights significant heterogeneity in caregiving trajectories, with individuals frequently transitioning between caregiving intensity levels, "no care," and "missing" categories over time. These transitions occur without clear or consistent patterns across the population. Many trajectories are marked by frequent, irregular shifts between caregiving intensity categories, with no evident progression or structured sequence. The high variability makes it difficult to identify distinct trends or groups through visual inspection alone. The observed variability and apparent randomness in caregiving trajectories suggest the presence of unobserved heterogeneity within the population. The complexity of this data structure makes Latent Class Analysis (LCA) a suitable method to reveal latent (unobserved) groups of participants with similar caregiving trajectories.

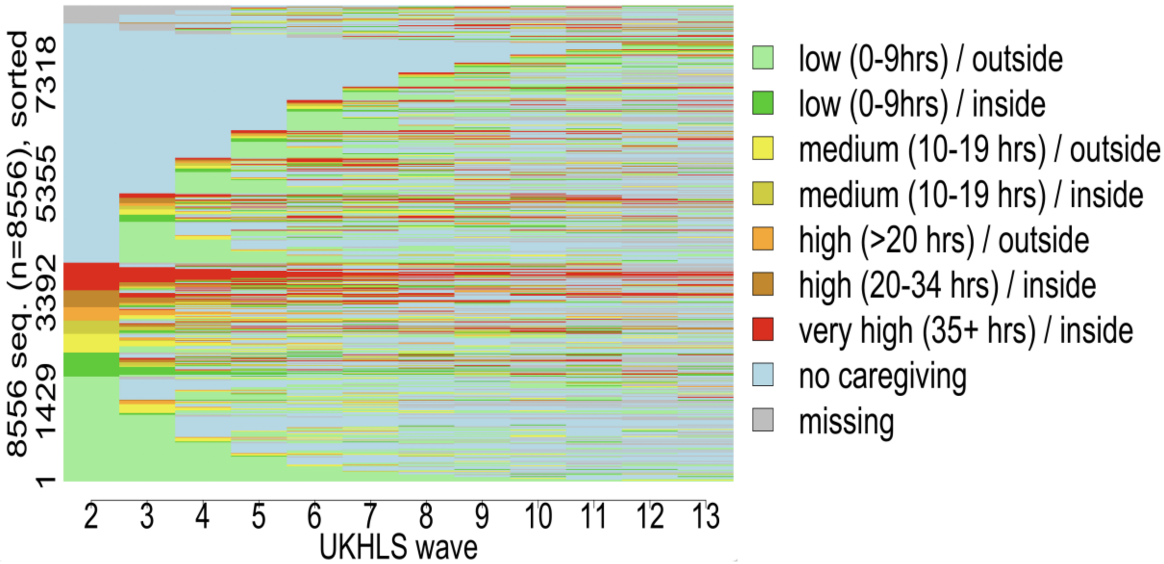


Figure 7.4 Sequence Index Plot of Caregiving Intensity; caregiving intensity patterns across UKHLS waves 2 to 13 among eligible participants (n=8,556) with at least two consecutive waves of caregiving intensity observed and one recorded baseline health behaviour outcome. Each row represents an individual sequence, sorted by caregiving intensity at baseline.

7.4.1.3 Model fitting

These eight models were fitted and according to BIC, the models with 5 classes performed best while in the aBIC, the models with more classes were favoured. In contrast, cAIC favoured the model with four classes followed by the five-class solution as seen in **Table 7.3**.

Table 7.3 Latent class model fit statistics for caregiving intensity trajectories based on UKHLS participants (n=8,556). Models were compared using log-likelihood, residual degrees of freedom, Bayesian Information Criterion (BIC), adjusted BIC (aBIC), consistent Akaike Information Criterion (cAIC), likelihood ratio tests, and entropy values

Model	log-likelihood	resid. df	BIC	aBIC	cAIC	likelihood-ratio	Entropy
Model 1 1 Class	-73215.54	8436	147517.6	147136.3	147637.6	8664.825	-
Model 2 2 Classes	-57852.05	8315	117886.2	117120.4	118127.2	5634.714	0.955
Model 3 3 Classes	-55340.12	8194	113957.9	112807.6	114319.9	5208.664	0.876
Model 4 4 Classes	-53130.26	8073	110633.8	109098.9	111116.8	4615.299	0.853
Model 5 5 Classes	-52524.42	7952	110517.7	108598.3	111121.7	4495.593	0.814
Model 6 6 Classes	-52025.84	7831	110616.1	108312.2	111341.1	4408.987	0.762
Model 7 7 Classes	-51532.67	7710	110725.4	108036.9	111571.4	4258.574	0.728
Model 8 8 Classes	-51130.64	7589	111016.9	107943.9	111983.9	4190.193	0.771

To aid decision-making, an elbow plot was generated **Figure 7.5** which suggests that saturation of classes was achieved in the four-class solution and that adding further classes does not improve fit indices by a large margin.

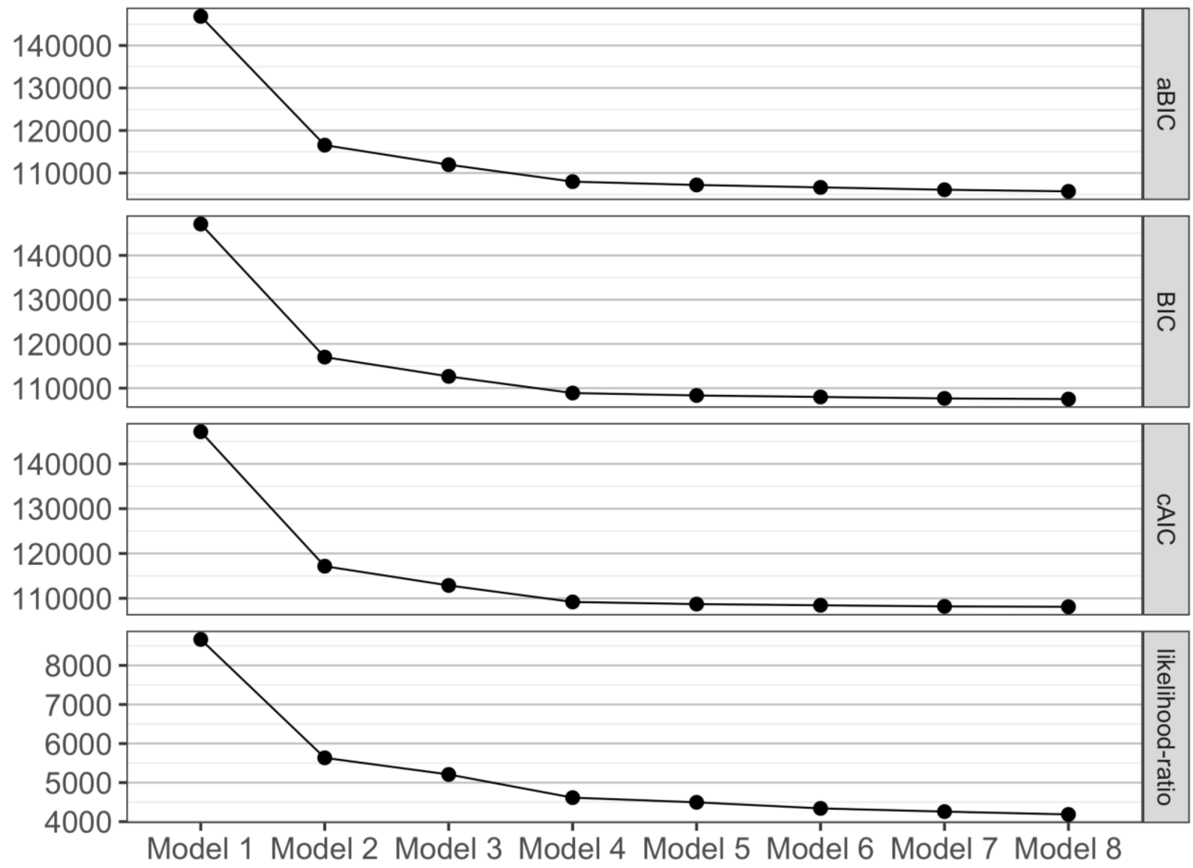


Figure 7.5 Elbow plot of model fit statistics for latent class analysis of caregiving intensity trajectories among UKHLS participants (n=8,556). The plot displays model fit values by number of latent classes, with a lower value indicating better model fit. The 'elbow' point suggests the optimal number of classes.

In the next step, posterior probabilities were computed for the four, five and six class solution. The model with four classes reveals four fairly stable classes as seen in **Figure 7.6**. In contrast, when adding a fifth class as depicted in **Figure 7.7**, a class emerges that had an increase in caregiving intensity while adding a sixth class as done in **Figure 7.8** only revealed a sixth stable class of medium caregiving intensity within the household. Therefore, the solution with the five classes seemed more appropriate because it addresses the research question best and seemed to align closer to the conceptual considerations of transitions of caregiving intensity.

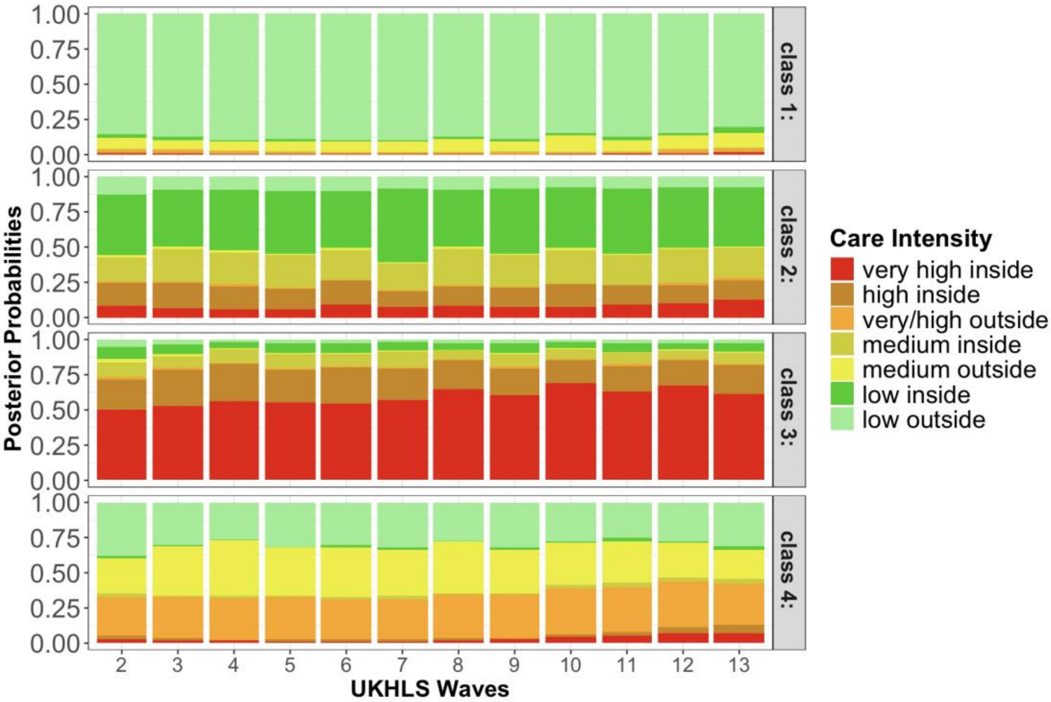


Figure 7.6 Posterior probability 4-class solution of caregiving intensity trajectories across UKHLS waves 2 to 13 for a possible four-class solution (n=8,556). Each panel represents a latent class, showing the distribution of caregiving intensity levels (by hours and place of care) over time. Posterior probabilities indicate the proportion of class members assigned to each care intensity category at each wave.

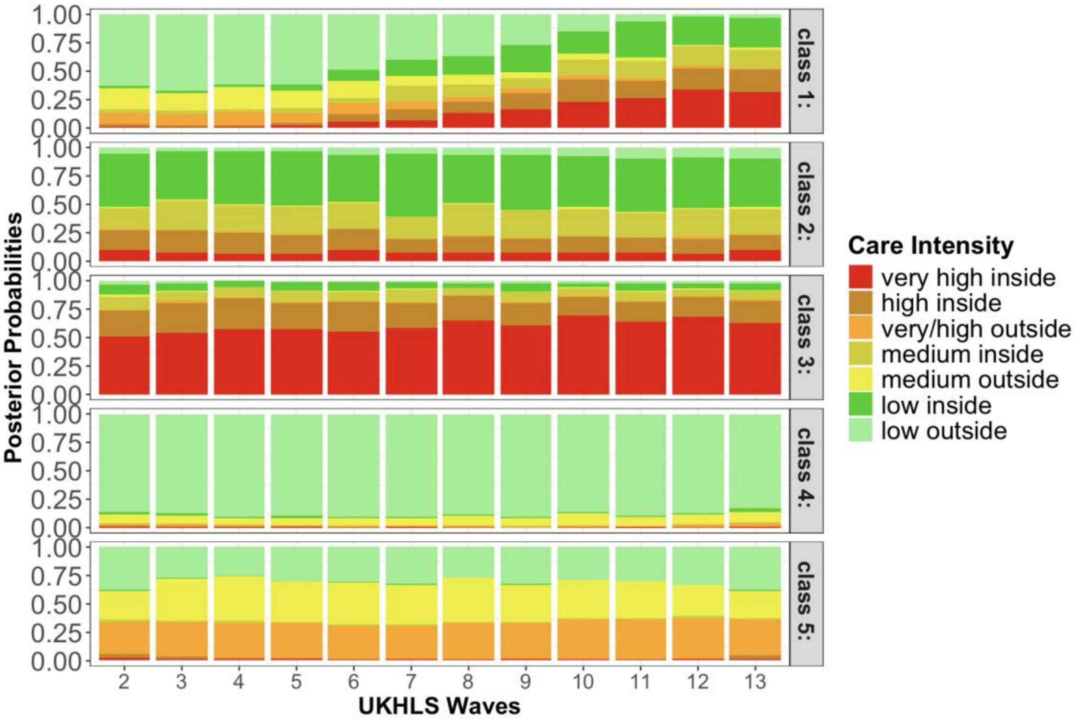


Figure 7.7 Posterior probability 5-class solution of caregiving intensity trajectories across UKHLS waves 2 to 13 for a possible five-class solution (n=8,556). Each panel represents a

latent class, showing the distribution of caregiving intensity levels (by hours and place of care) over time. Posterior probabilities indicate the proportion of class members assigned to each care intensity category at each wave.

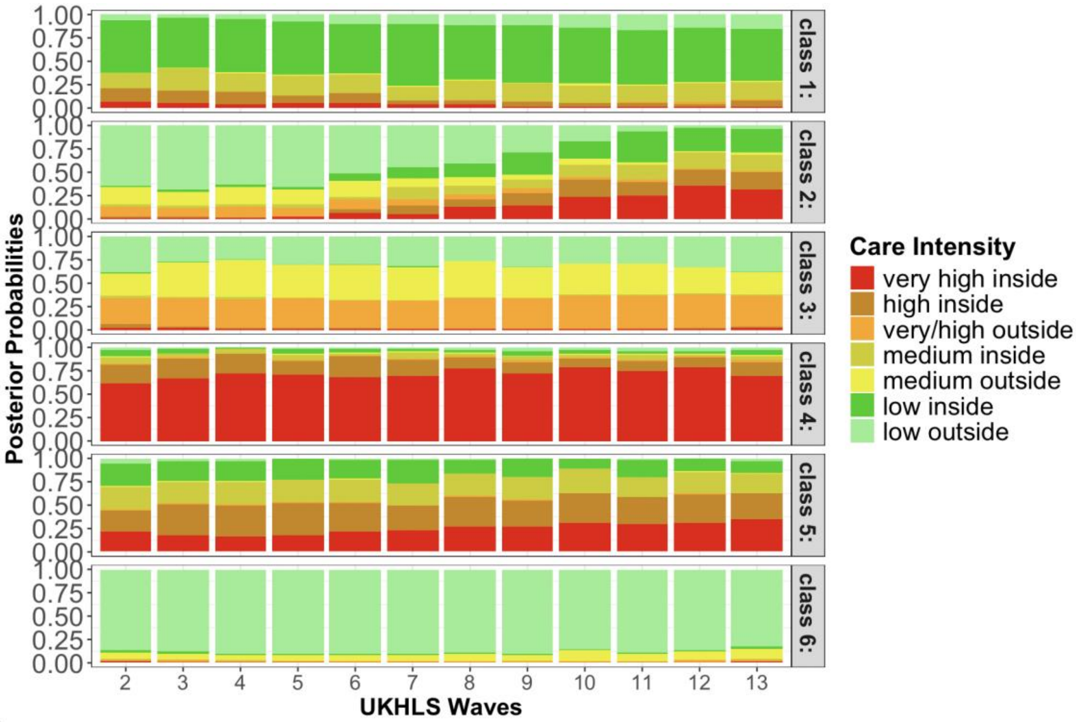


Figure 7.8 Posterior probability 6-class solution of caregiving intensity trajectories across UKHLS waves 2 to 13 for a possible six-class solution (n=8,556). Each panel represents a latent class, showing the distribution of caregiving intensity levels (by hours and place of care) over time. Posterior probabilities indicate the proportion of class members assigned to each care intensity category at each wave

7.4.1.4 Classification

In the next step, classification statistics were evaluated. As seen in **Table 7.4**, the entropy for the five-class solution was 0.81 which is an acceptable level. Further, the average posterior probabilities matrix was assessed, and the diagonal average probabilities were above 0.8 and the off-diagonal were close to 0. Therefore, both entropy and average posterior probabilities suggest a low level of misclassification in the current solution with five classes.

Table 7.4 Matrix of average posterior probabilities for the five-class latent class solution (n=8,556). Values represent the average probability of participants classified into each latent class (rows) being assigned to each possible class (columns). High diagonal values and low off-diagonal values indicate good classification quality.

	[1]	[2]	[3]	[4]	[5]
[1]	**0.91**	0.00	0.06	0.02	0.00
[2]	0.00	**0.92**	0.00	0.03	0.04
[3]	0.06	0.91	**0.89**	0.04	0.00
[4]	0.03	0.06	0.06	**0.82**	0.03
[5]	0.00	0.08	0.00	0.04	**0.87**

7.4.1.5 Interpreting classes

The next step included exploring the classes and their characteristics. For this, a State Distribution Plot was generated which shows the distribution of the states at each time point in **Figure 7.9**. Based on the state distribution plot, the classes could be described as the following:

- **Class 1:** In the beginning mainly low to moderate care outside the household with a later transition to higher hours of care inside the household.
- **Class 2:** Predominantly caregiving inside the household with mainly low to moderate hours of caregiving provided.
- **Class 3:** Predominantly very high or high hours of caregiving inside the household, fairly stable over time.
- **Class 4:** Predominantly low caregiving hours outside the household, fairly stable over time.
- **Class 5:** Low to high hours of care provided outside the household.

This State Distribution Plot indicates that there are four classes with fairly stable trajectories and one class with a change in caregiving intensity.

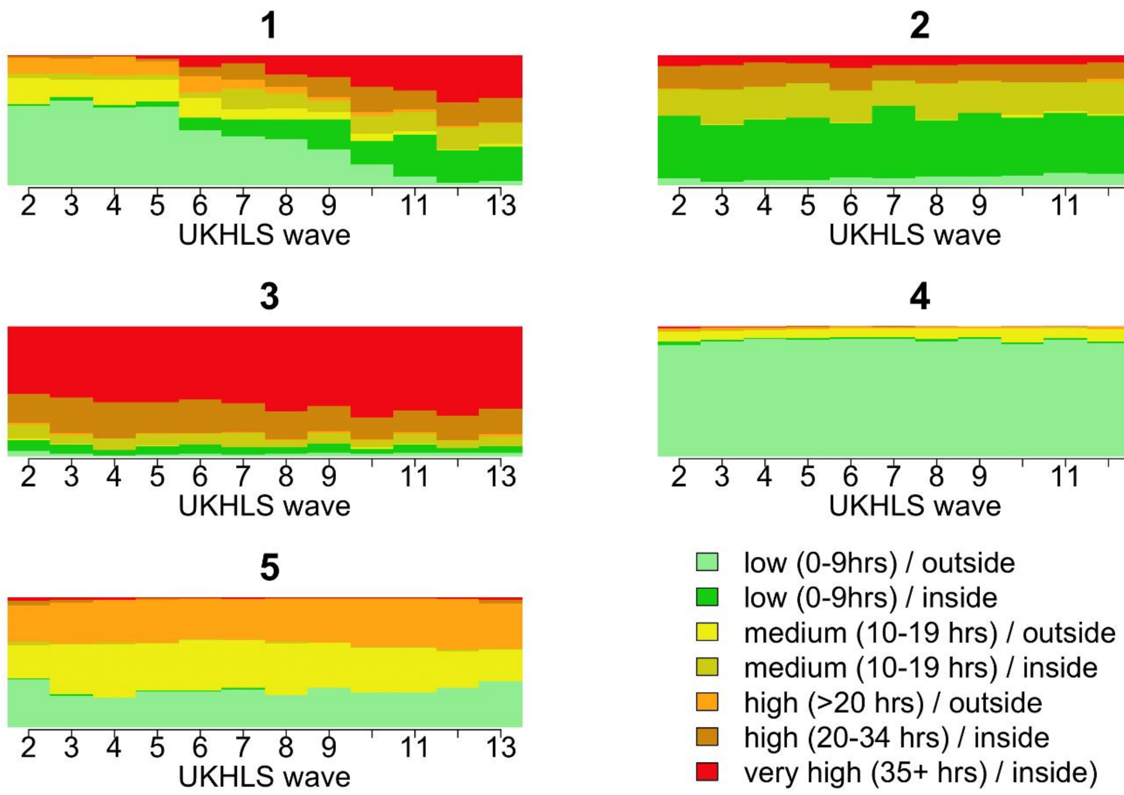


Figure 7.9 State Distribution Plot for five-class solution across UKHLS waves 2 to 13 (n=8,556). Each panel represents a latent class, displaying the distribution of caregiving intensity states.

However, as this only provides information on distribution, other visual tools might be helpful to name and label classes. For example, a sequence index plot, as seen in **Figure 7.10** was generated to assess the levels of transitions. According to this in can be seen:

- **Class 1:** Starts predominantly with lower intensity caregiving outside the household and frequent transitions to high intensity caregiving within the household
- **Class 2:** Higher proportions of participants with lower care intensity within the household with occasional transition between hours within the household
- **Class 3:** Dominated by higher care hours inside the household with some transitions from medium to higher caregiving intensity.
- **Class 4:** Class is dominated by low intensity outside the household with relatively few transitions to higher intensity.

- **Class 5:** There is a mix between low and medium-intensity caregiving outside the household with some transitions

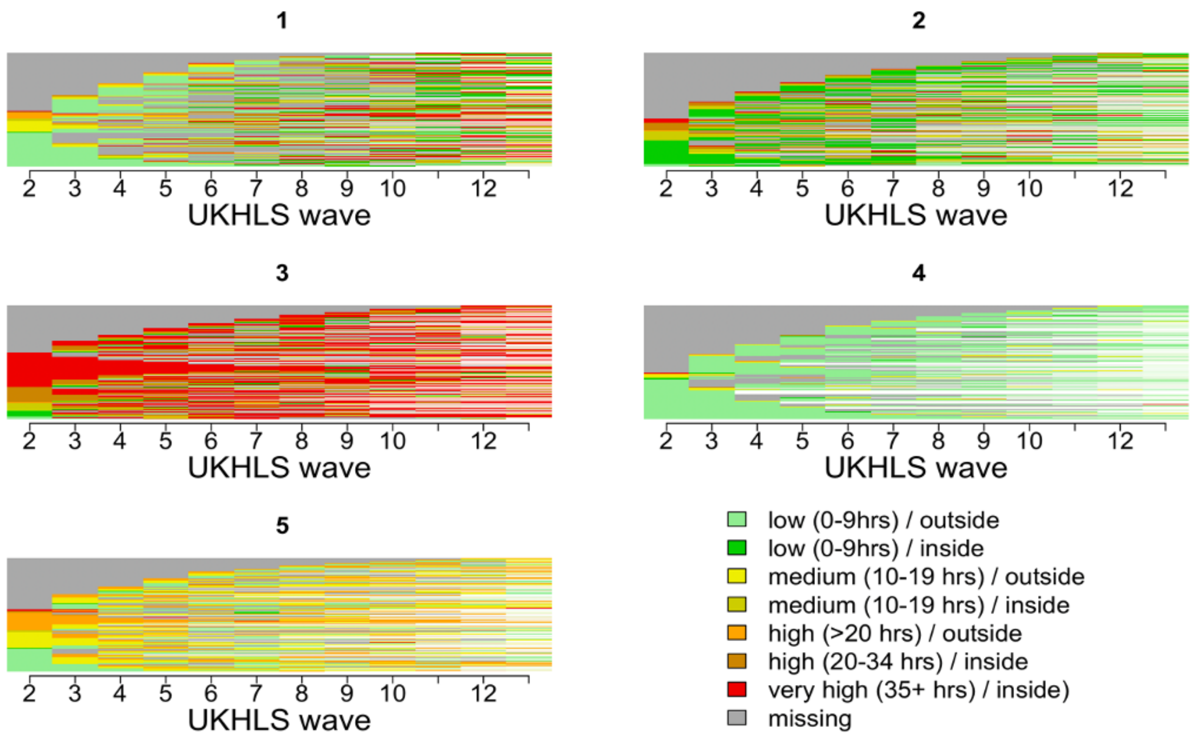


Figure 7.10 Sequence Index Plot for five-class solution across UKHLS waves 2 to 13 (n=8,556). Each line represents an individual participant's caregiving intensity trajectory, coloured by caregiving intensity states.

To gain a better understanding of the general caregiving intensity pattern, a sequence modal plot was generated, in **Figure 7.11**, which shows the distribution of caregiving intensity in each class. depicts the sequence modal plot and can be interpreted as the following:

- **Class 1:** low outside caregiving is the dominant state but all the other states are also present in this class.
- **Class 2:** Exclusively Caregiving inside the household a with lower intensity caregiving inside the household being the most frequent.
- **Class 3:** Exclusively Caregiving inside the household, with higher intensity caregiving inside the household being the most frequent.

- **Class 4:** Exclusively caregiving outside the household with low intensity caregiving outside the household observed most frequently.
- **Class 5:** Exclusively caregiving outside the household with fairly equal distribution between low, medium and high hours of care outside the household.

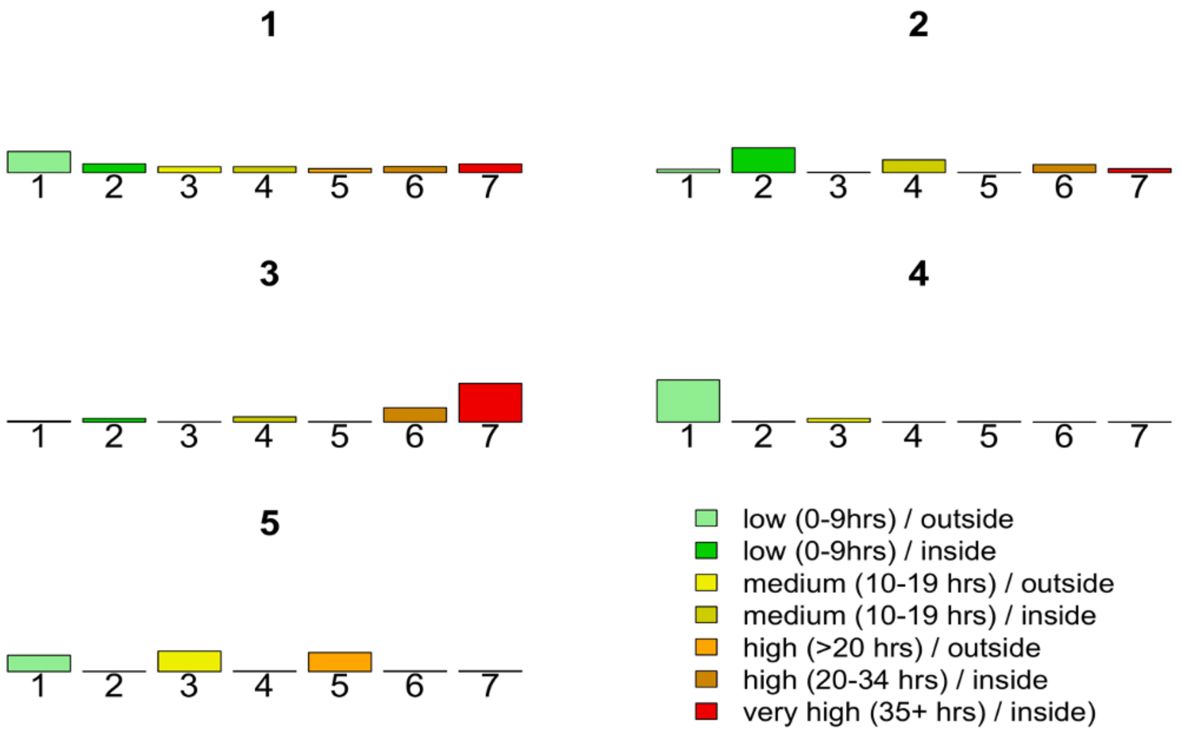


Figure 7.11 Sequence Modal Plot for five-class solution across UKHLS waves 2 to 13 (n=8,556). Each panel represents the most common caregiving intensity states over time for participants within each latent class.

Lastly, a sequence modal state plot was generated as seen in **Figure 7.12** which visualised the most frequent state at each time point in each class. Is particularly helpful to identify common trajectories or the 'modal sequence' for each class. Based on **Figure 7.12**, the sequence state model plot could be interpreted as the following:

- **Class 1:** Start with low intensity outside the household with transition to high intensity inside the household

- **Class 2:** Most individuals provide lower intensity caregiving **inside** the household. The bars are uniform at all states which suggest stable distribution throughout the observed time.
- **Class 3:** Stable class of participants with very high care intensity within the household.
- **Class 4:** Similar to Class 2, low intensity caregiving is provided with the difference that lower intensity care is provided **outside** the household.
- **Class 5:** All modal states indicate caregiving outside the household with variable caregiving intensities.

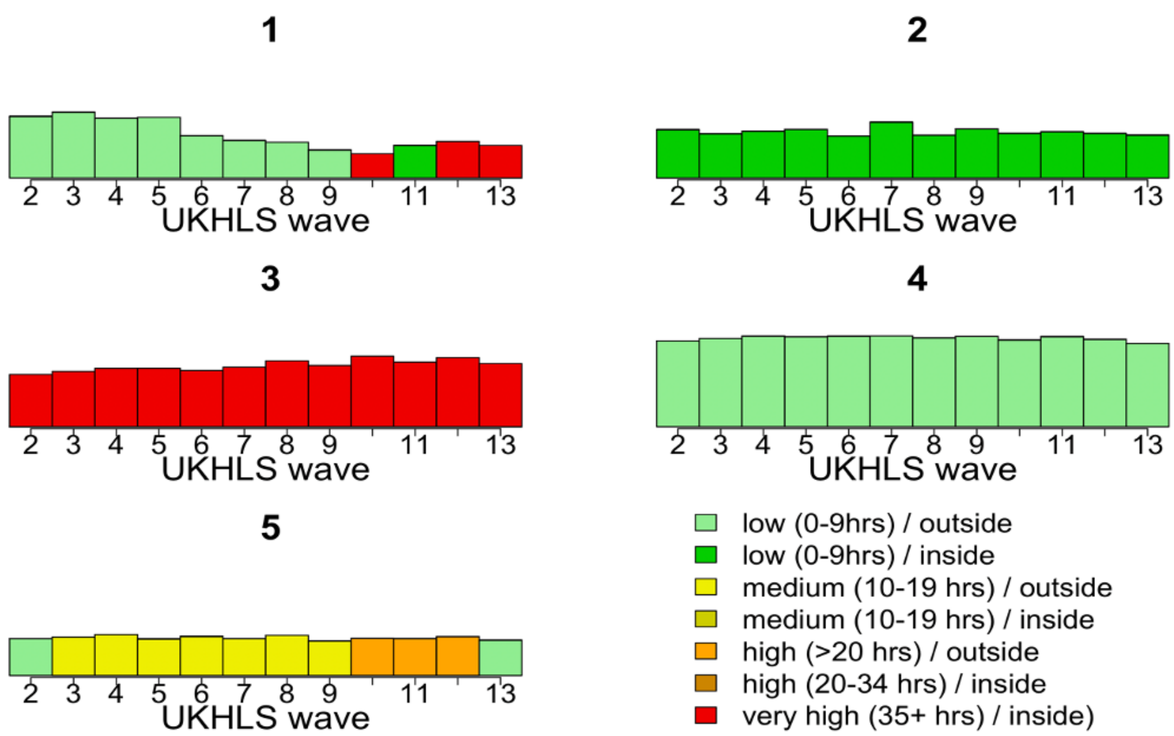


Figure 7.12 Sequence Modal State Plot for five-class solution across UKHLS waves 2 to 13 (n=8,556). Each panel represents the most frequent caregiving intensity state at each wave for participants within each latent class.

Based on the state distribution plot, sequence index plot and sequence state modal plot, the classes have been labelled are defined as follows in **Table 7.5**:

Table 7.5 Class definitions of latent classes

Class Number	Label	Definition
1	Increase	Caregivers who transition from lower intensity caregiving outside the household to higher intensity caregiving inside the household.
2	Low to medium inside	Caregivers with primarily low to medium intensity providing care inside the household.
3	High inside	Caregivers with primarily very high intensity providing care inside the household.
4	Low outside	Caregivers with primarily low intensity providing care outside the household .
5	Mixed outside	Caregivers with varying levels of intensity providing care outside the household.

The identified five caregiver classes align well with the caregiving role theory and also findings from previous analysis. For example, while caregiving role theory conceptualises increases in caregiving intensity, it does not explicitly conceptualise a decrease in caregiving intensity but rather exit from caregiving. Further, previous analysis from Chapter 5 and Chapter 6 showed that around 85% of participants who transition into care, transition into lower intensity care (less than 20 hours per week) whereas 80% of participant exit care from lower intensity which suggest an increase from lower to high intensity caregivers for a specific group of caregivers. Likewise, 69% of individuals transitioned into caregiving outside the household while only

64% exit from caregiving outside the household which implies that some caregivers transition from caregiving outside the household to caregiving inside the household.

7.4.2 Descriptive analysis

A descriptive analysis, as presented in **Table 7.6**, was performed that was stratified by latent class and accounted for complex survey design and results were pooled from 10 imputed data sets. The weighted sample size was 7,836. The ‘Low Outside’ class comprised the largest group (50.8%, n=3,979), followed by ‘Low to Medium Inside’ (17.8%, n=1,397), ‘High Inside’ (15.1%, n=1,180), Mixed Outside (11.4%, n=892), and ‘Increase’ (5.0%, n=388).

Outcomes

The prevalence of physical inactivity varied significantly across classes ($p < 0.001$). the ‘Low outside’ class had the lowest level of physical inactivity (49.8%) while the class ‘high inside’ had the highest level of physical inactivity (66.4%) and the class ‘Increase’ had a prevalence of physical inactivity of 54.7%. The mean daily portions of fruit and vegetables were highest in the ‘Low Outside’ class (4.0 ± 2.1) and lowest in the ‘High Inside’ class (3.3 ± 2.2) while the ‘Increase’ class had a mean daily fruit and vegetable consumption of 3.7 (± 2.3), with significant differences observed across groups ($p < 0.001$). Likewise, problematic drinking was associated with class membership ($p<0.001$). The prevalence of problematic drinking was highest in the ‘Low Outside’ class (53.6%) and was lowest in the ‘High Inside’ class (36.0%) while the ‘Increase’ class had a prevalence of 40.8%. Smoking was also associated with class membership ($p<0.001$) and the highest prevalence of smoking was observed in the ‘High Inside’ class (20,.8%) while the ‘Low outside’ class had the lowest smoking prevalence (10.6%) and the ‘Increase’ class had a prevalence of 12.5%.

Baseline health behaviours

In view of the health behaviour proxies at baseline, walking frequency was associated with class membership ($p<0.001$). Daily walking was most common in the 'Low Outside' class (16.3%) and least common in the 'High Inside' class (13.6%). Those reporting no walking days were highest in the 'High Inside' class (36.7%). From the 'Intensity' class, 25.1% never walked at baseline and 17.8% walked every day. Fruit and Vegetable Intake at baseline was also associated with class membership ($p<0.001$). The proportion of participants consuming 5+ portions of fruit and vegetables daily was highest in the 'Low Outside' class (28.5%) and lowest in the High Inside class (21.2%). In the 'Increase' class, 26.8% had 5 or more portions fruit and vegetable per day. The frequency of alcoholic drinks at bassline was also associated with class membership ($p<0.001$). Participants in the Low Outside class reported the highest weekly alcohol consumption, with 15.4% consuming 5 or more drinks per week. By contrast, only 11.9% of the 'High Inside' consumed five drinks or more per week and 12.9% for those who increased their caregiving intensity over time. Smoking status was also associated with class membership ($p<0.001$). The prevalence of current smokers was highest in the High Inside class (26.4%) and lowest in the Low Outside class (14.5%) and 20.1% in the 'Increase' class.

Covariates

Demographics

Mean age was similar across classes and was not associated with class membership ($p=0.08$), ranging from 51.33 ± 18.44 years in the Low to Medium Inside class to 53.60 ± 17.01 years in the High Inside class. However, age group was associated with class membership. 'High inside' was dominated by participants in early mid-adulthood (30-49) while the 'Low outside' class was dominated by participants in late mid-adulthood (50-64). Women were the dominant group in the 'High Inside' (63.3%) and Mixed Outside (70.8%) classes, while men were more prevalent in the 'Low to Medium Inside' class (51.0%, $p < 0.001$).

Socioeconomic and Household Characteristics

Participants with higher educational qualifications were most common in the Low Outside class (40.1%) and least common in the High Inside class (22.9%, $p < 0.001$). Management and professional occupations were most common in the Low Outside class (30.3%) and least common in the High Inside class (8.1%, $p < 0.001$). Notably, unemployment rates were highest in the High Inside class (71.3%). The proportion of participants in the highest income quintile (5) was greatest in the Low Outside class (28.9%) and lowest in the High Inside class (8.3%, $p < 0.001$). Married or cohabiting participants were most prevalent in the Increase class (82.0%) and least common in the Mixed Outside class (60.9%, $p < 0.001$). Single-person households were most frequent in the Mixed Outside class (27.1%) and least common in the Increase class (4.4%, $p < 0.001$). Households without children were most prevalent in the 'High inside' class (68.0%) and most common in the 'Low to Medium Inside' class (78.9%, $p<0.001$).

Health Status

General Health Questionnaire (GHQ) scores and SF-12 physical health scores (SF12-p) revealed significant differences. GHQ scores were highest in the High Inside class (13.59 ± 6.71, $p < 0.001$), while SF12-p scores were lowest in the same group (46.16 ± 12.30, $p < 0.001$). Self-Rated Excellent, very good, or good self-rated health was highest in the Low Outside class (85.7%) and lowest in the High Inside class (65.3%, $p < 0.001$). Fair or poor self-rated health was most prevalent in the High Inside class (34.7%).

Table 7.6 Descriptive statistics for the analysis of latent caregiving intensity classes, health behaviours, and selected covariates (n=8,557), based on pooled results after multiple imputation (m=10). Estimates account for complex survey design, including clustering at the household level.

	Latent Class	**Overall**	**low outside**	**increase**	**low to medium inside**	**high inside**	**mixed outside**	**p**
	Weighted N=7,836		3979 (50.8%)	388 (5.0%)	1397 (17.8%)	1180 (15.1%)	892 (11.4%)	
Outcomes								
Physical activity	Active	45.4%	50.2%	45.3%	40.8%	33.6%	45.5%	<0.001
	Inactive	54.6%	49.8%	54.7%	59.2 %	66.4%	54.5%	
Fruit and vegetable	Mean (SD)	3.7 (2.2)	4.0 (2.1)	3.7 (2.3)	3.4 (2.0)	3.25 (2.2)	3.8 (2.3)	<0.001
Problematic drinking	No	53.3%	46.4%	59.2%	61.4%	64.0%	55.7%	<0.001
	Yes	46.7%	53.6%	40.8%	38.6%	36.0%	44.3%	
Smoking	Non-smoker	86.1%	89.4%	87.5%	84.0%	79.2%	82.7%	<0.001
	Smoker	13.9%	10.6%	12.5%	16.0%	20.8%	17.3 %	
Baseline Health behaviours								
Walking frequency at baseline	none	25.9%	20.5%	25.1%	32.0%	36.7%	26.2%	<0.001
	1-2 days	35.3%	38.0%	34.2%	31.9%	31.0%	34.9%	
	3-4 days	13.0%	14.8%	13.8%	11.2%	9.5%	12.0%	
	5-6 days	9.9%	10.3%	9.2%	8.8%	9.2%	11.3%	

	Latent Class	Overall	low outside	increase	low to medium inside	high inside	mixed outside	p
	Every day	15.9%	16.3%	17.8%	16.1%	13.6%	15.6%	
Baseline fruit and vegetable	0 portions	0.9%	0.5%	1.4%	1.4%	1.6%	0.9%	<0.001
	1-3 portions	54.1%	50.8%	52.3%	58.1%	60.6%	54.5%	
	4 portions	18.9%	20.2%	19.5%	18.1%	16.6%	17.4%	
	5+ portions	26.0%	28.5%	26.8%	22.4%	21.2%	27.1%	
Baseline alcoholic drinks	no drinks	12.1%	8.3%	13.5%	15.7%	18.4%	14.7%	<0.001
	monthly or weekly	33.7%	30.3%	36.7%	36.6%	39.3%	34.8%	
	1-4 per week	40.0%	45.9%	36.9%	33.3%	30.4%	38.2%	
	5+ per week	14.2%	15.4%	12.9%	14.4%	11.9%	12.4%	
Baseline smoking	never smoked	42.7%	44.8%	40.3%	44.1%	36.1%	40.6%	<0.001
	ex-smoker	39.1%	40.7%	39.6%	37.5%	37.5%	36.4%	
	current smoker	18.2%	14.5%	20.1%	18.4%	26.4%	23.0%	
Covariates								
Age group at baseline	Early adulthood (16-29)	8.1%	6.4%	5.2%	16.0%	7.9%	4.9%	<0.001
	Early mid-adulthood (30-49)	31.5%	31.2%	33.4%	28.3%	35.2%	32.4%	
	Late mid-adulthood (50-64)	38.5%	43.9%	37.7%	28.4%	25.3%	47.9%	

	Latent Class	Overall	low outside	increase	low to medium inside	high inside	mixed outside	p
	Late adulthood (65+)	21.9%	18.5%	23.7%	27.4%	31.6%	14.7%	
Sex	men	41.7%	43.0%	38.9%	51.0%	36.7%	29.2%	<0.001
	women	58.3%	57.0%	61.1%	49.0%	63.3%	70.8%	
Education	No qualification	13.0%	8.3%	13.0%	17.0%	24.2%	12.6%	<0.001
	A-Level, GCSE, other qualification	52.7%	51.6%	55.5%	52.6%	53.0%	55.8%	
	Degree or other higher qualification	34.4%	40.1%	31.4%	30.4%	22.9%	31.7%	
Ethnicity	white	95.1%	96.4%	95.9%	92.1%	94.4%	94.9%	<0.001
	black	1.3%	1.0%	0.5%	1.8%	1.8%	1.7%	
	Indian	1.2%	1.0%	1.1%	2.2%	1.2%	0.8%	
	Pakistani/Bangladeshi	1.3%	0.6%	1.5%	2.9%	1.5%	1.4%	
	other Asian/other	1.1%	1.0%	1.%	1.1%	1.1%	1.2%	
Occupational class	not employed	45.4%	35.5%	48.4%	50.7%	71.3%	45.7%	<0.001
	Management & professional	23.4%	30.3%	22.9%	18.7%	8.1%	20.5%	
	intermediate	13.0%	15.4%	11.5%	11.6%	6.1%	14.4%	
	routine	18.1%	18.7%	17.3 %	19.0%	14.5%	19.3%	

	Latent Class	Overall	low outside	increase	low to medium inside	high inside	mixed outside	p
Income quintiles	1 (low)	16.8%	12.9%	19.6%	17.9%	24.3%	21.2%	<0.001
	2	20.2%	16.2%	18.8%	26.3%	26.7%	20.5%	
	3	20.3%	19.1%	17.8%	21.7%	24.3%	19.3%	
	4	20.8%	22.8%	21.3%	20.0%	16.3%	18.8%	
	5 (high)	21.9%	28.9%	22.5%	14.1%	8.3%	20.2%	
Employment status	not in paid employment	42.9%	33.3%	44.0%	48.2%	68.3%	43.2%	<0.001
	full-time employed	39.8%	47.5%	36.6%	37.6%	19.2%	37.3%	
	part-time employed	17.3%	19.2%	19.4%	14.2%	12.5%	19.6 %	
Number of children in the household	0	76.3%	77.6%	74.1%	78.9%	68.0%	78.2%	<0.001
	1	10.4%	10.6%	9.2%	9.1%	10.3%	11.8%	
	2	9.1%	9.3%	10.2%	7.5%	11.2%	7.2%	
	3+	4.3%	2.5%	6.5%	4.5%	10.4%	2.7%	
Cohabiting status	single, separated, widowed	27.2%	27.5%	18.0%	26.4%	21.3%	39.1%	<0.001
	married or cohabiting	72.8%	72.5%	82.0%	73.6%	78.7%	60.9%	
Self-rated general health	excellent, very good or good	79.0%	85.7%	75.4%	74.2%	65.3%	76.2%	<0.001
	fair or poor	21.0%	14.3%	24.6%	25.8%	34.7%	23.8%	

	Latent Class	Overall	low outside	increase	low to medium inside	high inside	mixed outside	p
Number of people in the household	1	12.5%	17.8%	4.4%	0.3%	0.6%	27.1%	<0.001
	2	41.0%	38.6%	49.9%	44.1%	46.5%	35.2%	
	3-4	36.8%	36.8%	31.5%	41.0%	37.8%	31.6%	
	5+	9.7%	6.8%	14.2%	14.6%	15.1%	6.0%	
Age	Mean (SD)	52.6 (14.6)	52.67 (15.01)	53.45 (14.49)	51.33 (18.44)	53.60 (17.01)	52.59 (12.38)	0.082
GHQ	Mean (SD)	11.7 (5.7)	10.85 (5.07)	11.66 (5.70)	11.86 (5.71)	13.59 (6.71)	12.40 (6.25)	<0.001
SF12-p	Mean (SD)	49.2 (10.8)	50.97 (9.53)	48.22 (11.56)	47.62 (11.44)	46.16 (12.30)	48.73 (10.78)	<0.001

7.4.3 Adjusted analysis

In the following analyses, for each outcome, three regression models were produced: (1) Model 1 was the unadjusted model which **e**xamined the association between the health behaviour outcome and latent class membership without any adjustment for other variables; (2) Model 2 is adjusted for baseline health behaviour measures, based on earlier question formats, to control for pre-existing behavioural differences despite changes in item wording across waves. (3) Model 3 which was the model adjusted selected covariates such as for health behaviour at baseline and demographics (age group, sex), socioeconomic and household characteristics (education, occupational class, income quintiles, household size, presence of children), as well as health characteristics (GHQ, self-rated health, and SF-12 for physical inactivity).

For all models, the class 'Low outside' was the reference category, so all results are compared to participants who provide less than 9 hours of care per week outside the household which can be conceptualised as the lowest intensity category. Additionally, all models accounted for complex survey design and were based on the pooled result of 10 imputed data set to account for missingness. The results are illustrated in the graphs below and the full results tables can be found in Appendix 7.3.

7.4.3.1 Physical activity

Increase

Figure 7.13 shows the ORs for physical inactivity by class. The 'Increase' caregiving group showed a slight, non-significant increase in the odds of physical inactivity compared to the reference group ('Low outside'). In the unadjusted model, the odds ratio (OR) was 1.21 (95% CI: 0.96–1.53). After adjusting for baseline walking frequency in Model PA2, the OR decreased slightly to 1.20 (95% CI: 0.95–1.51) and further attenuated in the model adjusted for all selected covariates (PA3: OR=1.11, 95% CI: 0.87–1.42). This suggest that there was no evidence for an association between caregiving intensity increase and physical inactivity from his analysis.

Low to Medium Inside

Caregivers in the ‘Low to Medium Inside’ group consistently showed significantly higher odds of physical inactivity across all models. In the unadjusted model (PA1), the OR was 1.46 (95% CI: 1.26–1.68). After accounting for walking frequency, the OR decreased slightly to 1.39 (95% CI: 1.20–1.61) in Model PA2, and further to 1.32 (95% CI: 1.12–1.55) in Model PA3. Despite adjustments, the association remained significant, suggesting that caregiving responsibilities of low to medium intensity within the household significantly increased the odds of physical inactivity.

High inside

The ‘High Inside’ caregiving group demonstrated the strongest association with physical inactivity. In the unadjusted model, caregivers in this group had nearly double the odds of being physically inactive compared to the reference group (OR=1.98, 95% CI: 1.70–2.32). Adjustments for walking frequency and covariates slightly attenuated this association, with ORs of 1.84 (95% CI: 1.58–2.16) in Model PA2 and 1.48 (95% CI: 1.24–1.77) in Model PA3. These results indicate that high-intensity caregiving within the household was strongly associated with physical inactivity, even after accounting for confounding.

Mixed outside

Caregivers in the ‘Mixed Outside’ group initially showed a significant association with physical inactivity in the unadjusted model (OR=1.21, 95% CI: 1.03–1.42). However, the strength of this association decreased in Model PA2 (OR=1.18, 95% CI: 1.01–1.38) and became non-significant in Model PA3 (OR=0.98, 95% CI: 0.83–1.15). This suggests that the relationship between mixed caregiving outside the household and physical inactivity is largely explained by the confounding characteristics.

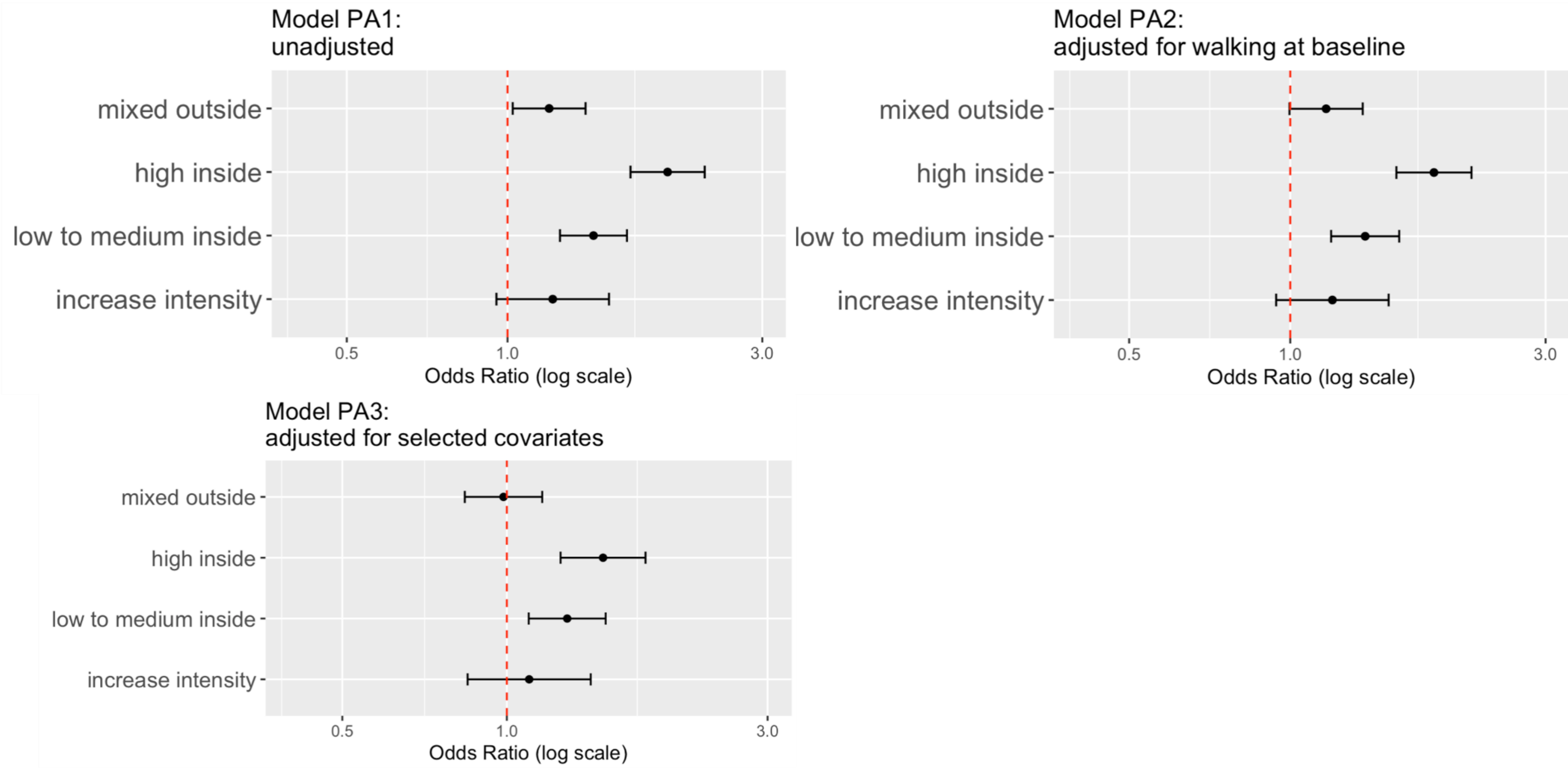


Figure 7.13 Regression models for physical inactivity; logistic regression models predicting physical inactivity across latent caregiving intensity classes among UKHLS participants (n=8,556), showing pooled Odds Ratios from multiple imputation (m=10) and accounting for complex survey design and household-level clustering. Results are shown for three models: PA1 (unadjusted), PA2 (adjusted for walking at baseline), and PA3 (adjusted for selected covariates). The reference category is the 'low outside' caregiving intensity class.

7.4.3.2 Fruit and vegetable consumption

Increase

Figure 7.14 shows the coefficients of daily fruit and vegetable consumption by class. The 'Increase' caregiving group demonstrated a small, non-significant reduction in daily fruit and vegetable portions compared to 'Low outside' caregivers. In DIET1, the coefficient was -0.2 (95% CI: -0.5, 0.0). After adjusting for baseline consumption of fruits and vegetables in DIET2, the coefficient remained unchanged (-0.2, 95% CI: -0.4, 0.1), and in DIET3, it attenuated slightly to -0.1 (95% CI: -0.4, 0.1). These findings suggest that an increase in caregiving intensity had a minimal and non-significant association with fruit and vegetable intake.

Low to medium outside

Caregivers in the 'Low to Medium Inside' group showed a significant reduction in daily portions of fruits and vegetables across all models compared to the 'Low outside' caregivers. In DIET1, the coefficient was -0.6 (95% CI: -0.7, -0.5). After adjusting for baseline consumption in DIET2, the reduction attenuated to -0.4 (95% CI: -0.6, -0.3) and further to -0.3 (95% CI: -0.4, -0.1) in DIET3. Despite attenuation, the association remained significant, indicating that caregiving of low to medium intensity inside the household was associated with a reduction in daily fruit and vegetable consumption compared to caregivers who provided low intensity care outside the household.

High inside

The 'High Inside' caregiving group showed the largest reduction in daily portions of fruits and vegetables. In DIET1, the coefficient was -0.7 (95% CI: -0.9, -0.5). Adjustments for baseline consumption in DIET2 attenuated this association to -0.5 (95% CI: -0.6, -0.3), and in DIET3, the reduction was further attenuated to -0.3 (95% CI: -0.4, -0.1). These findings suggest that high-intensity caregiving inside the household was strongly associated with a significant reduction in fruit and vegetable consumption, even after controlling for confounding factors.

Mixed outside

The 'Mixed Outside' caregiving group showed a small and non-significant reduction in daily fruit and vegetable portions in DIET1 (Coefficient=-0.1, 95% CI: -0.3, 0.0). This association remained largely unchanged in DIET2 (Coefficient=-0.1, 95% CI: -0.2, 0.1) and became negligible in DIET3 (Coefficient=0.0, 95% CI: -0.1, 0.2). These results suggest that there was no difference in fruit and vegetable consumption between caregivers 'Mixed outside' caregivers and 'Low outside' caregivers.

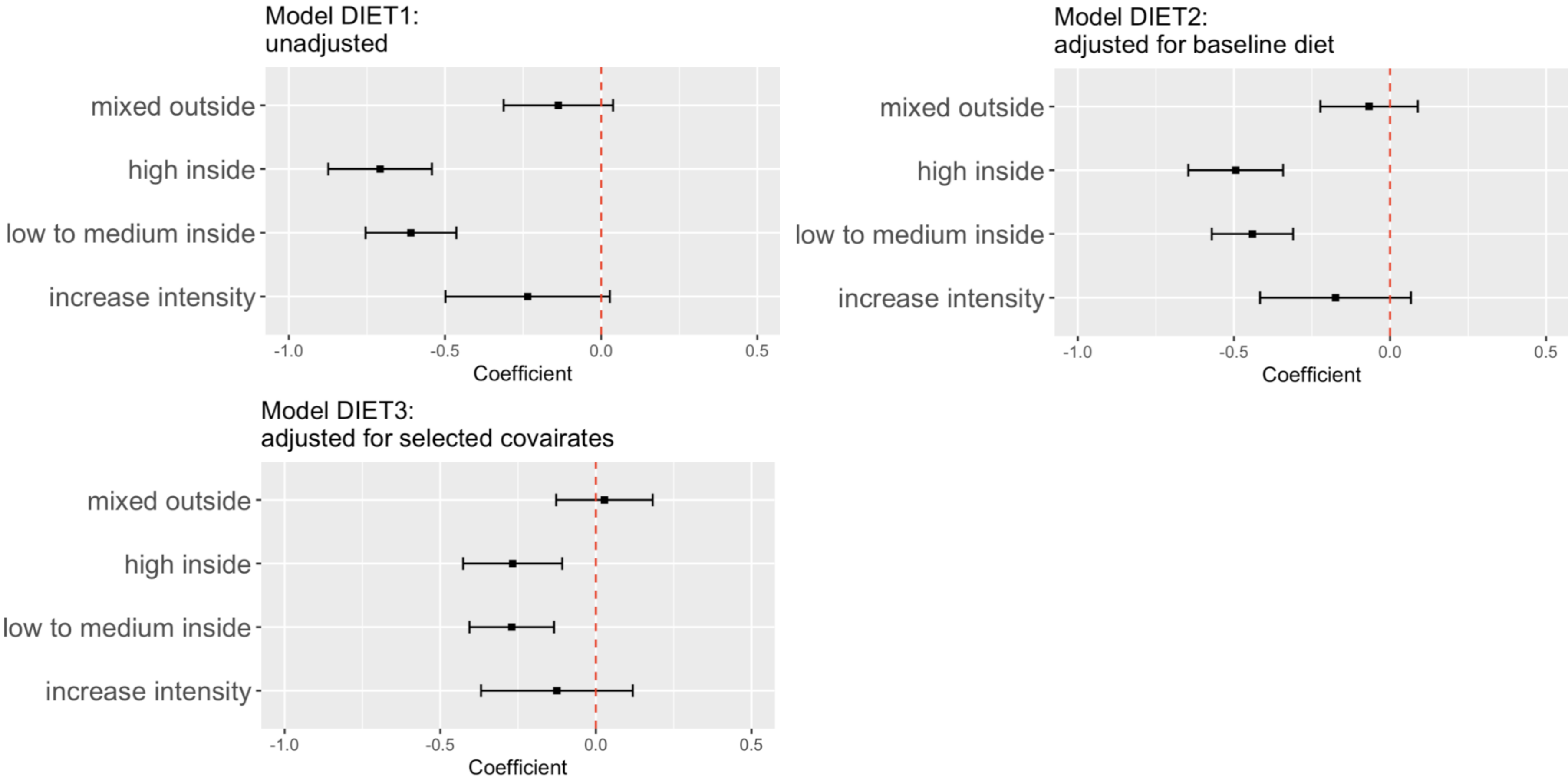


Figure 7.14 Regression models for diet; linear regression models predicting average daily fruit and vegetable intake across latent caregiving intensity classes among UKHLS participants (n=8,556), showing pooled coefficient estimates from multiple imputation (m=10) and accounting for complex survey design and household-level clustering. Results are shown for three models: DIET1 (unadjusted), DIET2 (adjusted for fruit and vegetable intake at baseline), and DIET3 (adjusted for selected covariates). The reference category is the 'low outside' caregiving intensity class.

7.4.3.3 Problematic Drinking

Increase

Figure 7.15 shows the ORs for problematic drinking by class. Caregivers in the 'Increase' group demonstrated a significantly lower likelihood of problematic drinking compared to the reference group ('Low outside). In the unadjusted model (ALC1), an increase in caregiving intensity was associated with lower odds of problematic drinking (OR=0.60 (95% CI: 0.48–0.75). After adjusting for walking frequency, the OR increased slightly to 0.69 (95% CI: 0.53–0.91) in Model ALC2. In the model adjusted for all selected covariates (ALC3), the association became non-significant, with an OR of 0.77 (95% CI: 0.57–1.04). These results suggest that an increase in caregiving intensity was associated with a decrease in the odds of problematic drinking, but the association was partially explained by confounding of other observed characteristics.

Low to medium outside

The 'Low to Medium Inside' caregiving group consistently showed a significantly lower likelihood of problematic drinking. In the unadjusted model (ALC1), the OR was 0.55 (95% CI: 0.47–0.63). After adjusting for drinks frequency at baseline in Model ALC2, the OR increased slightly to 0.63 (95% CI: 0.53–0.75), and further to 0.71 (95% CI: 0.59–0.85) in the model adjusted for all selected covariates (ALC3). These results indicate that caregiving inside the household with low to medium hours was associated with reduced odds of problematic drinking compared to caregivers who provided low hours of care outside the household.

High inside

Caregivers in the 'High Inside' group had the lowest odds of problematic drinking across all caregiving classes. In the unadjusted model, the OR was 0.49 (95% CI: 0.42–0.57). This association attenuated slightly in Model ALC2 (OR = 0.66, 95% CI: 0.54–0.80) and Model ALC3 (OR = 0.75, 95% CI: 0.61–0.93). These results indicate that caregiving inside the household with high care hours was associated with reduced odds of problematic drinking compared to caregivers who provided low hours of care outside the household.

Mixed outside

The 'Mixed Outside' group showed a moderate decrease in the likelihood of problematic drinking in the unadjusted model compared to 'Low outside' caregivers (OR=0.69, 95% CI: 0.59–0.81). However, this association weakened and became non-significant after adjusting for drinks frequency at baseline (ALC2: OR=0.84, 95% CI: 0.70–1.01) and in the model adjusted for all selected covariates (ALC3: OR=0.86, 95% CI: 0.71–1.04). This suggests that the association between 'Mixed outside' caregiving and problematic drinking was largely explained by the baseline consumption of alcoholic drinks.

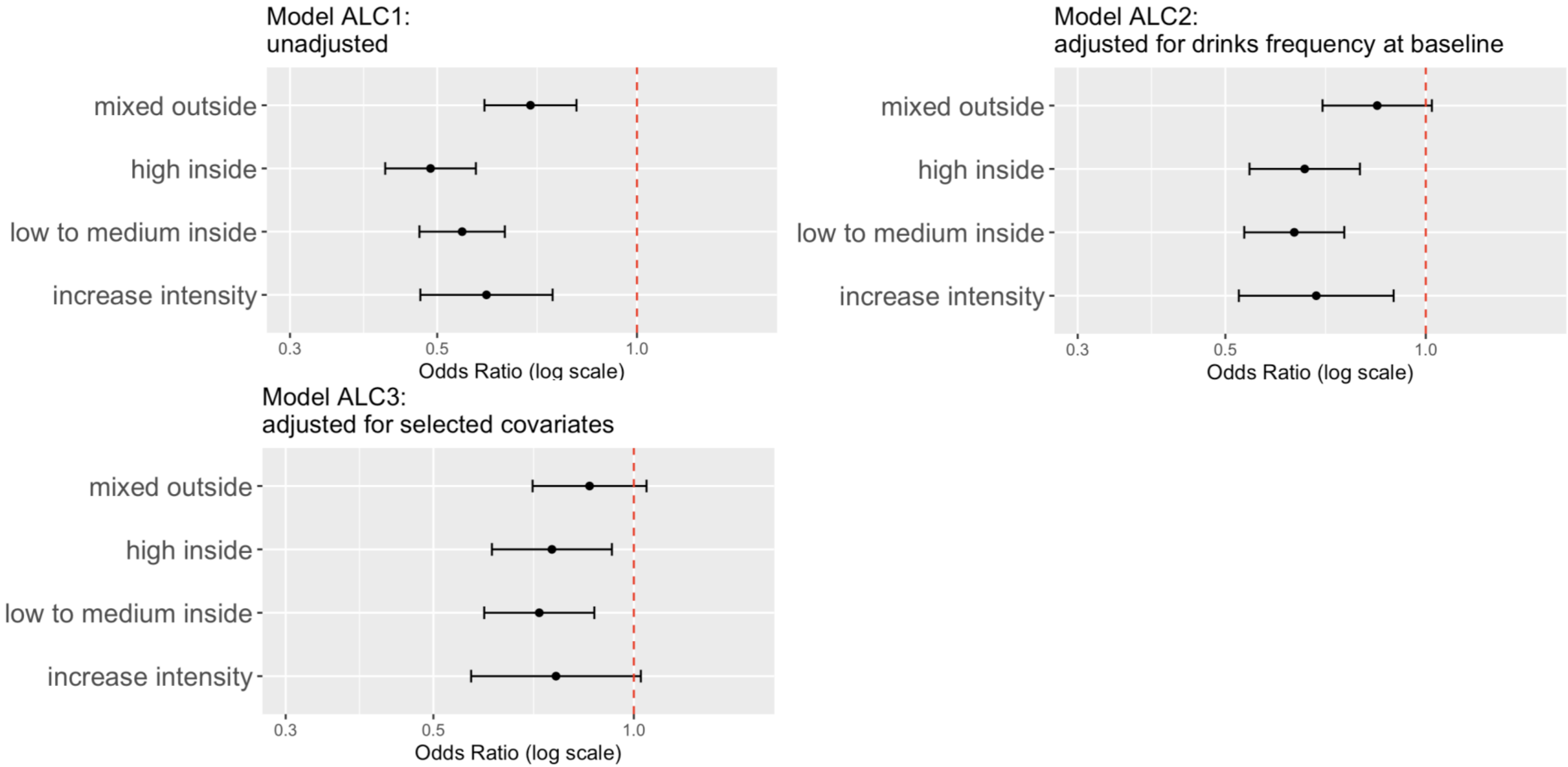


Figure 7.15 Regression Models for Problematic Drinking; logistic regression models predicting problematic drinking across latent caregiving intensity classes among UKHLS participants (n=8,556), showing pooled odds ratio estimates from multiple imputation (m=10) and accounting for complex survey design and household-level clustering. Results are shown for three models: ALC1 (unadjusted), ALC2 (adjusted for drinks frequency at baseline), and ALC3 (adjusted for selected covariates). The reference category is the 'low outside' caregiving intensity class.

7.4.3.4 Smoking

Increase

Figure 7.16 shows the ORs for smoking by class. The 'Increase' caregiving group exhibited a weak and non-significant association with smoking across all models. In the unadjusted model (SMOK1), the OR was 1.21 (95% CI: 0.86–1.71), indicating a slight, non-significant increase in the likelihood of smoking compared to the reference group ('Low outside'). After adjusting for baseline smoking status, the OR decreased to 0.80 (95% CI: 0.50–1.26) in SMOK2 and further to 0.90 (95% CI: 0.54–1.51) in SMOK3 model adjusted for covariates. These findings suggest that there was no evidence for an association between an increase in caregiving intensity and smoking.

Low to Medium Inside

Caregivers in the 'Low to Medium Inside' group consistently showed significantly higher odds of smoking across all models. In SMOK1, the OR was 1.61 (95% CI: 1.31–1.97). This association strengthened slightly after adjusting for baseline smoking in SMOK2 (OR=1.70, 95% CI: 1.25–2.29) and remained significant in the model adjusted for all selected covariates (SMOK3: OR=1.75, 95% CI: 1.26–2.42). These results highlighted a significant association between caregiving of low to medium intensity inside the household and an increased likelihood of smoking compared to low intensity caregivers outside the household.

High Inside

The 'High Inside' caregiving group demonstrated the strongest association with smoking in the unadjusted model (SMOK1), with an OR of 2.23 (95% CI: 1.82–2.72). This association attenuated somewhat after adjusting for smoking status at baseline in SMOK2 (OR=1.50, 95% CI: 1.13–2.00) and in the model adjusted for all selected covariates SMOK3 (OR=1.58, 95%

CI: 1.14–2.19). However, the associations remained significant which suggest that providing higher intensity caregiving inside the household is associated with higher odds of smoking compared to providing low intensity caregiving outside the household.

Mixed Outside

The ‘Mixed Outside’ caregiving group showed a significant association with smoking in the unadjusted model (SMOK1: OR=1.78, 95% CI: 1.43–2.21). However, this association became non-significant when adjusting for smoking status at baseline in SMOK2 (OR=1.28, 95% CI: 0.95–1.74) and became non-significant in the model adjusted for all selected covariates (SMOK3: OR=1.19, 95% CI: 0.86–1.65). These results suggest that caregiving with mixed hours outside the household was not associated with higher odds of smoking compared to low intensity caregiving outside the household after accounting for smoking status at baseline and covariates.

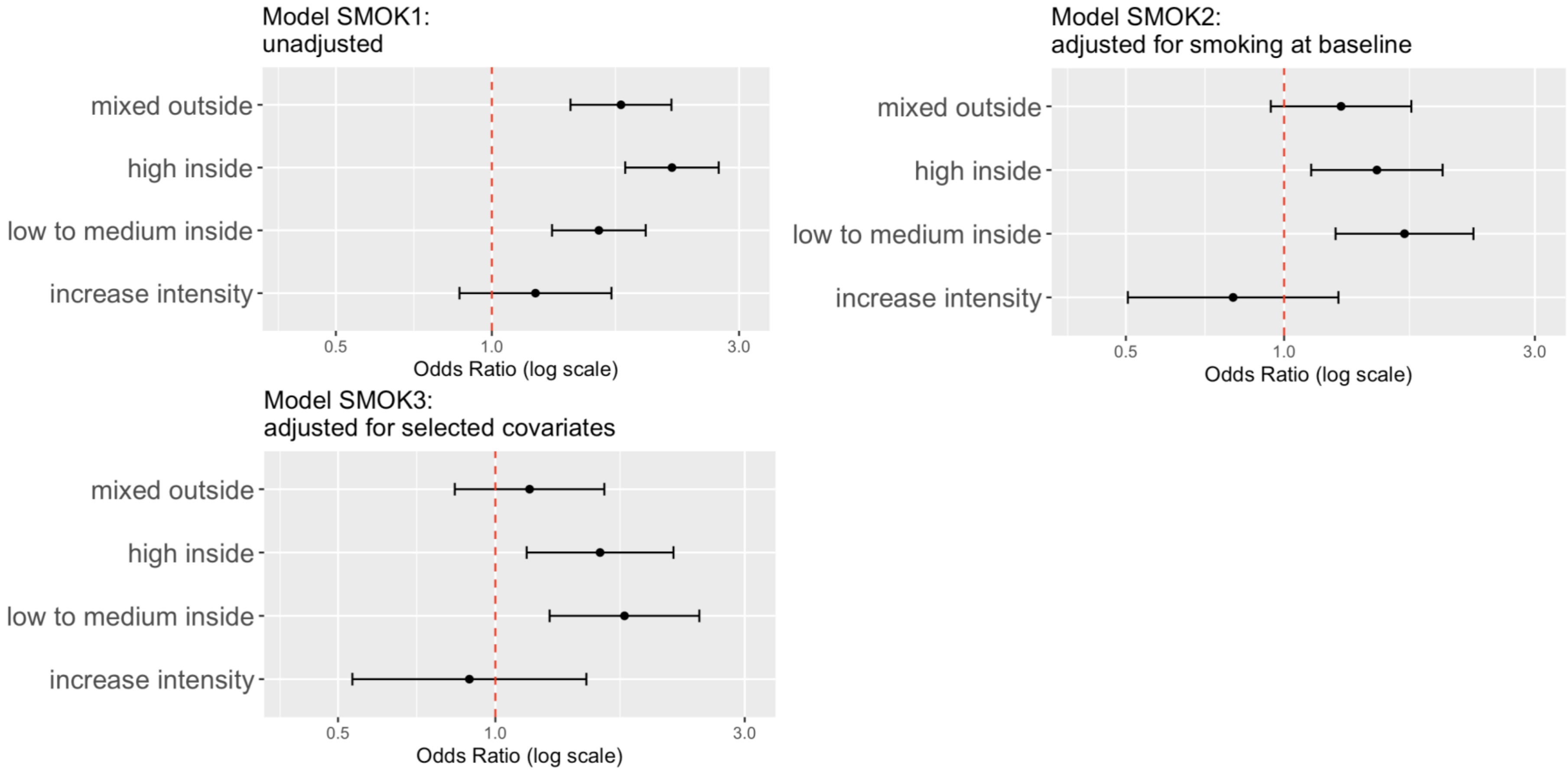


Figure 7.16 Regression Models for Smoking; logistic regression models predicting smoking status across latent caregiving intensity classes among UKHLS participants (n=8,556), showing pooled odds ratio estimates from multiple imputation (m=10) and accounting for survey weights and household-level clustering. Results are shown for three models: SMOK1 (unadjusted), SMOK2 (adjusted for smoking status at baseline), and SMOK3 (adjusted for selected covariates). The reference category is the 'low outside' caregiving intensity class.

7.4.4 Interactions

In the final step of the analysis, each model, that was adjusted for all selected covariates, was tested for interactions by introducing an interaction term between class membership and sex as well as class membership and age group at baseline in a separate model. Then the statistical significance of each interaction was tested using the Wald test. **Table 7.7** illustrates the p-value for the interaction terms of each model. There was no evidence for an interaction between latent class membership and sex for physical inactivity (p=0.12), fruit and vegetable consumption (p=0.95), problematic drinking (p=0.72) and smoking (p=0.46). Besides, there was no evidence for an interaction between class membership and age group at baseline for physical inactivity (p=0.39), fruit and vegetable consumption (p=0.60), problematic drinking (p=0.72) and smoking (p=0.46). The analysis suggests that sex and lifecourse stage of caregivers did not modify the relationship between caregiving intensity and health behaviours.

Table 7.7 Wald test p-values for interaction terms between latent caregiving intensity classes and sex or age group, predicting health behaviours among UKHLS participants (n=8,556). Pooled results from multiple imputation (m=10), accounting for survey weights and household-level clustering.

	Sex	**Age group**
Physical activity	0.12	0.39
Fruit and vegetable consumption	0.95	0.60
Alcohol	0.72	0.68
Smoking	0.46	0.29

7.4.5 Sensitivity analysis

Participants were included in this study if they had caregiving intensity observed for at least two consecutive waves. This criterion intended to minimise misclassification due to large temporal gaps, which may reflect periods of caregiving cessation and subsequent re-entry, rather than genuine changes in caregiving intensity over time. As a result, 1,644 participants who had at least two observations of caregiving intensity were excluded due to substantial gaps between these observations. A sequence index plot illustrating the timing of caregiving episodes among excluded individuals is presented in Appendix 7.9.

To assess the implications of this exclusion, a sensitivity analysis was conducted by running the Latent Class Analysis (LCA) on a broader sample of 10,200 participants, including those with non-consecutive caregiving observations (Appendix 7.9). As expected, model fit indices indicated poorer model performance under the relaxed inclusion criteria. Both entropy values and the average posterior probability matrix suggested higher levels of classification uncertainty compared to the model based on participants with consecutive observations. These findings support the decision to apply a stricter inclusion criterion, as including participants with large observation gaps would have increased sample size at the expense of greater uncertainty and potential misclassification.

7.5 Discussion

LCA revealed five distinct classes representing different patterns of caregiving intensity over time that differed in their composition. Two of these classes revealed caregivers with stable caregiving trajectories outside the household either with low hours or higher than low hours (‘mixed’). Further, two classes with stable trajectories emerged for caregivers inside the household which were divided into ‘low to medium’ hours and ‘high’ hours. Only one class emerged in which participants transition from low intensity care outside the household to higher intensity care inside the household. A class of decreasing caregiving intensity did not emerge during the LCA.

The descriptive and regression analyses highlighted that caregivers inside the household and caregivers outside the household show contrasting health behaviours: low-intensity caregivers outside the household were more physically active, had a higher fruit and vegetable consumption, smoked less but were more likely to drink alcohol problematically compared to caregivers inside the household. In contrast, high-intensity caregivers inside the household were more likely to be physically inactive, had lower fruit and vegetable consumption, higher odds of smoking and lower odds of problematic drinking compared to caregivers with lower intensity caregiving outside the household. An interesting finding was that caregivers inside the household were quite similar with their health behaviour regardless of how many hours of care they reported. This might be due to the fact that caregivers inside the household might underestimate the care they provide or may perceive the provided care as part of their normative role within the household.[8,310,311]

Participants with increased caregiving intensity displayed health behaviours that were somewhat in-between caregivers outside and inside the household, but after adjustment, no significant differences were observed. This is surprising given the significant differences between low- and high-intensity caregivers. A possible explanation is that the group with increased caregiving intensity is underpowered, as it included only 434 participants (388 weighted). The relatively small sample size, combined with the low magnitude of the associations, may have limited the ability to detect significant differences.

7.5.1 Limitations

Some researchers might disagree with the way the LCA was performed as observation within time points in which 'no caregiving' was observed were coded to zero. This was to identify participants who had a change in caregiving intensity rather than identifying transition in and out of caregiving. Appendix 7.2 contains an attempt to depict latent classes when ‘no caregiving’ was not coded as zero and it can be seen that the LCA achieved its goal to identify trajectories of caregiving intensity without considering transition in and out of caregiving. Besides, classification statistic including entropy and average posterior probabilities indicated that the classification within classes was appropriate.

Some might have advocated for a higher number of imputed data sets but as it can be seen in the result from complete cases and results from imputation were almost identical and additional imputations were not considered to enhance findings while making the process of analysis more complex and time-consuming. The results of the complete case analysis can be seen in Appendix 7.4.

Also, given that this was a longitudinal analysis using trajectories, the questions must be raised why baseline weights were preferred over longitudinal weights. The reason was to enhance sample size and to avoid selective attrition. A sensitivity analysis was performed, and the full analysis was repeated with longitudinal weights as in Appendix 7.7. From this it can be seen what was anticipated, confidence intervals are wider, and some associations become non-significant although the overall inference does not change across the outcomes. For this reason, the analysis with the baseline weight was preferred.

7.6 Chapter conclusion

This chapter aimed to investigate the relationship between changes in caregiving intensity and health behaviours across the lifecourse in the UK. For this, Latent Class Analysis was performed on a variable that encompassed information on caregiving hours and place of care. Class membership of these intensity classes was associated with all health behaviour. Providing care inside the household was associated with higher odds physical inactivity, higher odds of smoking, lower odds of problematic drinking and lower fruit and vegetable consumption compared to caregivers who provided lower hours of care outside the household. However, transitions form low intensity caregiving to higher intensity caregiving was not significantly associated with any of the health behaviour outcomes. Likewise, providing care outside the household with higher than low caregiving hours was not associated with health behaviour outcomes after adjusting for confounding. There was no evidence that sex or age of the caregiver modified these associations. While this chapter focused on patterns of caregiving intensity, the following chapter will investigate the influence of multiple caregiving transitions on health behaviours.

8 Multiple caregiving transitions and changes in health behaviours

8.1 Introduction

The previous chapters have investigated entering caregiving, exiting caregiving and intensity changes within caregiving in relation to health behaviours. While caregiving research often focuses on caregiving as a singular or present event, caregiving unfolds, for many individuals, as a dynamic process that is characterised by multiple transitions. These transitions, which may involve entering and exiting caregiving several times throughout the lifecourse, are increasingly recognised as a critical but underexplored dimension of the caregiving experience. Unlike single transitions, multiple transitions present unique challenges and opportunities which may shape caregivers' wellbeing and health behaviours in distinct and complex ways.[312–314]

Understanding multiple caregiving transitions is crucial for several reasons. First, from a lifecourse perspective, caregiving transitions are likely to accumulate and interact over time, compounding stress, disrupting routines, and potentially influencing health behaviours such as smoking, alcohol consumption, physical inactivity or fruit and vegetable consumption. While some caregivers may develop adaptive strategies to manage these transitions, others may experience cumulative strain that exacerbates negative health outcomes.[152,312,313] Second, caregiving transitions are not uniform; their impact varies depending on factors such as caregiving intensity, the duration of caregiving episodes, and the broader social and economic context as well as the lifecourse stage in which they occur.[315,316] These dynamics highlight the need to move beyond static analyses of caregiving to a more nuanced understanding of its temporal complexity.

Despite these considerations, the phenomenon of multiple caregiving transitions remains poorly understood within the existing literature. Many empirical studies on caregiving use cross-sectional samples and even studies with a longitudinal design focus on the initial transition into caregiving or caregiving exit, with limited attention paid to the cumulative or sequential effects of repeated caregiving transitions over the lifecourse.[317–319]

This gap in understanding has significant implications for policy and practice, as existing caregiver support systems may be ill-equipped to address the needs of individuals who navigate caregiving roles repeatedly.[320,321] Recurrent episodes of caregiving can lead to frequent changes in eligibility for financial support, such as Carer's Allowance, creating income insecurity and administrative complexity.[322] Moreover, many employment-related policies, including the right to carer's leave or flexible working, are often designed for singular, sustained caregiving episodes. These frameworks rarely account for the dynamic nature of caregiving trajectories, where individuals may alternate between caregiving and non-caregiving phases. As highlighted by Hamblin et al. (2023),[323] this inflexibility can leave recurrent caregivers without adequate job protection, income support, or access to longer-term planning around work–care arrangements, potentially undermining their financial wellbeing, labour force participation, and health. This analysis seeks to fill this gap by investigating if and how multiple caregiving transitions influence caregivers' health behaviours over time.

8.2 Chapter aims & objectives

It is the aim of this chapter to address Objective 4, namely, to investigate the relationship between multiple caregiving transitions and changes in health behaviours across the lifecourse. Chapter objectives include:

4a. Comparing different methodological approaches to identifying patterns of multiple transitions into and out of unpaid caregiving over time.

4b. Investigating the association between multiple caregiving transitions and changes in health behaviours over time.

4c. Assessing whether the association between multiple caregiving transitions and health behaviours are modified by sex or life course stage of the caregiver.

8.3 Methods

8.3.1 Study design

This study is a secondary longitudinal data analysis using data from UKHLS as described in Chapter □: Data & Measures.

8.3.2 Data

UKHLS contains data on caregiving status, caregiving hours and caregiving place in all its 13 waves. However, as we have seen in previous chapters, the health behaviour module is only available in wave 2,5,7,9,11, and 13. Another challenge was that health behaviour questions changed with wave 7 and remained the same for wave 9,11,13. Hence, caregiving data from wave 2 to wave 13 will be used in this study. Health behaviour baseline measures for adjustment will be taken from wave 2 or 5, while outcome measures will be taken from wave 7,9,11, or 13 because it was not possible to completely harmonise the health behaviour outcomes from wave 7 and onwards with the health behaviour variables from wave 2 and 5.

8.3.3 Measures

8.3.3.1 Exposure: Measuring multiple transitions

Conceptual framework for analysing multiple transitions of unpaid caregiving

Before conducting analysis, it is necessary to reflect on the definition and conceptualisation of multiple caregiving transitions that may be observed. **Figure 8.1** represents a conceptualisation of caregiving trajectories and the resulting caregiving status that may be observed within an empirical longitudinal study. Depending on whether participants are caregivers at baseline and how they transition through caregiving, the following transitioning groups could emerge. The distinction between caregivers and non-caregivers at baseline was considered important because prior caregiving experience may influence both the probability of future caregiving episodes and their impact.[324] For example, those who start the study as caregivers may already have strategies to adjust, while those transitioning into caregiving for the first time may need to develop coping mechanisms for the first time.[325] Distinguishing between caregivers and non-caregivers at baseline also allows to examine whether the consequences of caregiving, such as health behaviours, differ depending on prior exposure, which may reveal cumulative associations across the lifecourse.

On the left side of the branch in **Figure 8.1**, participants are caregivers at baseline and may transition through the following states:

- **Long-term caregiver:** someone being caregiver at baseline and remaining caregiver throughout the study.
- **Former caregiver:** someone being a caregiver at baseline but exiting caregiving during the study without re-entering caregiving.
- **Recurrent caregiver:** someone being a caregiver at baseline but exiting and re-entering caregiving during the study.

On the right side of branch in **Figure 8.1** are participants who were non-caregivers at the beginning of the study and based on their caregiving transitions. They can be categorised into the following groups:

- **Non-caregiver:** someone who is non-caregiver at baseline and never enters caregiving during the study.
- **Emerging caregiver:** someone who is a non-caregiver at baseline, enters caregiving and remains caregiver until the end of the observation period.
- **Temporary caregiver:** someone who was non caregiver at baseline, enters caregiving but exit caregiving again without re-entering caregiving. This group of individuals may also be conceptualised as ***former caregivers.***
- **Multiple transition caregiver:** someone who was a non-caregiver at baseline and enters caregiving at least twice during the observation period. These group of caregivers may also be conceptualised as ***recurrent caregivers.***

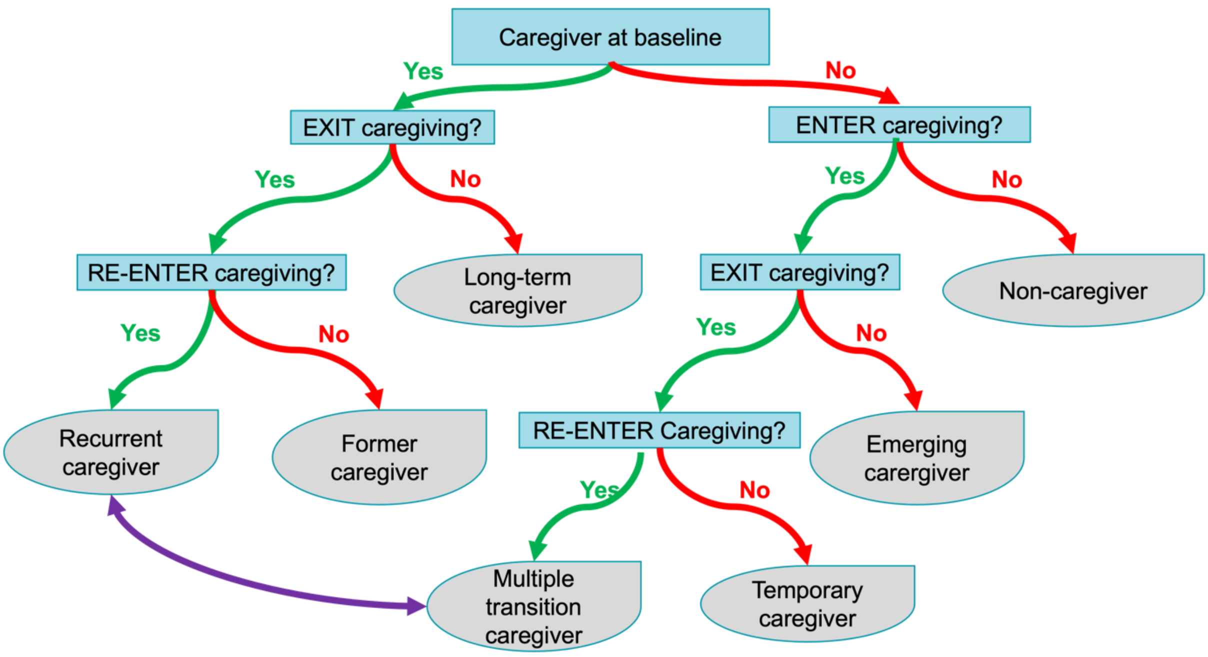


Figure 8.1 Conceptual framework for analysing multiple transition

It must be acknowledged that all these transition patterns are inherently dynamic and may change outside the period of observation. For example, an individual classified as a former or temporary caregiver during the study may re-enter caregiving in future waves not captured in the current analysis, which would alter their classification. For instance, a long-term caregiver at one point of observation may become a former caregiver subsequently; and a former care caregiver may become a recurrent caregiver. Likewise, a non-caregiver may become an emerging caregiver; an emerging caregiver may become a temporary caregiver; and a temporary caregiver may become a caregiver with multiple transitions.

Measuring multiple transitions

While the conceptual framework above intends to capture the sequence and order of caregiving transitions within the study period, it has the limitation that it does not consider the duration of each episode. Given these complex dynamics of caregiving, the question must be raised which approach is best suited to capture these distinct and potentially varied transition patterns. For the purpose of this thesis, two approaches were considered, namely: (1) Using Observed Transitions; and (2) Latent Class Analysis (LCA).

Observed Transitions variable

It would be possible to re-shape the data set and generate a variable that aligns with the conceptualised groups as in **Figure 8.1** above. The advantage to this approach is that it is straightforward, and the generated variable is in line with the conceptual framework. However, the downside of generating such a variable is that it would solely focus on transitions without considering the length of each caregiving and non-caregiving episode. For example, people who transitioned into caregiving would be classed as ‘emerging caregiver’ if they transitioned into caregiving regardless of whether they transitioned into caregiving one year ago or ten years ago. Hence, using the observed transition variable might introduce bias as the groups are based on somewhat arbitrary rules rather than underlying data patterns.

To test this, a variable of observed transitions was generated based on the following information: (1) caregiving status at baseline; (2) number of transitions into caregiving; and (3) caregiving status at the last wave of participation. To count the number of transitions, the data set was reshaped into long format and a dummy caregiving variable was created which was a copy of the original caregiving status variable in each wave. To handle missingness between states (Appendix 8.2; **Figure A8.7**, **Figure A8.8**, **Figure A8.9**) in the copied variable, forward filling was performed, and a variable created that was coded as "1" when a transition from 'no caregiving' to 'caregiving' occurred. Then, per participants the number of transitions were summed into a variable, the dummy caregiving variable was dropped, the data set reshaped to wide and merged back with the main data set. The variable that counted the number of transitions was then used to create the observed transition groups.

Latent Class Analysis

To explore how different methods might shape the identification and interpretation of caregiving trajectories, Latent Class Analysis (LCA) was used as a second approach to the observed transition variable. This comparison aimed to investigate the different kinds of insights each method can offer, particularly in terms of capturing underlying patterns or classes in caregiving transitions that may not be immediately apparent through observed classifications alone. This is because LCA could be used as a powerful statistical tool to identify hidden subgroups of caregivers with similar trajectories. It could help to simplify complex trajectory patterns into smaller meaningful classes and can deal with missing values.[326] The major disadvantage of LCA, however, is that the number and labelling of classes may be subjective to the researcher's selection.[327] LCA models can also be over or under-fitted and participants may be misclassified into the incorrect class.[328] Although LCA can be conducted with missingness, the higher the degree of missingness, the higher the uncertainty which may lead to misclassification of participants into classes.[329]

The LCA was performed using the binary variable 'caregiving status' over the 12 observation points (Wave 2 to Wave 13). The models were fitted using the poLCA function and the process was started by fitting a model with one class and with each new model the number of classes was increased by one. Key model fit indices, including log-likelihood, corrected AIC, adjusted BIC and relative entropy were extracted for each model and presented in a table for comparison of the models. Additionally, an elbow plot of the fit indices was created to help determine the optimal number of latent classes by visually identifying the point at which improvements in model fit level off. This plot was used alongside fit indices to guide the selection of the most appropriate class solution for the LCA. During further exploration of classes, average posterior probabilities were computed which is a matrix that can be used to assess the level of misclassification in within and across classes.

Sequence Analysis

Sequence Analysis (SA) was considered as an complementary approach to LCA, although, LCA is viewed as a superior approach by many scholars.[330–332] However, SA has its merit within lifecourse research and is recognised as a sophisticated method to identify trajectories and transition patterns which can be combined into clusters.[333] More importantly, the major advantage of SA in the light of this study is the ability to impute gaps within a given sequence as this is described in this fairly new approach developed by Halpin in 2016[334] and advanced by Emery and colleagues in 2024.[335] This may reduce uncertainty and produce more robust results compared to LCA. The disadvantage of SA is that it is computationally highly intensive and that there is a high number of distance measures between sequences and clustering approaches of these differences which makes it a complex approach.[336,337]

In summary, using the Observed Transitions might be a simple approach to capture caregiving transition patterns, but it may be subject to several biases. In contrast, LCA may provide a more powerful framework for analysing latent classes of caregiving transitions but arises with some challenges regarding class determination and misclassification. Sequence analysis, on the other hand, is a much more complex process and required a deep understanding of distance measures, sequence imputation and clustering methods while probably not being superior compared to LCA. Given these considerations, this chapter will focus on Observed Transitions and LCA as the primary analytical approaches while results from sequence imputation and sequence analysis are presented in Appendix 8.2.

8.3.3.2 Caregiving characteristics

In addition to the variables created to measure multiple caregiving transitions, additional descriptive variables were used to characterise both the transition groups identified through the observed approach and the latent classes derived from the LCA. These variables provided contextual information to help interpret and compare the composition and distinguishing features of each group.

Hours of care

A variable on care hours was derived from UKHLS, with the original nine categories recoded into four groups for analysis: low (0–9 hours), medium (10–19 hours), high (20–34 hours), and very high (35+ hours) per week; varying hours under 20 were grouped with medium (10-19 hours), and varying hours over 20 with very high (35+ hours).

Place of care

A variable was created from two UKHLS questions (waves 2–13) to classify caregiving as inside the household, outside the household, or dual (both inside and outside) as described in Chapter 4.4.

Relationship

Lastly, a variable was created that indicated the relationship between caregiver and recipient in each wave. If a caregiver had more than one care recipient, they were coded as having two or more care recipient. The categories for the relationship variable were: (1) parents/parents-in-law; (2) child; (3) partner; (4) grandparents; (5) brother/sister; (6) other relative; (7) non-relative; and (8) two or more care recipient. This variable was introduced in this chapter specifically to explore whether changes in the reported relationship between caregiver and care recipient could serve as a proxy for changes in the care recipient, as direct information on this was not available for caregiving provided outside the household

Based on the generated relationship variable for each wave, an additional variable was created which indicated changes in the caregiver-recipient relationship between waves. It captured whether there was continuity, a shift in relationship type or a change in the number of care recipients. This variable contained three categories: (1) "no change" which indicated that relationships between caregiver and care recipient remained consistent between waves; (2) "changed relationship" which indicated that participants experienced a shift in the type of relationship with the care recipient (for example from parent to non-relative); and (3) "changed number of care recipients" which indicates if participants experienced a change in the number of care recipients.

8.3.3.3 Outcomes

The outcomes of interest were physical inactivity (inactive/active), number of daily fruit and vegetable, problematic drinking (problematic drinking/no problematic drinking and smoking (current smoker / no current smoker) as defined in Chapter 4.4.

8.3.3.4 Health behaviours at baseline

As in the previous chapter on care intensity, baseline measures capturing either a different aspect of the same health behaviour or an alternative way of measuring it were included in the adjusted model to account for pre-existing behavioural patterns This was because health behaviour questions changed from wave seven onwards and could not be harmonised with the earlier waves two and five. For physical inactivity, walking frequency at baseline as a categorical variable will be used as a proxy for physical inactivity because the physical activity module in UKHLS in wave two and five only contained questions on walking. For fruit and vegetable consumption, a categorical variable of fruit and vegetable consumption will be used. To adjust for alcohol consumption at baseline, a categorical variable will be used that contains the frequency of alcoholic drinks at baseline. For smoking, a categorical variable was used that contained information on smoking status at baseline.

8.3.3.5 Covariates

Covariates were drawn from each participant's baseline wave, defined as the first wave in which the caregiving status was observed first after meeting inclusion criteria. The same covariates as defined in previous chapters were used including sex (male/female); age groups (early adulthood:16-29; early mid-adulthood: 30-49; late mid-adulthood: 50-64; and late adulthood: 65 and older), cohabiting status (single, widowed, separated / married or cohabiting), highest education attainment (no qualification / A-levels, GCSE, other qualifications / degree or other higher qualification), ethnicity (white / black / Indian / Pakistani / Bangladeshi / other Asian or other), occupational class (not employed / management and professional/intermediate/routine), income quintiles (from 1 [lowest] to 5 [highest], employment status (not employed/full-time employed/part-time employed), number of children living in the household, household size, self-rated general health (excellent, very good or good / fair or poor), psychological distress (GHQ score) and physical limitations (SF12 score).

Additionally, for each of the outcomes, a variable was created to indicate in which waves the outcomes were observed, as this observation period spans over eight years. This variable was used in the adjusted models to account for changes in outcomes over time or possible period effects.

8.3.4 Statistical analysis

Data cleaning was performed in Stata Version 17 while all analyses were conducted in R Studio Version 2024.12.0. Latent Class Analysis (LCA) was used to identify unobserved subgroups of individuals based on their patterns of caregiving transitions. LCA groups individuals into unobserved (latent) classes based on similarities in their caregiving transitions, with each person assigned to a class based on probability.[290] Models with different numbers of classes were tested using the poLCA package,[287] and the optimal number of classes was determined using a combination of model fit indices (e.g. BIC, AIC, entropy) and visual inspection of an elbow plot (see Section 8.3.3.1).

Sequence Analysis (SA) was used as a supplementary method to explore the ordering and timing of caregiving states across the observation period. This approach treats individual caregiving histories as sequences and analyses their similarities or dissimilarities over time. SA was performed using the TraMineR package[288] and missing caregiving data within sequences were imputed using the seqimpute package.[335] Full sequence analysis results are presented in Appendix 8.2.

Regression analysis

Following LCA, a class variable was generated that assigned each individual to their most likely latent class based on posterior probabilities of class membership. Regression modelling was then performed to assess associations between these LCA-derived caregiving transition classes and health behaviours. A parallel set of regression analyses was conducted using the observed caregiving transition groups to compare findings across the two approaches. Linear regression was performed for fruit and vegetable consumption and logistic regression for physical inactivity, problematic drinking and smoking. For each outcome, three models were estimated: (1) Model 1 which was an unadjusted model of the outcome containing only the class variable; (2) Model 2 was the partially adjusted model which contained the latent class variable and was adjusted for the corresponding health behaviour. The main purpose of this model was to assess whether the baseline health behaviour predicted the outcome and to assess to what extend this attenuated the relationship between latent class membership and health behaviour outcome; and (3) which was the model adjusted for all selected covariates which accounted for the health behaviour at baseline and the covariates including sex, age group, education, ethnicity, occupational class, income quintiles, employment status, household size, number of children living in the household, cohabiting status, self-rated general health, psychological distress, Additionally, the model adjusted for all selected covariates for physical inactivity were adjusted for baseline physical health (SF-12).

Lastly, interactions were tested for sex and age group at baseline for each model. For this, in each model adjusted for all selected covariates an interaction term was introduced between class membership and sex, and in a separate model between class membership and age group at baseline (which acted as a proxy for the lifecourse stage of participant). Then, an overall p-value for this interaction term was computed using the Wald test. If the p-value was 0.05 or smaller, the null-hypothesis was rejected that models with interaction term was similar to the model without interaction term stratified results were produced.

8.3.5 Survey design

To account for the complex survey design of UKHLS and minimise potential bias, the survey package in R[296] was used for all descriptive analyses and regression models. This ensured that the survey's stratified, clustered, and weighted design was appropriately incorporated, producing adjusted estimates and standard errors.

The weighting conventions of UKHLS also require consideration, particularly the assignment of zero weights to certain participants. As discussed in Chapter 7 (Intensity Change), these zero weights are intentional and a consequence of the sample design and fieldwork issuing rules.[338] For this analysis, the baseline cross-sectional weight (indscub_xw) was chosen over longitudinal weights, as it accommodates participants who were present for at least four waves rather than all 13. While this approach does not fully address attrition, the inclusion of outcome measures from earlier waves (7, 9, and 11) was considered useful to mitigate potential bias. Nevertheless, a sensitivity analysis was performed with longitudinal weights and regression results from an analysis incorporating longitudinal weights can be found in Appendix 8.7 (in **Figure A8.19** for Observed Transition **Figure A8.20** and for LCA).

8.3.6 Multiple imputation

To address item non-response, multiple imputation (MI) was performed using the same approach as discussed in Chapter 7 (Intensity change). This decision was based on the assumption that data were missing at random (MAR), and on the potential for complete case analysis to introduce bias and reduce statistical power.[339] A calculation on the recommended number of imputation was used based on the approach from von Hippel[300] as seen in **Table A8.22**. According to this, 10 imputations would suffice to address variability in imputations across outcomes. Further, outcomes were imputed and retained in the pooled analysis as this was discussed in Chapter 7 (Intensity Change).

All variables in the substantive model were included in the imputation model, with imputation methods assigned based on variable type. Ordinal regression was used for education and income, binary logistic regression for smoking and physical inactivity, multinomial regression for ethnicity and employment status, and predictive mean matching for continuous variables to avoid implausible values.[309] An analysis of missingness (Appendix 8.9) confirmed its association with health behaviours at baseline and other covariates, except for sex.

In preparation for the multiple imputation, a predictor matrix and default method for the imputation method was defined. Ordinal regression was defined for education, income quintiles, number of children in the household, household size. Variables defined for binary logistic regression were sex, general self-rated health, relationship status, as well as physical inactivity (outcome), smoking status (outcome) and problematic drinking (outcome) at the last observation. For multinominal regression, variables defined were ethnicity, occupational class and working status. The continuous variables age at baseline, GHQ at baseline, SF12 physical at baseline and fruits and vegetable consumption (outcome])at last observation were defined for the imputation model. Continuous variables were imputed using predictive mean matching as this allowed to preserve the distribution of the data and ensures that imputed values are plausible and within the observed range. The results in this chapter will be presented using multiple imputation, and in Appendix 8.8, a complete case analysis can be found. Multiple imputation of covariates was performed in R using the mice[297] package and mitools[340] package to combine complex survey design with multiple imputation.

After inclusion criteria were applied, missingness (item non-response) was assessed and 77.0% of the sample were complete cases whereas 23.0% had at least one item missing (Appendix 8.9). GHQ, general self-rated health and the physical component of the SF12 questionnaire accounted for most of the missingness in all the covariates (10.8%; 10.0%; and 16.1% respectively). Missingness in outcomes was low and physical inactivity had with 3.2% the highest proportion of missingness of all eligible participants. Missingness in baseline health behaviours was below 1% apart from drinks at baseline which had missingness of 10.7%.

8.3.7 Analytical sample

Participants were included in this study if the variable ‘caregiving status’ was observed for at least four times over the twelve years observation period between their baseline wave and the wave at which the outcome was measured. This criteria ensured that there were sufficient repeated observations to capture potential ‘multiple transition’ into and out of caregiving within the exposure period. Further, participants were included if they had a valid baseline measure of each health behaviour (wave 2 or 5), a valid outcome measure at the end of the study at Wave 13, 11, 9 or 7. Participants who met the above inclusion criteria were eligible for analysis.

Sample Size

The data set contained 87,966 participants who had information on caregiving between Wave 2 and Wave 13 of the UK Household Longitudinal Study (UKHLS). This total reflects the pooled sample across all waves, including temporary sample members, and represents all individuals with at least one caregiving observation during the study period, following data cleaning. To capture multiple caregiving transitions, participants who reported their caregiving status for less than four waves were excluded (n=38,010), leaving 49,956 individuals with caregiving data for at least four waves. Next, participants who had none of the four outcome measures observed were excluded (n=16,711) resulting in 33,245 participants with at least one outcome recorded. A further 8,193 participants were removed because none of the four health behaviours at baseline had been observed, reducing the sample to 25,052. Finally, an additional 3 participants were excluded because, for these individuals, data on both the outcome and the corresponding baseline measure of the same health behaviour were not available. This left a sample of 25,049 eligible participants who had at least one outcome observed alongside the corresponding health behaviour at baseline (**Figure 8.2**).

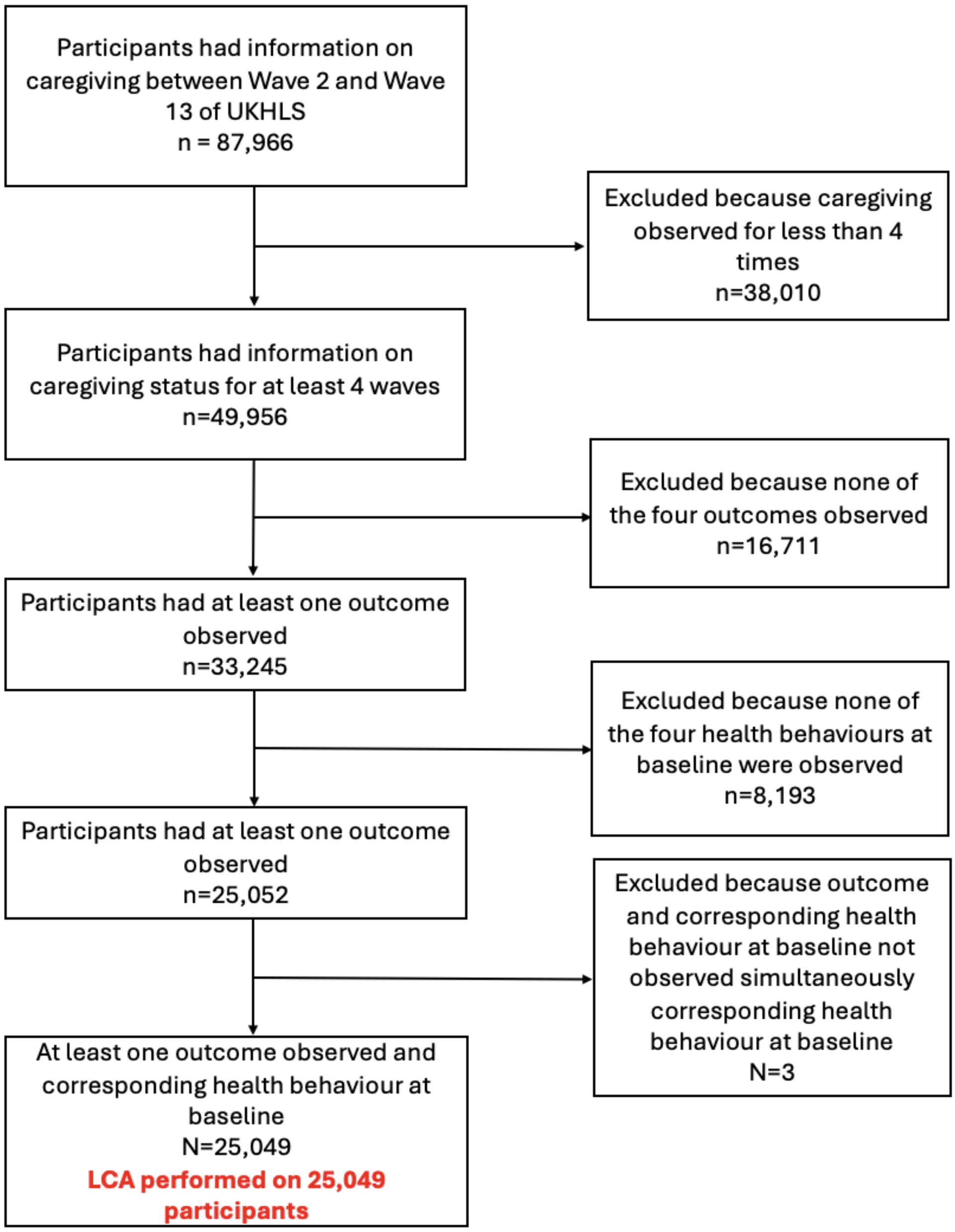


Figure 8.2 Sample size flow chart of analysis of multiple caregiving transition

Physical inactivity

The analysis of physical inactivity included 25,049 eligible participants. Among them, 807 (3.2%) were excluded because physical inactivity at the outcome stage was not observed, leaving 24,242 (96.8%) participants with observed physical inactivity outcomes. Twenty-five participants (0.1%) were excluded due to missing baseline walking data, resulting in 24,217 participants with observed walking behaviour at baseline. Among these, 4,212 participants

(17.5%) had missing covariate data, including education (n=51), ethnicity (n=10), occupational class (n=189), income quintiles (n=27), working status (n=2), cohabiting status (n=3), General Health Questionnaire (GHQ) score (n=2,592), self-rated health (n=2,379), and SF-12 (n=3,851). As a result, 20,030 participants (80%) constituted the complete case sample. To address missing data, multiple imputation (m=10) was conducted for the covariates and missing outcomes, leaving a substantive analytical sample of 25,049 participants .The sample size flow chart for physical inactivity is below in **Figure 8.3** while sample size flow charts for the other outcomes can be found in Appendix 8.1.

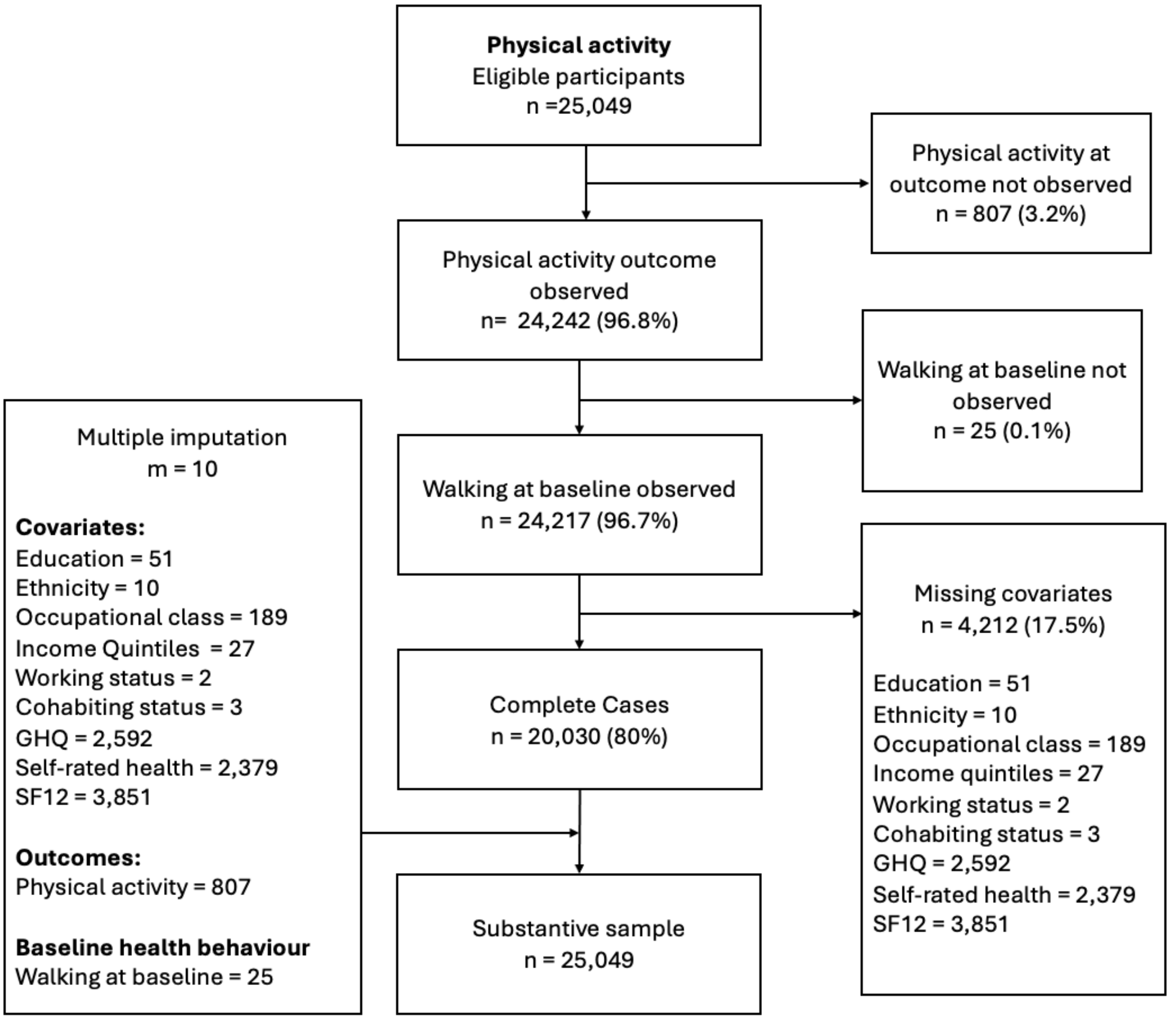


Figure 8.3 Sample size flow chart for physical inactivity of eligible participants following application of inclusion criteria.

Fruit and vegetable consumption

The analysis of fruit and vegetable consumption included 25,049 eligible participants. Among them, 442 (1.8%) were excluded because fruit and vegetable consumption at the outcome stage was not observed, leaving 24,607 (98.2%) participants with observed fruit and vegetable consumption. Next, 42 participants (0.2%) were excluded due to missing baseline dietary data, resulting in 24,565 participants with observed diet at baseline. Among these, 2,910 participants (11.8%) had missing covariate data, including education (n=53), ethnicity (n=9), occupational class (n=190), income quintiles (n=28), working status (n=2), cohabiting status (n=4), General Health Questionnaire (GHQ) score (n=2,642), and self-rated health (n=2,429). As a result, 21,697 participants (86.6%) were available for the complete case sample. To address missing data, multiple imputation (m=10) was conducted for the covariates and missing outcomes resulting in a substantive analytical sample of 25,049 participants (**Figure A8.1**).

Problematic drinking

The analysis of problematic drinking included 25,049 eligible participants. Among them, 564 (2.3%) were excluded because problematic drinking at the outcome stage was not observed, leaving 24,485 (97.8%) participants. Further, a total of 2,545 participants (10.4%) were excluded due to missing baseline drinking frequency data, resulting in 21,940 participants with observed drinking frequency at baseline. Among these, 465 participants (2.1%) had missing covariate data, including education (n=46), ethnicity (n=10), occupational class (n=156), income quintiles (n=23), working status (n=2), cohabiting status (n=2), General Health Questionnaire (GHQ) score (n=199), and self-rated health (n=36). As a result, 21,475 participants (85.7%) constituted the complete case sample. To address missing data, multiple imputation (m=10) was conducted for the covariates and missing outcomes, leaving a substantive sample of 25,049 participants (**Figure A8.2**).

Smoking

The analysis of smoking included 25,049 eligible participants. Among them, 17 (0.1%) were excluded because smoking status at the outcome stage was not observed, leaving 25,032 participants. Next, two participants were excluded due to missing baseline smoking status data, resulting in 25,030 participants. Among these, 2,982 participants (11.9%) had missing covariate data, including education (n=53), ethnicity (n=10), occupational class (n=195), income quintiles (n=28), working status (n=2), cohabiting status (n=4), General Health Questionnaire (GHQ) score (n=2,707), and self-rated health (n=2,490). As a result, 22,050 participants (88.0%) were included in the complete case sample. To address missing data, multiple imputation (m=10) was conducted for the covariates and missing outcomes, leaving a substantive sample of 25,047 participants (**Figure A8.3**).

8.4 Results

8.4.1 Comparison of approaches

8.4.1.1 Observed Transitions

To create a variable that was based on the Observed Transition patterns as defined in the conceptual framework, participants were grouped as show in **Table 8.1** below:

Table 8.1 Labels and definitions for Observed Transition groups based on caregiving status across UKHLS waves 2 to 13. Groups are defined by caregiving status at baseline, transitions into and out of caregiving, and caregiving status at last observation.

Label	**Definition**			
	Caregiver at baseline?	Transition into care?	Exiting care?	Caregiver at last observation?
Non-caregiver	No	No	No	No
Emerging caregiver	No	Yes	No	Yes
Temporary caregiver	No	Yes	Yes	No
Long term caregiver	Yes	No	No	Yes
Former caregiver	Yes	No	Yes	No
Multiple transition / current non-caregiver	Yes or No	Yes, several	Yes	No
Multiple transitions / current caregiver	Yes or No	Yes, several	Yes	Yes

Table 8.2 shows the proportions of categories based on the Observed Transitions. Participants who were Non-caregiver were the largest group (48.6%), followed by Temporary caregivers (15.5%). Multiple transitions were relatively frequent amongst this sample and 11.9% had Multiple caregiving transitions and were non-caregivers at the end of the study while 9.5% experienced Multiple caregiving transitions and were caregivers at the last observation. The other groups were relatively small and consisted of Former caregivers (6.8%), Emerging caregivers (5.8%) and Long-term caregivers were the smallest group (2.2%). Amongst caregivers, Multiple transitions were quite frequent and over 40% of caregivers experienced multiple transitions during the study period.

Table 8.2 Sample size and proportion across Observed Transition groups, based on UKHLS participants with caregiving status observed at least four times between waves 2 and 13 and at least one recorded health behaviour outcome (n=25,049). Proportions are shown for the full sample and among participants who provided care at any point (n=12,872).

Group	**Count (n=25,049)**	**Proportion all (n=25,049)**	**Proportion amongst caregivers (n=12,872)**
Non-caregiver	12,177	48.6%	-
Emerging caregiver	1,457	5.8%	11.3%
Temporary caregiver	3,837	15.3%	29.8%
Long-term caregiver	568	2.2%	4.4%
Former caregiver	1,656	6.6%	12.9%
Multiple transitions / currently caregiver	2,973	11.9%	23.1%
Multiple transitions – currently non-caregiver	2,389	9.5%	18.6%

To better understand the caregiving characteristics of different groups, various visual tools from sequence analysis were utilised to describe groups such as state distributions plots (showing the distribution of states at each time point), sequence index plots (displaying individual sequences across time), sequence modal state plots (a 'typical' sequence for each group) and sequence modal plots (the modal states for each group). Below is a state distribution Plot (**Figure 8.4**) and a sequence index plot (**Figure 8.5**) of the defined groups. Each panel illustrates how caregiving status evolves over time, with the x-axis representing the study waves (UKHLS wave 2 to 13) and the y-axis representing the proportion of individuals in caregiving (dark blue) and non-caregiving (light blue) states. The plots show that Non-caregivers remained consistently in the non-caregiving state across waves, while Long-term caregivers remained in the caregiving state. Emerging caregivers gradually transitioned into caregiving, whereas temporary caregivers provided care for a limited period before returning to non-caregiving. Former caregivers began in a caregiving role but subsequently exited and remained non-caregivers. Groups with multiple transitions display alternating episodes of caregiving and non-caregiving, with some individuals provided care in the last wave of observation while others were non-caregivers.

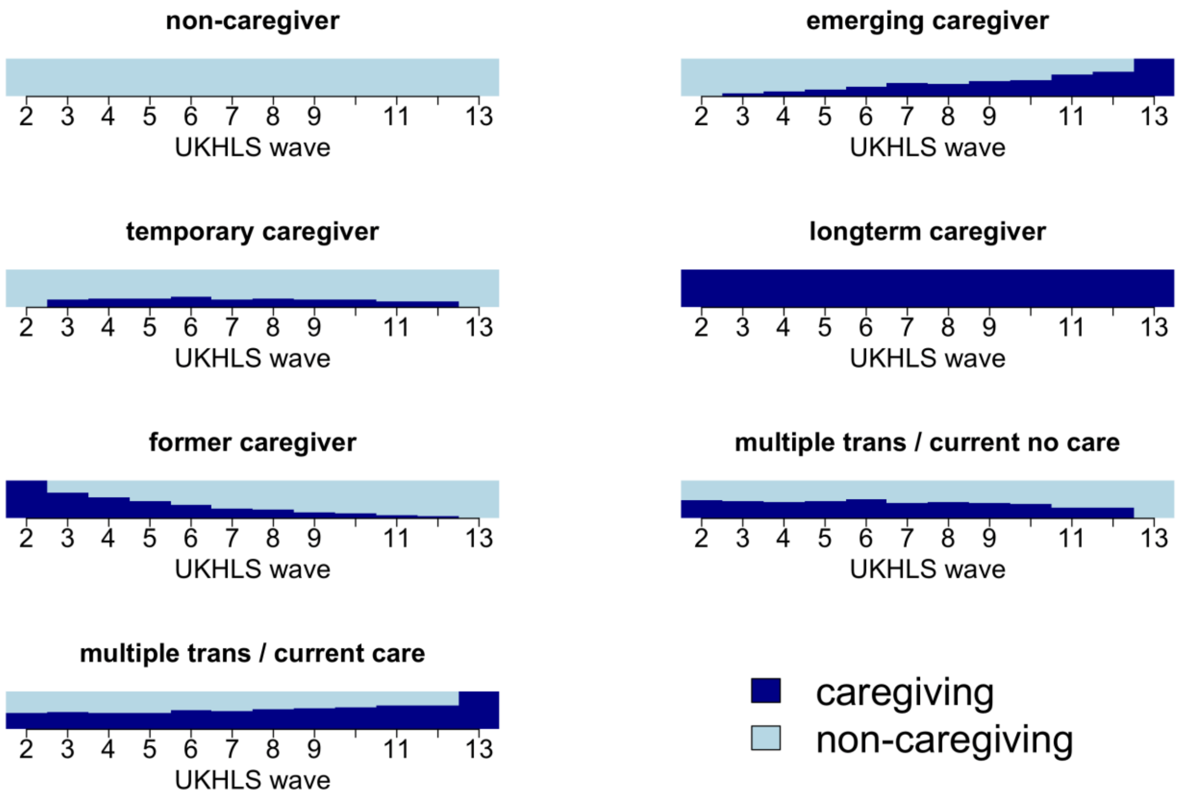


Figure 8.4 State Distribution Plot for Observed Transitions groups across UKHLS waves 2 to 13 (n=25,049). Each panel represents an Observed Transitions group, displaying the distribution of caregiving status over time.

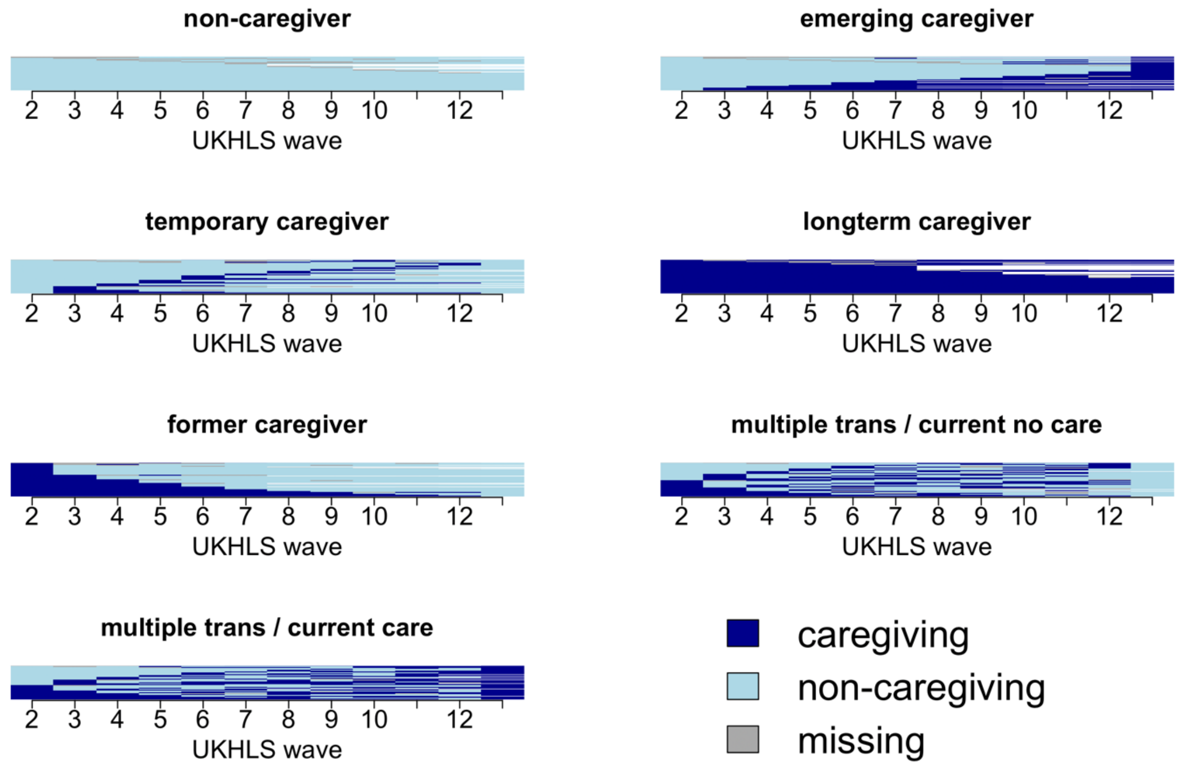


Figure 8.5 Sequence Index Plot for Observed Transition groups across UKHLS waves 2 to 13 (n=25,049). Each line represents an individual participant's caregiving status trajectory, coloured by Observed Transitions group classification.

Below is a sequence modal state plot in **Figure 8.6**. These plots show that the multiple transition groups differ from one another and the group that is currently not a caregiver has non-caregiving as dominant state while the group who is currently caregiver seemed to have transitioned from primarily non-caregiving to caregiving states. This is confirmed by the sequence modal plot in **Figure 8.7** below which shows that caregiving is the dominant state in the multiple transition group that is caregiving state at the last wave of observation whereas non-caregiving is the dominant state for participants who transitioned multiple times into caregiving but were non-caregivers at the last wave of observation.

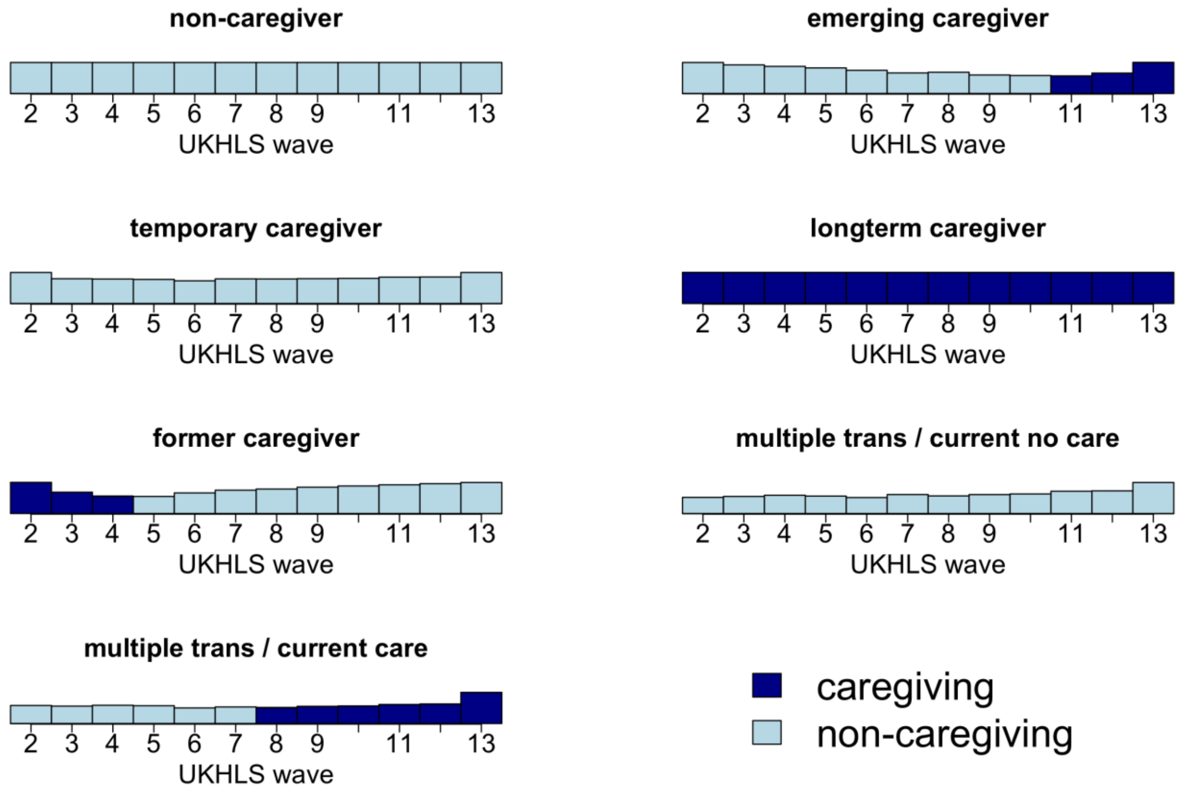


Figure 8.6 Sequence Modal State Plot for Observed Transition groups across UKHLS waves 2 to 13 (n=25,049). Each panel shows the most frequent caregiving status at each wave for participants within each Observed Transitions group.

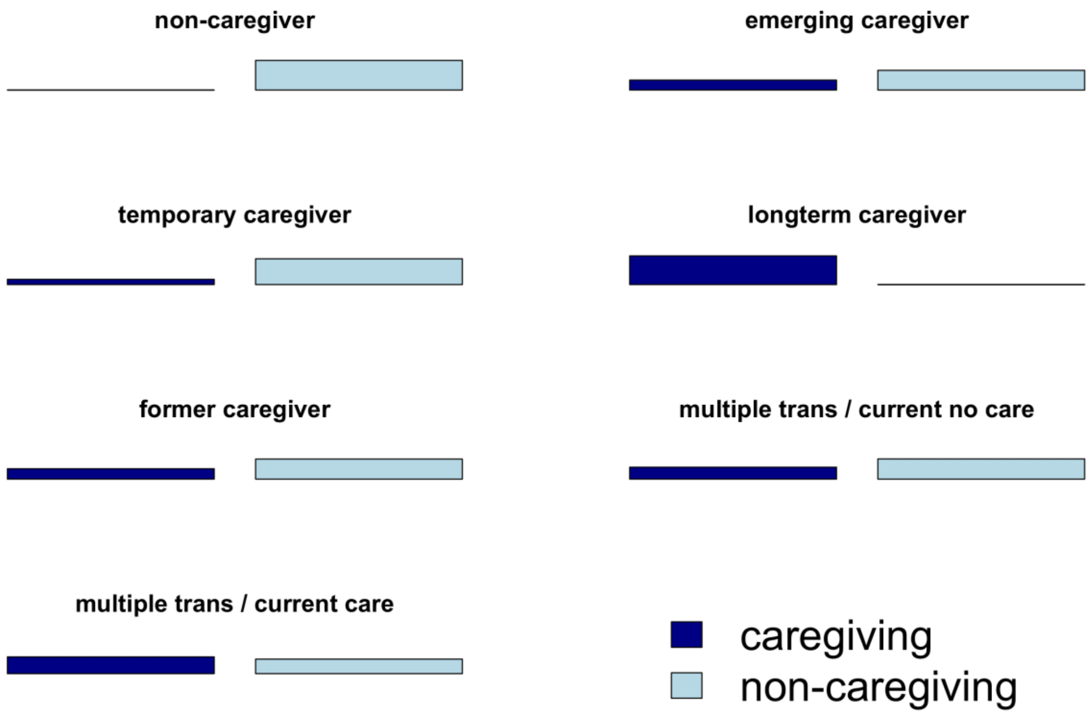


Figure 8.7 Sequence Modal Plot for Observed Transition groups across UKHLS waves 2 to 13 (n=25,049). Each panel displays the most common caregiving status for participants within each Observed Transitions group.

Understanding composition of different groups

These groups were further described in view of their place of care, care hours, and the relationship between caregiver and recipient. These tools included sequence index plots, state distribution plots, sequence modal plots, and sequence modal state plots. In Appendix 8.10, the plots for place of care are illustrated. The general trend shows that caregiving outside the household was more common, except among Long-term caregivers, who had higher proportions of caregiving within the household. For groups with Multiple transitions, moving from outside to inside the household seemed common. Regarding care hours (Appendix 8.10), caregivers with higher care hours were more dominant in the long-term care group. Participants with Multiple transitions exhibited more unstable and fluctuating trajectories of caregiving hours. In terms of caregiver-recipient relationships (Appendix 8.10), long-term caregivers seemed to have more stable trajectories. In contrast, those with multiple transitions had fluctuating relationships with care recipients, suggesting that the care recipient changed more frequently over time.

8.4.1.2 Latent Class Typology

After investigating the variable with observed transition patterns, Latent Class Analysis (LCA) was performed to identify potentially unobserved trajectories of caregiving. The LCA reveals that fit indices improve with each class that gets added to the model as seen in **Table 8.3**. Additionally, an elbow plot was generated, as seen in **Figure 8.8**, which shows that after the models with 5 classes, adding a new class did not improve the fit by a large margin. Hence, to assess which LCA solution aligned best with conceptual considerations, each class in each solution was inspected with the aim to identify a class that would best characterise multiple transition caregivers.

Table 8.3 Latent class model fit statistics for caregiving status across UKHLS waves 2 to 13 (n=25,049). Models were compared using log-likelihood, Bayesian Information Criterion (BIC), adjusted BIC (aBIC), consistent Akaike Information Criterion (cAIC), likelihood ratio tests, and entropy values.

Model	log-likelihood	resid. df	BIC	aBIC	cAIC	likelihood-ratio	Entropy
Model 01 1 Class	-127934.37	4083	255990.3	255952.1	256002.3	53175.387	-
Model 02 2 Classes	-99580.99	4070	199415.2	199335.7	199440.2	17896.530	0.878
Model 03 3 Classes	-95659.54	4057	191704.0	191583.2	191742.0	12284.815	0.834
Model 04 4 Classes	-92366.03	4044	185248.6	185086.5	185299.6	7971.218	0.806
Model 05 5 Classes	-91520.51	4031	183689.2	183485.9	183753.2	6717.801	0.789
Model 06 6 Classes	-90861.68	4018	182503.3	182258.6	182580.3	5786.904	0.769
Model 07 7 Classes	-90302.51	4005	181516.6	181230.6	181606.6	5015.204	0.742
Model 08 8 Classes	-90023.77	3992	181090.8	180763.5	181193.8	4587.958	0.739
Model 09 9 Classes	-89845.60	3979	180866.1	180497.5	180982.1	4338.780	0.735
Model 10 10 Classes	-89624.33	3966	180555.2	180145.3	180684.2	3987.019	0.728
Model 11 11 Classes	-89522.35	3953	180483.0	180031.7	180625.0	3848.659	0.719
Model 12 12 Classes	-89437.06	3940	180444.0	179951.5	180599.0	3705.483	0.704

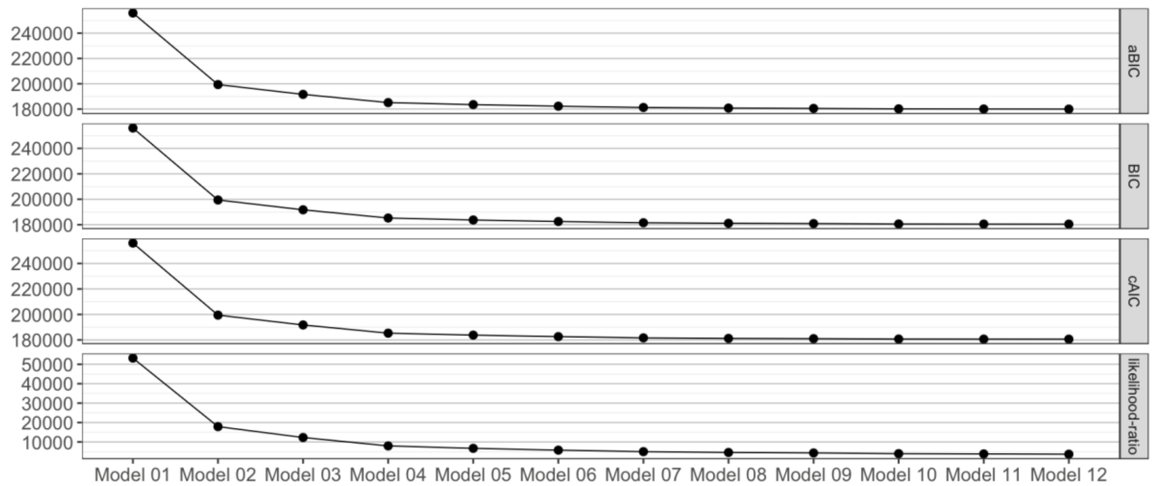


Figure 8.8 Elbow Plot of model fit statistics for latent class analysis of caregiving status trajectories across UKHLS waves 2 to 13 (n=25,049). The plot displays fit indices (e.g., BIC, aBIC, cAIC) across different class solutions, with the 'elbow' indicating the optimal number of latent classes.

Next, posterior probabilities were depicted for different class solutions, as illustrated in **Figure 8.9** for the 7-class solution, **Figure 8.10** for the 8-class solution, and **Figure 8.11** for the 9-class solution. Although elbow plots suggested a 4- or 5-class solution, higher class solutions were explored to examine when a group with recurring caregiving pattern emerges. Notably, a group characterised by recurring caregiving patterns only emerged with the 8-class solution, which justified further consideration of models beyond the initial fit-based recommendations. The 7-class solution included two groups with emerging caregiving patterns varying in the length of caregiving, two classes of former caregivers with varying lengths of caregiving, one class of non-caregivers, one class of long-term caregivers, and one class of temporary caregivers. A class with recurrent transitioning caregiving patterns only emerged in the 8-class solution. The 9-class solution revealed an additional class similar to temporary caregiving class, which did not add significant value and the other groups looked quite similar. Therefore, the 8-class solution was preferred to answer the research question, as it allowed for an analysis focused on participants with recurrent caregiving transition patterns.

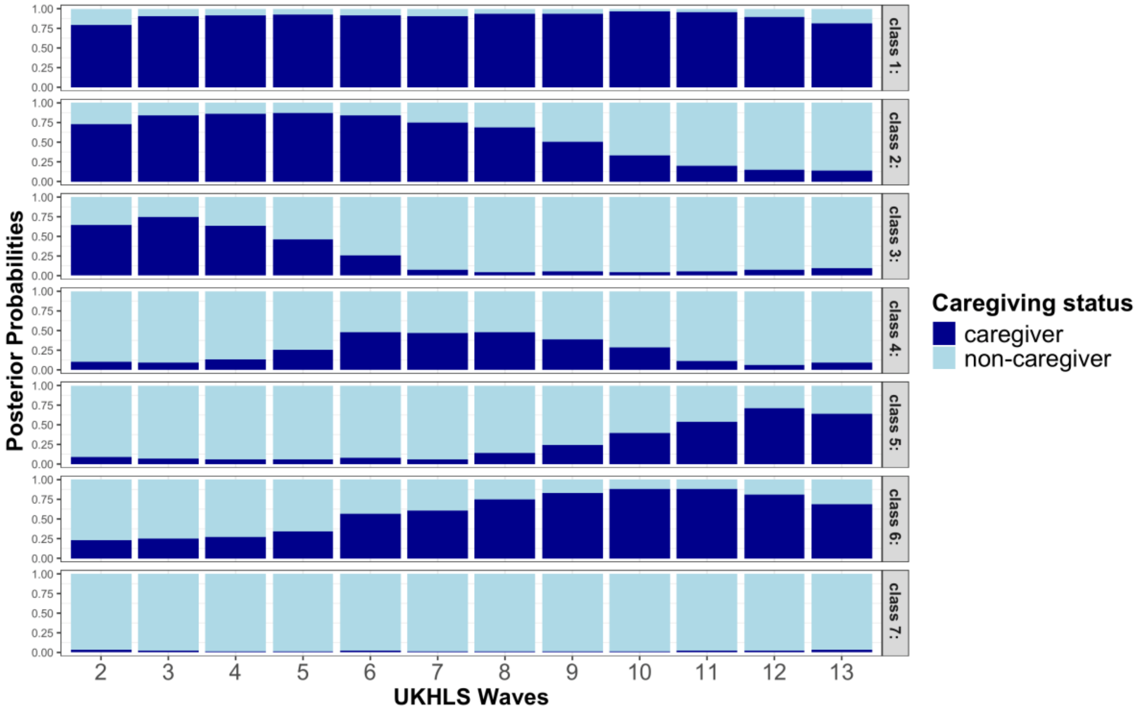


Figure 8.9 Posterior probability for seven-class solution across UKHLS waves 2 to 13 (n=25,049). Each panel represents a latent class, showing the distribution of caregiving status over time.

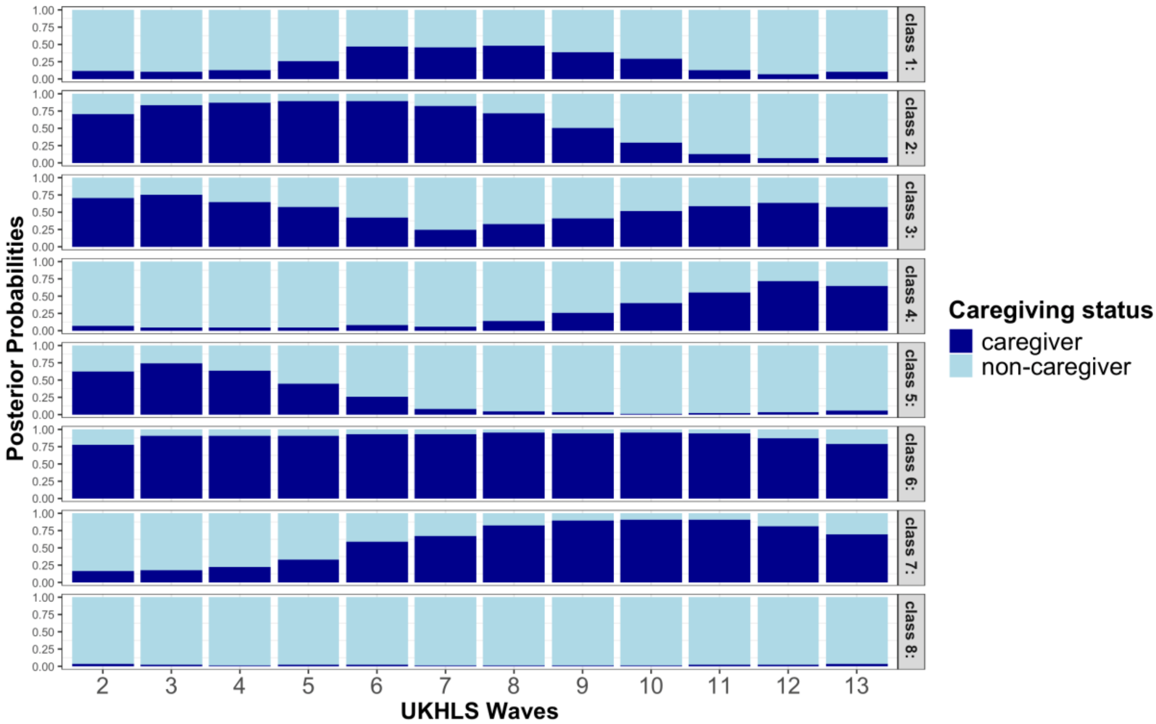


Figure 8.10 Posterior probability for eight-class solution across UKHLS waves 2 to 13 (n=25,049). Each panel represents a latent class, showing the distribution of caregiving status over time.

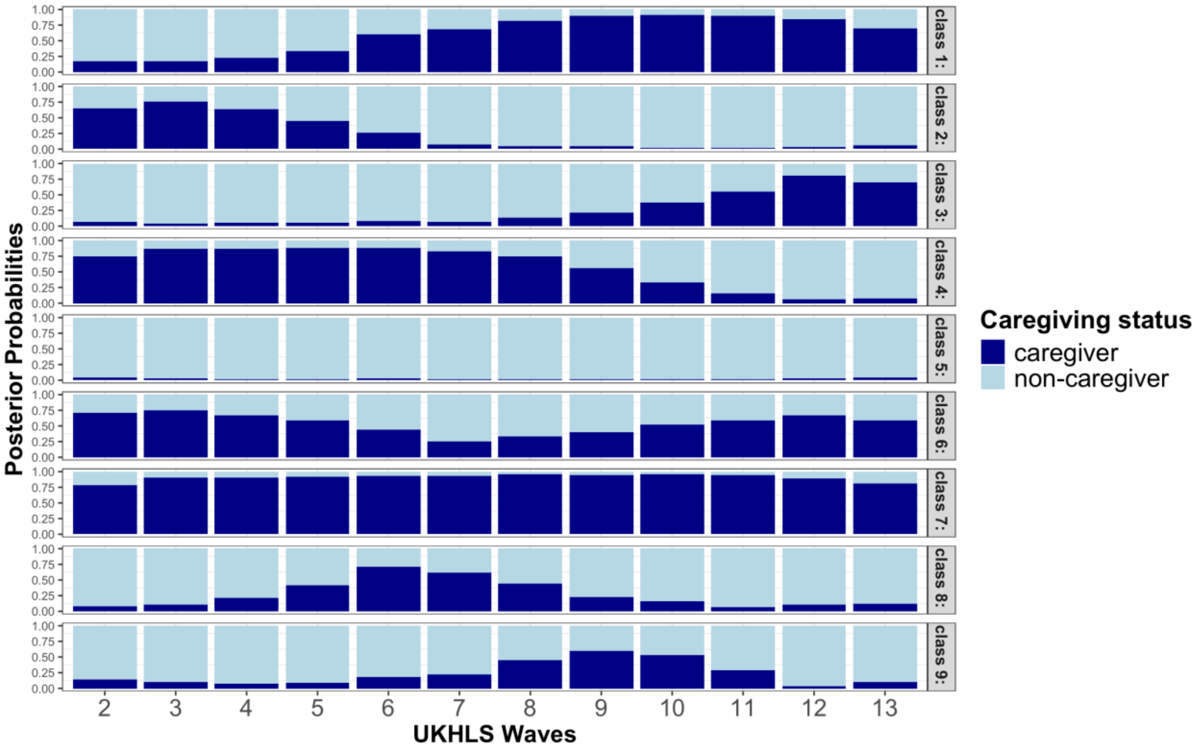


Figure 8.11 Posterior probability for nine-class solution across UKHLS waves 2 to 13 (n=25,049). Each panel represents a latent class, showing the distribution of caregiving status over time.

Next, a class specification diagnostic was performed by assessing entropy (**Table 8.3**), and average posterior probabilities (**Table 8.4**). As described in the previous chapter (intensity change), an entropy value above 0.80 is desirable. The entropy for the preferred 8-class solution was borderline at 0.74. While the literature suggests that an entropy above 0.8 is generally acceptable, other authors argued that an entropy of 0.7 and above can be seen acceptable if the LCA is supported by theoretical considerations.[341,342 341,342]

For the assessment of average posterior probabilities, diagonals should ideally be above 0.80 and off-diagonals close to zero. For three classes out of eight classes, the average posterior probabilities ranged between 0.71 and 0.78, while the off-diagonals were all close to zero (**Table 8.4**). Hence, the borderline entropy and average posterior probabilities may suggest some degree of misspecification among the classes. However, given that the identification of classes was theory-driven and that the 8-class solution would address the research question, the 8-class solution was preferred, acknowledging that some participants within the classes may be misspecified.

Table 8.4 Matrix of average posterior probabilities for latent class assignment in the eight class solution across UKHLS waves 2 to 13 (n=25,049). Values represent the average probability of participants classified into each latent class (rows) being assigned to each possible class (columns). High diagonal values and low off-diagonal values indicate good classification quality.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
[1]	**0.73**	0.03	0.02	0.06	0.04	0.00	0.06	0.06
[2]	0.06	**0.80**	0.05	0.00	0.05	0.04	0.01	0.00
[3]	0.04	0.06	**0.71**	0.04	0.04	0.05	0.05	0.00
[4]	0.06	0.00	0.02	**0.81**	0.00	0.00	0.04	0.07
[5]	0.05	0.03	0.04	0.01	**0.82**	0.00	0.00	0.05
[6]	0.00	0.08	0.03	0.00	0.00	**0.83**	0.05	0.00
[7]	0.07	0.01	0.05	0.05	0.00	0.04	**0.78**	0.00
[8]	0.03	0.00	0.00	0.03	0.02	0.00	0.00	**0.93**

In the state distribution plot below (**Figure 8.12**), the eight classes are depicted and could be interpreted as follows:

- **Class 1:** Non-caregiver at baseline with transition into caregiving and exit again, compatible with ***Temporary caregivers*** from conceptual framework.
- **Class 2:** Caregiver at baseline, with longer caregiving periods and exit to caregiving prior the last observation, compatible with ***Former caregivers.***

- **Class 3:** This group is characterised by caregiving at baseline, exit of caregiving and re-entering of caregiving which would be compatible with ***Recurrent caregivers*** from the conceptual framework.
- **Class 4:** Non-caregiver at baseline with transition into care, the caregiving period is relatively short for this group and this group is compatible with ***Emerging caregivers*** from the conceptual framework.
- **Class 5:** This group is similar to Class 2 and starts with caregiving and exit caregiving albeit with shorter caregiving duration compared to Class 2. This class is compatible with ***Former caregivers*** from the conceptual framework.
- **Class 6:** This group is characterised by caregiving in most of the time points albeit some with one or several breaks, but overall, this class would be compatible with the ***Long-term caregivers*** from the conceptual framework
- **Class 7:** This class is similar to Class 4 and starts with non-caregiving and transitions into care but has a longer caregiving period compared to class 4. This class is compatible with ***Emerging caregivers*** from the conceptual framework
- **Class 8:** Primarily non-caregivers at baseline and at each time point with a very low proportion of caregiving at each wave, compatible with ***Non-caregivers*** from the conceptual framework.

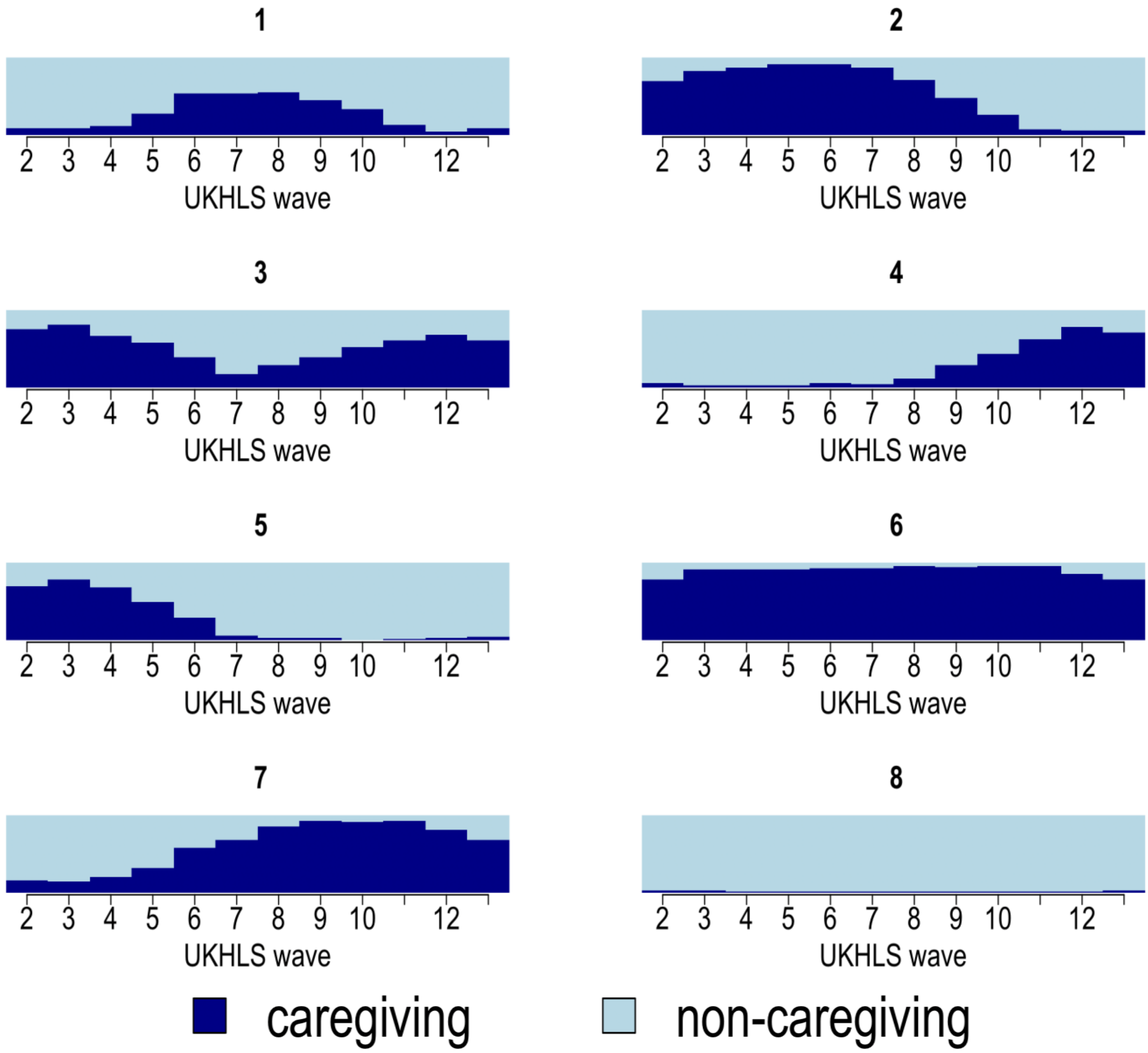


Figure 8.12 State Distribution Plot for eight-class solution across UKHLS waves 2 to 13 (n=25,049). Each panel represents a latent class, displaying the distribution of caregiving status over time.

Next, a sequence index plot was computed, as seen in **Figure 8.13**, to assess whether the initial descriptions from the state distribution plot can be confirmed. Interestingly, it can be seen from this sequence index plot that the absolute number of transitions between caregiving and non-caregiving does not define the classes. Rather, the classes are defined by the overall transition patterns that characterise each trajectory. It can be seen in several panels that individuals may experience several transitions but what stands out is the general trend or stability in the trajectory. For example, Class 8 which could be labelled as 'Non-caregivers' has participants with short, temporary caregiving episodes. This may reflect the fact that latent class models group individuals based on dominant patterns rather than perfectly 'clean' categories.

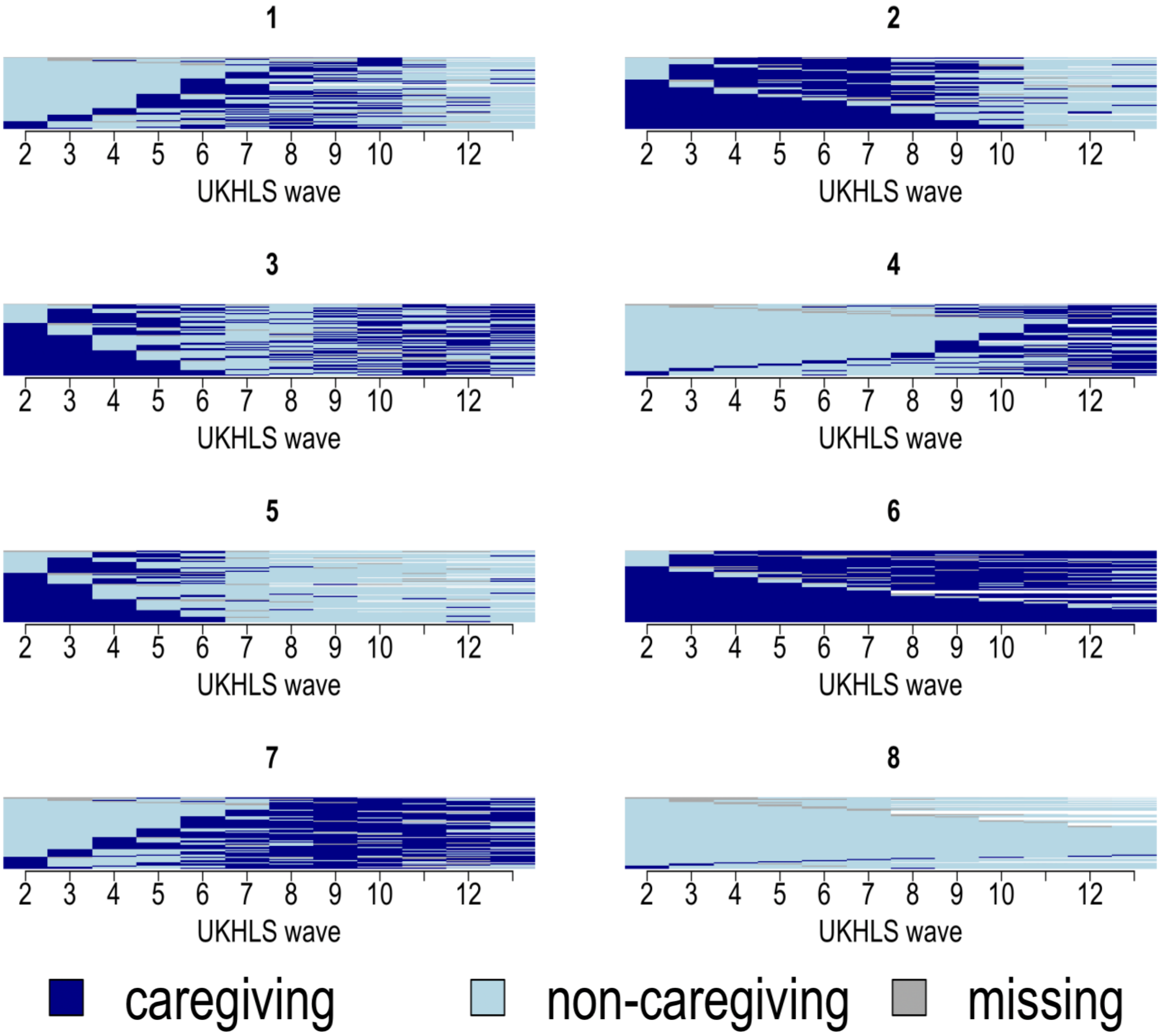


Figure 8.13 Sequence Index Plot for eight-class solution across UKHLS waves 2 to 13 (n=25,049). Each line represents an individual participant's caregiving status trajectory, coloured by latent class membership.

Lasty, sequence modal state plots, as seen in **Figure 8.14**, were computed to understand the classes better. They align with the initial description from the state distribution plot. Particularly the class with recurrent patterned shows very clear transitions from caregiving to non-caregiving and re-transition into caregiving. Therefore, classes were defined and labelled as in **Table 8.5**.

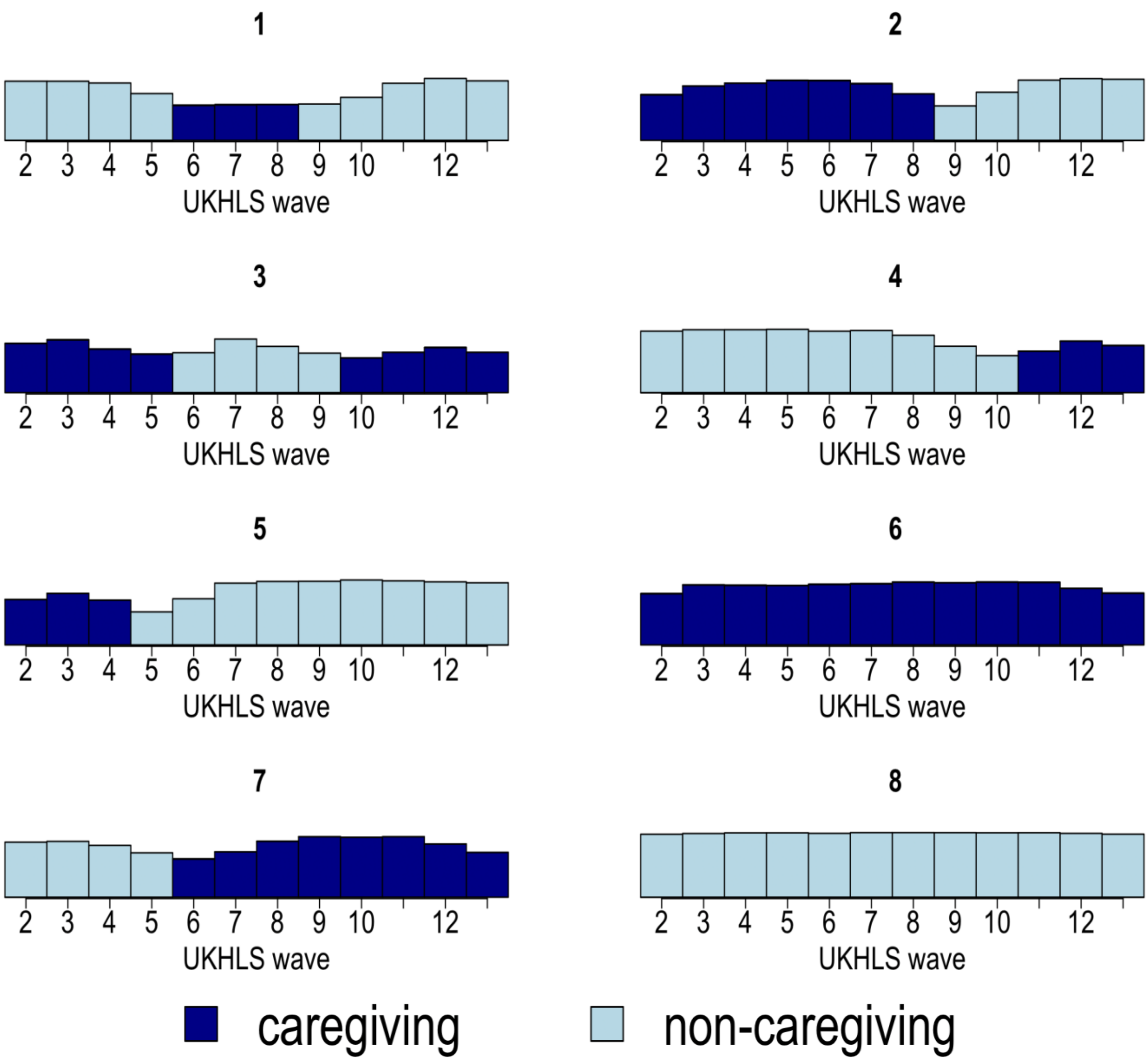


Figure 8.14 Sequence Modal State Plot for eight-class solution across UKHLS waves 2 to 13 (n=25,049). Each panel shows the most frequent caregiving status at each wave for participants within each latent class.

Table 8.5 Labels and definitions for latent classes identified through latent class analysis of caregiving status trajectories across UKHLS waves 2 to 13 (n=25,049). Latent classes are based on patterns of caregiving transitions over time.

Class	Label	Definition
Class 1	Temporary caregiver	Non-caregiver at start of the study, transition into caregiving and exit before last observation.
Class 2	Former-long caregiver	Caregiver at start of study with a longer caregiving period prior exit (and short duration being non-caregiver) prior to last observation.
Class 3	Recurrent caregiver	Caregiving at baseline with longer period of non-caregiving followed by a transition back to caregiving.
Class 4	Emerging-short caregiver	Non-caregiver at start of study with longer period of non-caregiving followed by transition into care and short caregiving period until end of observation.
Class 5	Former-short caregiver	Caregiver at start of study with a shorter caregiving period prior exit (and longer duration being non-caregiver) prior to last observation.
Class 6	Long-term caregiver	Predominantly care-giver throughout observation period with occasional periods of non-caregiving.
Class 7	Emerging-long caregiver	Non-caregiver at start of study with shorter period of non-caregiving followed by transition into care and longer caregiving period until end of observation.
Class 8	Non-caregiver	Predominantly non-caregivers throughout observation period with some, rare short-term transition into care..

In view of distribution (**Table 8.6**), non-caregivers were the largest class (62.9%) while all the other caregiver classes were relatively small within the sample. However, within caregiving classes, Former-short and Temporary caregivers were the largest class and Recurrent caregivers was with 6.34% the smallest class.

Table 8.6 Sample size and proportion of participants across latent classes identified through latent class analysis of caregiving status trajectories (n=25,049). Proportions are shown for the full sample and among participants who were classified to one caregiver class (n=9,289).

Class	**Count**	**Proportion all n=25,049**	**Proportion amongst caregivers N=9,289**
1 – Temporary caregiver	1,853	7.4%	20.0%
2 – Former-long caregiver	1,014	4.1%	10.9%
3 – Recurrent caregiver	581	2.3%	6.3%
4 - Emerging-short caregiver	1,432	5.7%	15.4%
5 – Former-short caregiver	1,875	7.5%	20.2%
6 – Long-term caregiver	1,455	5.8%	15.7%
7 – Emerging-long caregiver	1,079	4.3%	11.6%
8 – Non-caregiver	15,760	62.9%	-
Total	25,049		

Lastly, similarly to the observed transition variable, descriptive sequence analysis tools were used to investigate the composition of each class in view of the place of care, care hours and relationship to care recipient. Regarding place of care (Appendix 8.11), caregiving outside the household was the most common state in all classes apart from long-term caregivers who had a higher proportion of caregivers inside the household. This trend was similar for care hours (Appendix 8.11) where lower intensity caregiving was most common in most classes apart from Long-term caregivers who had a higher proportion of individuals with higher care hours. In view of relationship to care recipient (Appendix 8.11), a change in relationship seemed to be more frequent for Recurrent caregivers, Long-term caregivers and Emerging-long caregivers which may suggests that caregivers in these classes look after different care recipients over the study period.

8.4.1.3 Synthesis

The observed approach tracks discrete transitions between caregiving states over time, whereas latent class analysis (LCA) assigns individuals to trajectory-based groups based on underlying patterns of caregiving. These two approaches categorise participants differently and individuals may fall into different categories depending on the method used. To visualise the cross-tabulation between the Observed Transitions and LCA a Sankey diagram was created with the Sankeymatic tool[343] in **Figure 8.15**. A Sankey diagram is a type of flow diagram that illustrates how elements from one category connect and distribute into another. The width of the lines is proportional to the quantity they represent, which makes it especially useful for showing differences in allocations between the Observed Transition and LCA.

The Sankey diagram illustrates that some individuals classified as Non-caregivers in the LCA were assigned to Emerging or Temporary caregiving groups under Observed Transitions. This suggests that while they may have reported short-term caregiving episodes, their overall pattern is more similar to the Non-caregiving trajectory. Similarly, some Temporary caregivers in LCA were assigned to the Temporary or Multiple transition groups in Observed Transitions. Former caregivers in LCA were frequently placed in Multiple transition under Observed Transitions. Long-term caregivers under LCA were more consistently categorised as Long-term or Multiple transition caregivers. In contrast, Recurrent caregivers under LCA were exclusively assigned to the Multiple transition groups under the observed transitions approach.

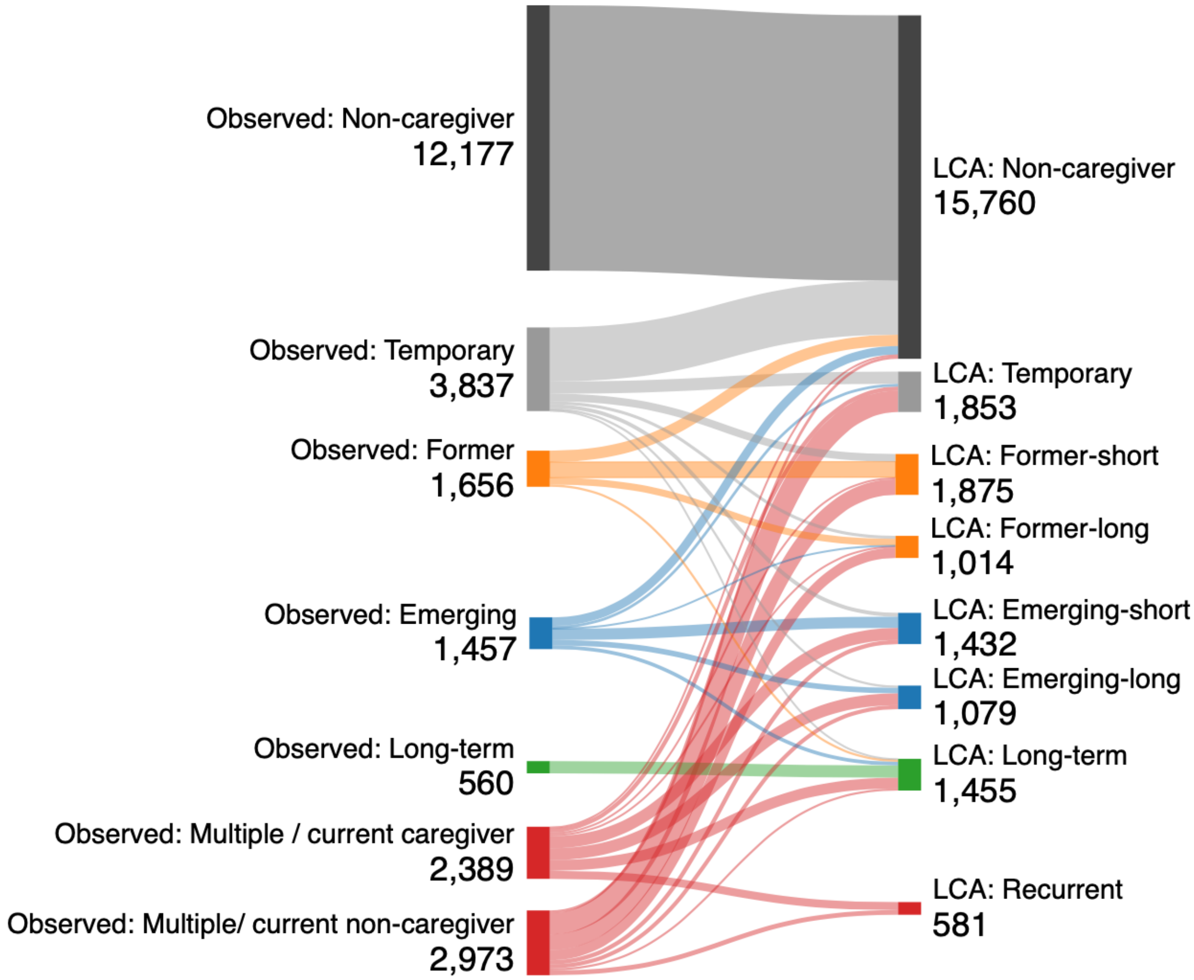


Figure 8.15 Sankey diagram of Observed Transition groups and latent classes identified through latent class analysis of caregiving status trajectories across UKHLS waves 2 to 13 (n=25,049). Counts represent the number of participants classified into each observed group or latent class.

The groups and classes derived from the observed variable and the LCA differ due to their underlying methodological approaches. In the observed variable approach, group membership was primarily determined by the absolute number of transitions, offering a transparent and easily interpretable categorisation based on observed data. This method's strength lies in its straightforward application. However, it may oversimplify complex longitudinal patterns by focusing on frequency rather than structure.

In contrast, latent class analysis (LCA) classified individuals based on the overall pattern and stability of transitions over time which captured more nuanced transition patterns that may not be apparent from transition counts alone. This model-based approach allowed for classification based on probability of class membership and can reveal latent heterogeneity in caregiving patterns. A key limitation, however, was the borderline entropy observed in the LCA model, which indicates some degree of uncertainty in class assignment and potential misclassification. While this comparative overview is informative, a more detailed assessment of the strengths and weaknesses of each method is provided in the Discussion section.

8.4.2 Descriptive analysis

This section presents a descriptive analysis examining how caregiving groupings, either derived from both the Observed Transitions variable or latent class analysis (LCA), relate to key health behaviours and selected covariates.

8.4.2.1 Observed Transitions

This section presents the descriptive statistic of health behaviours, baseline characteristics, and covariates across different caregiving trajectories, with a particular focus on individuals experiencing Multiple caregiving transitions compared to Non-caregivers and Long-term caregivers. The full descriptive statistic can be found in **Table 8.7** and a descriptive analysis of complete cases can be found in Appendix 8.8.

Health Behaviours Across Caregiving Groups

Table 8.7 reveals distinct differences in health behaviours between individuals who have never provided care, those with multiple caregiving transitions, and long-term caregivers. Multiple transition caregivers, whether currently providing care or not, reported similar levels of physical inactivity (54.4.9%–57.1% physically inactive) compared to Non-caregivers (54%). However, Long-term caregivers had the lowest proportion of physically inactive individuals (58.6%). Regarding diet, Multiple transition caregivers reported slightly higher fruit and vegetable consumptions (mean=3.7–3.8) compared to Non-caregivers (mean=3.5). Interestingly, Former caregivers had the highest number of fruits and vegetable portions per day (mean=3.8) while Long-term caregivers had one of the lowest daily fruit and vegetable consumption (mean=3.5). In terms of alcohol consumption, Multiple transition caregivers exhibited a lower prevalence of problematic drinking (44.8%–44.9%) compared to Non-caregivers (49%). However, Long-term caregivers had the lowest prevalence of problematic drinking (43.3%). Smoking prevalence was notably higher among Multiple transition caregivers who were currently providing care (14.2%), second only to Long-term caregivers (15.6%). Non-caregivers, in contrast, had the lowest smoking rates (11.6%).

Baseline Health Behaviours and Caregiving Transitions

Regarding walking frequency at baseline, Long-term caregivers had the highest proportion of participants who walked every day for at least 30 minutes (18.4%) while participants who were Non-caregivers had the lowest prevalence of daily walking (14.3%) although p-value for difference in baseline walking was statistically not significant (p=0.10). Participants with Multiple transitions had a daily walking prevalence between 15.6%-15.9%. In terms of fruit and vegetable consumption, Multiple transition caregivers had better fruit and vegetable consumption at baseline compared to Non-caregivers, with a higher proportion consuming at least five portions of fruit and vegetables per day (24.2%–26.8% vs. 20.7%). In contrast, only 21.3% of long-term caregivers consumed five or more portions of fruits and vegetables daily.

Smoking patterns at baseline also varied, with Multiple transition caregivers having higher rates of current smoking (19.3%-20.1%) compared to Non-caregivers (17.7%). Long-term caregivers had the highest percentage of current smokers (23.0%). Alcohol consumption at baseline further differentiates caregiving groups. Multiple transition caregivers had drinking patterns similar to non-caregivers, with around 12.8%–14.8% reporting drinking five or more times per week. However, Long-term caregivers had a lower prevalence of frequent drinking (13.8%).

Covariates

Women were more likely to be caregivers, particularly among Long-term caregivers (64.1%), followed by Multiple transition caregivers (55.3%–59.1%). Non-caregivers had the lowest proportion of women (49.2%). Multiple transition caregivers were younger on average (mean age = 48.1–50.8 years) compared to Long-term caregivers (mean = 50.6 years). Multiple transition caregivers had relatively high educational attainment, with 38.7% holding a degree or higher qualification, comparable to Non-caregivers (37.2%) and higher than Long-term caregivers (31.8%). In terms of employment, Multiple transition caregivers had higher rates of full-time employment compared to Long-term caregivers, who were more likely to be out of paid work (50.5%). Income distribution followed a similar pattern, with Multiple transition caregivers exhibiting a more even distribution across income quintiles. Cohabitation with someone was slightly more common among Multiple transition caregivers compared to Non-caregivers, but Long-term caregivers were most likely to be cohabiting. Psychological distress, measured by the General Health Questionnaire (GHQ), was higher among multiple transition caregivers (mean GHQ score=11.5) compared to non-caregivers (mean=10.7) but lower than Long-term caregivers (mean=12.5). Self-rated general also differed, with Multiple transition caregivers reporting slightly poorer self-rated health than non-caregivers but better than long-term caregivers.

Table 8.7 Descriptive statistics for Observed Transition groups (n=25,049), based on pooled results from multiple imputation (m=10). Estimates account for complex survey design and clustering at the household level.

	Observed Transitions	**Non-caregiver**	**Emerging caregiver**	**Temporary caregiver**	**Long-term caregiver**	**Former caregiver**	**Multiple trans / current no care**	**Multiple trans / current care**	**p**
n		10926	1270	3423	474	1488	2607	2050	
Outcome									
Fruit & Veg.	Mean(SD)	3.5 (2.2)	3.6 (2.2)	3.6 (2.2)	3.5 (2.0)	3.8 (2.2)	3.8 (2.3)	3.7 (2.3)	<0.001
Physical activity	Active	46.0%	49.4%	44.9%	41.4%	38.9%	42.9%	45.6%	<0.001
	Inactive	54.0%	50.6%	55.1%	58.6%	61.1%	57.1%	54.4%	
Problematic drinking	No	51.0%	53.8%	52.9%	56.7%	56.3%	55.1%	55.2%	<0.001
	Yes	49.0%	46.2%	47.1%	43.3%	43.7%	44.9%	44.8%	
Smoking Status	No	88.4%.	87.7%	87.6%	84.4%	89.0%	87.8%	85.8%	0.02
	Yes	11.6%	12.3%	12.4%	15.6%	11.0%	12.2%	14.2%	
Health behaviour at baseline									
Walking frequency at baseline	none	25.3%	25.1%	26.4%	28.0%	25.3%	25.4%	23.5%	0.10
	1-2 days	37.1%	37.8%	34.6%	30.7%	38.5%	35.0%	37.5%	
	3-4 days	13.2%	13.6%	13.8%	12.2%	12.1%	13.0%	13.7%	
	5-6 days	10.1%	9.0%	9.4%	10.7%	9.3%	10.9%	9.4%	
	Every day	14.3%	14.4%	15.8%	18.4%	14.8%	15.6%	15.9%	
Fruit and vegetable consumption at baseline	0 portions	0.9%	0.8%	0.8%	1.8%	0.5%	0.8%	1.2%	<0.001
	1-3 portions	60.4%	57.0%	56.7%	58.0%	54.4%	53.6%	54.2%	
	4 portions	18.0%	17.5%	18.5%	18.9%	18.3%	18.8%	20.3%	

	Observed Transitions	Non-caregiver	Emerging caregiver	Temporary caregiver	Long-term caregiver	Former caregiver	Multiple trans / current no care	Multiple trans / current care	p
	5+ portions	20.7%	24.7%	24.0%	21.3%	26.7%	26.8%	24.2%	
Smoking status at baseline	never smoked	46.3%	43.7%	42.2%	39.4%	43.8%	40.9%	43.1%	<0.001
	ex-smoker	36.1%	36.1%	37.7%	37.6%	40.7%	39.8%	36.8%	
	current smoker	17.7%	20.1%	20.0%	23.0%	15.6%	19.3%	20.1%	
Drinks frequency at baseline	no drinks	10.3%	10.0%	10.3%	13.4%	10.6%	10.5%	10.3%	0.002
	monthly or weekly	33.4%	35.0%	32.9%	35.1%	31.8%	31.8%	34.6%	
	1-4 per week	43.9%	41.9%	41.6%	37.7%	41.8%	43.0%	42.2%	
	5+ per week	12.4%	13.1%	15.2%	13.8%	15.8%	14.8%	12.8%	
Covariates									
Sex	men	50.8%	44.1%	44.1%	35.9%	41.7%	44.7%	40.9%	<0.001
	women	49.2%	55.9%	55.9%	64.1%	58.3%	55.3%	59.1%	
Age group at baseline	16-29	26.5%	14.7%	15.4%	5.5%	9.4%	10.0%	11.4%	<0.001
	30-49	36.8%	45.5%	36.3%	42.8%	25.6%	34.4%	41.3%	
	50-64	21.8%	26.9%	30.5%	36.0%	41.6%	37.5%	34.2%	
	65+	14.9%	12.9%	17.8%	15.7%	23.3%	18.0%	13.1%	
Education	No qualification	10.9%	10.3%	11.6%	17.0%	13.2%	12.5%	10.8%	<0.001
	A-Level, GCSE, other qualification	51.9%	52.3%	53.4%	51.2%	52.3%	53.8%	50.4%	
	Degree or other higher qualification	37.2%	37.4%	35.0%	31.8%	34.6%	33.7%	38.7%	
Ethnicity	white	92.5%	94.6%	94.1%	94.7%	96.4%	94.8%	94.5%	<0.001

	Observed Transitions	Non-caregiver	Emerging caregiver	Temporary caregiver	Long-term caregiver	Former caregiver	Multiple trans / current no care	Multiple trans / current care	p
	black	2.0%	1.2%	1.6%	1.4%	0.8%	1.1%	1.6%	
	Indian	2.0%	1.4%	1.5%	1.6%	1.1%	1.1%	1.5%	
	Pakistani/Bangladeshi	1.2%	1.3%	1.2%	1.7%	0.8%	1.4%	1.3%	
	other Asian/other	2.4%	1.5%	1.5%	0.6%	0.9%	1.5%	1.2%	
Occupational Class at baseline	not employed	38.2%	35.2%	38.6%	54.5%	46.2%	40.7%	36.0%	<0.001
	Management & professional	29.3%	30.5%	27.6%	17.7%	22.7%	26.1%	29.2%	
	intermediate	14.0%	15.6%	13.7%	10.9%	12.9%	14.5%	14.7%	
	routine	18.5%	18.7%	20.1%	16.9%	18.2%	18.8%	20.1%	
Income quintiles at baseline	1 (low)	15.0%	15.3%	14.5%	14.0%	13.5%	15.5%	15.0%	<0.001
	2	16.9%	19.9%	18.8%	24.8%	20.1%	19.7%	19.5%	
	3	19.4%	19.8%	18.6%	25.0%	16.8%	19.4%	18.5%	
	4	22.1%	19.5%	22.3%	19.0%	23.4%	21.6%	20.6%	
	5 (high)	26.6%	25.4%	25.8%	17.1%	26.2%	23.9%	26.4%	
Working status at baseline	not in paid employment	33.9%	33.0%	36.0%	50.5%	43.6%	37.9%	33.5%	<0.001
	full-time employed	50.1%	49.9%	46.3%	33.7%	39.4%	43.9%	46.8%	
	part-time employed	16.0%	17.1%	17.7%	15.8%	17.0%	18.2%	19.7%	
Children living in the household at baseline	0	71.5%	66.9%	73.8%	68.7%	82.6%	75.6%	70.6%	<0.001
	1	13.3%	15.0%	11.2%	13.0%	8.6%	11.2%	13.2%	
	2	11.6%	14.2%	10.8%	12.2%	6.2%	9.8%	11.8%	

	Observed Transitions	Non-caregiver	Emerging caregiver	Temporary caregiver	Long-term caregiver	Former caregiver	Multiple trans / current no care	Multiple trans / current care	p
	3+	3.6%	3.9%	4.2%	6.1%	2.5%	3.4%	4.4%	
Cohabiting status at baseline	single, separated, widowed	39.4%	27.8%	31.0%	23.4%	27.9%	29.5%	27.5%	<0.001
	married or cohabiting	60.6%	72.2%	69.0%	76.6%	72.1%	70.5%	72.5%	
Self-rated general health at baseline	excellent, very good or good	85.9%	83.9%	83.4%	76.2%	82.2%	82.2%	82.1%	<0.001
	fair or poor	14.1%	16.1%	16.6%	23.8%	17.8%	17.8%	17.9%	
Household size at baseline	1	15.6%	9.7%	14.2%	4.3%	11.2%	13.8%	10.7%	<0.001
	2	32.0%	36.1%	38.2%	39.6%	46.3%	41.2%	35.1%	
	3-4	41.6%	44.5%	37.5%	43.2%	34.8%	36.2%	42.9%	
	5+	10.8%	9.6%	10.1%	12.9%	7.7%	8.7%	11.3%	
Wave when outcome was observed	7	9.3%	9.5%	5.2%	17.6%	7.7%	1.9%	3.9%	<0.001
	9	7.5%	6.9%	5.0%	8.1%	5.5%	3.3%	5.6%	
	11	7.4%	7.9%	8.5%	7.1%	8.2%	6.6%	6.9%	
	13	75.7%	75.8%	81.4%	67.2%	78.5%	88.2%	83.6%	
Age at baseline	Mean(SD)	43.5 (18.1)	46.4 (15.3)	48.4 (16.5)	50.6 (13.1)	53.2 (15.4)	50.8 (14.9)	48.10 (14.2)	<0.001
GHQ at baseline	Mean(SD)	10.7 (5.1)	11.3 (5.5)	11.1 (5.3)	12.5 (6.1)	11.21(5.3)	11.4 (5.5)	11.5 (5.4)	<0.001
SF12 at baseline	Mean(SD)	51.3 (10.2)	50.5 (10.2)	50.2 (10.6)	48.5 (11.1)	49.5 (10.7)	49.6 (10.7)	50.1 (10.7)	<0.001

8.4.2.2 Latent Class Analysis

This section presents the descriptive statistic of health behaviours, baseline characteristics, and covariates across different caregiving trajectories from LCA, with a particular focus on individuals who are classified as 'Recurrent' caregivers in the latent class analysis. This approach was taken to maintain alignment with the chapter's central objective, which was to examine multiple caregiving transitions, with recurrent caregiving representing the most relevant pattern in this context. The full descriptive analysis can be found in **Table 8.8**.

Health Behaviours

Recurrent caregivers exhibited higher levels of physical activity, with 48.5% classified as physically inactive, fewer than Non-caregivers (54.2%) and Long-term caregivers (57.5%). Recurrent caregivers reported slightly better fruit and vegetable consumption, with an average daily fruit and vegetable consumption of 3.8, comparable to Long-term caregivers (3.7) and marginally better than Non-caregivers (3.6). Problematic drinking was less prevalent among Recurrent caregivers (40.9%) compared to Non-caregivers (48.5%) and Long-term caregivers (43.5%). However, Recurrent caregivers had the highest prevalence of smoking (17.4%), exceeding both Non-caregivers (11.8%) and Long-term caregivers (13.7%).

Baseline Health Behaviours

Recurrent caregivers displayed similar patterns of physical activity at baseline, with 17.7% engaging in daily walking, slightly above Non-caregivers (14.6%) and Long-term caregivers (16.7%). Their dietary habits at baseline were relatively healthy, with 24.9% consuming five or more portions of fruit and vegetables per day, higher than Non-caregivers (21.3%) but slightly lower than Long-term caregivers (25.1%). Smoking prevalence at baseline was also highest among Recurrent caregivers (22.7%), compared to 18.2% for Non-caregivers and

20.7% for Long-term caregivers. Alcohol consumption patterns at baseline showed that Recurrent caregivers had less frequent alcoholic drinks compared to Non-caregivers.

Covariates

Recurrent caregivers were predominantly women (60.2%), aligning with Long-term caregivers (63.8%) while only 50.4% of Non-caregivers were female. Recurrent caregivers were younger than Long-term caregivers (mean age: 49.5 years vs. 49.8 years) but older than Non-caregivers (44.5 years). Regarding education, Recurrent caregivers had a higher proportion of participants with degree-level qualifications (35%) compared to Long-term caregivers (33.7%) but lower than Non-caregivers (36.9%). Regarding ethnicity, Recurrent caregivers were predominantly white (94.6%), a distribution similar to Non-caregivers (92.7%) and Long-term caregivers (95.2%).

In terms of occupational class, Recurrent caregivers had a slightly lower proportion in management and professional roles (27.6%) than Non-caregivers (29.1%) but higher than Long-term caregivers (24.6%). Family structure showed that a slightly higher proportion of Recurrent caregivers lived in multi-person households compared to Non-caregivers. Further, Recurrent caregivers rated their general health slightly lower than Non-caregivers, reported higher GHQ scores compared to non-caregivers and lower SF12 scores compared to Non-caregivers.

Table 8.8 Descriptive statistics for latent classes identified through latent class analysis of caregiving status trajectories (n=25,049), based on pooled results from multiple imputation (m=10). Estimates account for complex survey design and clustering at the household level.

	Latent Classes	no care	temporary	former-long	recurrent	emerging-short	former-short	longterm	emerging-long	p
n		14116	1612	884	492	1254	1686	1243	952	
Outcome										
Fruit & veg.	Mean(SD)	3.6 (2.2)	3.7 (2.3)	3.8 (2.2)	3.8 (2.3)	3.8 (2.3)	3.8 (2.2)	3.7 (2.2)	3.6 (2.2)	<0.001
Physical inactivity	Active	45.8%	43.7%	37.8%	51.5%	46.1%	43.0%	42.5%	44.8%	<0.001
	Inactive	54.2%	56.3%	62.2%	48.5%	53.9%	57.0%	57.5%	55.2%	
Problematic drinking	No	51.5%	54.4%	55.2%	59.1%	53.6%	54.8%	56.5%	53.5%	<0.001
	Yes	48.5%	45.6%	44.8%	40.9%	46.4%	45.2%	43.5%	46.5%	
Smoking Status	No	88.2%	87.2%	87.7%	82.6%	88.8%	88.2%	86.3%	86.6%	0.021
	Yes	11.8%	12.8%	12.3%	17.4%	11.2%	11.8%	13.7%	13.4%	
Health behaviour at baseline										
Walking frequency at baseline	none	25.4%	28.5%	23.8%	25%	22.9%	25.7%	25.8%	23.4%	0.317
	1-2 days	36.8%	34.5%	37.4%	35.5%	38.8%	35.4%	33.9%	36.5%	
	3-4 days	13.2%	13.0%	13.8%	13.5%	14.5%	13.6%	12.3%	13.2%	
	5-6 days	10.0%	8.9%	10.0%	8.3%	9.8%	9.7%	11.3%	10.7%	
	Every day	14.6%	15.1%	15.0%	17.7%	14.1%	15.6%	16.7%	16.2%	
Fruit and vegetable consumption at baseline	0 portions	0.9%	1.2%	0.6%	1.4%	0.8%	0.7%	1.7%	0.6%	<0.001
	1-3 portions	59.7%	56.3%	51.9%	53.9%	55.4%	53.6%	53.5%	56.3%	
	4 portions	18.2%	17.6%	20.6%	19.9%	19.1%	16.7%	19.6%	20.7%	

	Latent Classes	no care	temporary	former-long	recurrent	emerging-short	former-short	longterm	emerging-long	p
	5+ portions	21.3%	25.0	26.9%	24.9%	24.7%	29.0%	25.1%	22.4%	
Smoking status at baseline	never smoked	45.3%	40.8%	43.9%	38.3%	44.1%	41.5%	43.9%	43.1%	0.003
	ex-smoker	36.5%	40.3%	38.4%	39.0%	37.6%	40.3%	35.4%	36.3%	
	current smoker	18.2%	18.9%	17.7%	22.7%	18.4%	18.2%	20.7%	20.7%	
Drinks frequency at baseline	no drinks	10.3%	11.0%	9.5%	11.0%	9.3%	11.1%	11.3%	9.5%	0.024
	monthly or weekly	33.3%	33.4%	32.8%	33.0%	33.2%	31.6%	35.9%	33.9%	
	1-4 per week	43.6%	40.9%	41%	42.0%	43.2%	41.3%	40.1%	44.1%	
	5+ per week	12.8%	14.8%	16.8%	13.9%	14.3%	16.1%	12.7%	12.4%	
Covariates										
Sex	men	49.6%	44.7%	37.7%	39.8%	45.7%	44.8%	36.2%	40.9%	<0.001
	women	50.4%	55.3%	62.3%	60.2%	54.3%	55.2%	63.8%	59.1%	
Age group at baseline	16-29	24.1%	14.3%	7.7%	9.9%	11.0%	10.3%	6.3%	13.7%	<0.001
	30-49	36.9%	33.0%	28.0%	36.0%	47.9%	28.8%	43.9%	39.5%	
	50-64	23.5%	34.1%	44.3%	40.2%	29.7%	38.1%	36.3%	33.3%	
	65+	15.5%	18.7%	20%	13.8%	11.4%	22.8%	13.5%	13.5%	
Education	No qualification	11.1%	13.1%	13.2%	12.5%	7.9%	12.8%	14.1%	10.5%	<0.001
	A-Level, GCSE, other qualification	52.1%	53.5%	54.5%	52.5%	50.7%	52.9%	52.2%	52.1%	
	Degree or other higher qualification	36.9%	33.4%	32.3%	35.0%	41.4%	34.3%	33.7%	37.4%	

	Latent Classes	no care	temporary	former-long	recurrent	emerging-short	former-short	longterm	emerging-long	p
Ethnicity	white	92.7%	94.5%	96.5%	94.6%	94.7%	96.0%	95.2%	95.2%	<0.001
	black	1.9%	1.3%	0.5%	1.6%	1.3%	0.9%	1.3%	1.4%	
	indian	2.0%	1.5%	0.9%	1.3%	1.2%	0.7%	1.3%	0.9%	
	pakistani/ bangladeshi	1.2%	1.4%	1.2%	1.4%	1.2%	1.3%	1.4%	1.3%	
	other asian/other	2.2%	1.4%	0.9%	1.1%	1.7%	1.0%	0.8%	1.2%	
Occupational Class at baseline	not employed	38.2%	41.2%	45.1%	40.4%	29.2%	44.8%	45.2%	36.2%	<0.001
	Management & professional	29.1%	24.5%	22.5%	27.6%	34.1%	23.8%	24.6%	28.3%	
	intermediate	14.0%	14.0%	14.2%	13.2%	15.5%	12.7%	13.2%	15.4%	
	routine	18.7%	20.3%	18.1%	18.8%	21.3%	18.7%	17%	20.1%	
Income quintiles at baseline	1 (low)	14.8%	16.9%	15.1%	13.9%	13.6%	13.2%	16%	16.2%	<0.001
	2	17.3%	19.6%	21.1%	23.2%	18.0%	20.3%	21%	19.6%	
	3	19.2%	19.6%	17.7%	19.5%	19.4%	17.8%	22.3%	17.6%	
	4	22.1%	20.9%	22%	20.3%	21.7%	23.4%	19.1%	20.8%	
	5 (high)	26.7%	23.0%	24.1%	23.1%	27.3%	25.3%	21.6%	25.8%	
Working status at baseline	not in paid employment	34.3%	38.1%	42.5%	38.7%	27.2%	42.1%	42.9%	33.1%	<0.001
	full-time employed	49.5%	43.6%	39.1%	40.9%	56%	40.4%	40.2%	45.3%	
	part-time employed	16.3%	18.3%	18.4%	20.4%	16.8%	17.4%	16.9%	21.6%	
Children living in the household at baseline	No children	71.9%	74.5%	78.8%	74.2%	67.9%	80.3%	70.1%	70.5%	<0.001
	1	13.0%	11.4%	9.7%	11.0%	13.5%	10.4%	12.4%	12.9%	

	Latent Classes	no care	temporary	former-long	recurrent	emerging-short	former-short	longterm	emerging-long	p
	2	11.5%	9.8%	7.5%	11.7%	14.6%	6.6%	12.2%	12.2%	
	3+	3.6%	4.2%	4%	3.1%	3.9%	2.7%	5.3%	4.4%	
Cohabiting status at baseline	single, separated, widowed	37.5%	30.9%	25.9%	31.5%	25.1%	30.2%	24.2%	28.4%	<0.001
	married or cohabiting	62.5%	69.1%	74.1%	68.5%	74.9%	69.8%	75.8%	71.6%	
Self-rated general health at baseline	excellent, very good or good	85.3%	80.8%	82.1%	79.4%	85.9%	83.4%	78.4%	83.6%	<0.001
	fair or poor	14.7%	19.2%	17.9%	20.6%	14.1%	16.6%	21.6%	16.4%	
Household size at baseline	1	15.1%	13.1%	12.2%	13.3%	11.1%	13.8%	8%	9.3%	<0.001
	2	33.4%	39.1%	44.6%	38.3%	35.0%	43.8%	37.9%	37.9%	
	3-4	41.0%	37.5%	34.4%	38.2%	44.1%	34.7%	42.9%	41.3%	
	5+	10.5%	10.3%	8.8%	10.2%	9.9%	7.7%	11.1%	11.5%	
Wave when outcome was observed	7	8.4%	7.8%	2.9%	0.2%	0.0%	9.1%	10.1%	2.7%	<0.001
	9	6.8%	4.9%	5.6%	6.1%	3.0%	6.4%	6.3%	6.6%	
	11	7.4%	7.8%	9.6%	6.3%	8.6%	7.9%	6.2%	6.8%	
	13	77.4%	79.5%	81.9%	87.4%	88.3%	76.7%	77.4%	83.8%	
Age at baseline	Mean(SD)	44.5 (17.9)	49.6 (16.2)	53.1 (14.2)	49.5 (14.6)	47.0 (13.8)	52.5 (15.7)	49.8 (12.9)	47.5 (14.7)	<0.001
GHQ at baseline	Mean(SD)	10.8 (5.2)	11.2 (5.4)	11.5(5.5)	11.5 (5.5)	11.3 (5.3)	11.2 (5.4)	12.0 (5.8)	11.2 (5.1)	<0.001
SF12 at baseline	Mean(SD)	51.1 (10.2)	48.92(11.1)	49.5 (10.9)	49.6 (10.7)	51.4 (9.7)	49.8 (10.8)	49.2 (10.9)	49.7 (10.5)	<0.001

8.4.3 Adjusted analysis

This section presents the results from regression modelling for physical inactivity (PA), fruit and vegetable consumption (DIET), problematic drinking (ALC) and smoking (SMOK). For each outcome in each approach (classes from LCA or groups from Observed Transitions), three models will be estimated: (1) unadjusted models containing latent class from LCA or the variable from the observed transitions; (2) a partially adjusted model which will be adjusted for the health behaviour at baseline; and (3) the model adjusted for all the covariates including sex, education and ethnicity as well as covariates at baseline such as age group, occupational class, income quintiles, working status, household size, number of children living in the household, cohabiting status, self-rated general health, wave when outcome was observed, GHQ and SF12-p score for physical inactivity.

Models which present the Observed variable will contain the annotation 'b' while models with the latent class will be annotated with 'a'. For all models within this chapter, Non-caregivers serve as the reference category. For this section, regression models will be presented in graphs and the full results with estimates can be found in Appendix 8.5 for the Observed Transitions analysis and in Appendix 8.6 for the LCA. All models are based on pooled results from multiple imputation and account for the complex survey design. A complete case analysis for the Observed Transitions analysis can be found in Appendix 8.8.

8.4.3.1 Physical activity

Observed Transitions

Figure 8.16 shows the regression models for physical inactivity and Observed Transitions. In the unadjusted model (Model PA1b), several caregiving trajectories were associated with increased odds of physical inactivity compared to non-caregivers. Former caregivers had the highest likelihood of physical inactivity (OR=1.34, 95% CI: 1.18–1.51), followed by those with Multiple caregiving transitions who were no longer providing care (OR=1.13, 95% CI: 1.03–1.25). Long-term caregivers also had higher odds of physical inactivity (OR=1.20, 95% CI: 0.99–1.47), though this association was marginally non-significant. In contrast, Emerging caregivers were significantly less likely to be physically inactive compared to Non-caregivers (OR=0.87, 95% CI: 0.77–0.99).

Adjusting for walking frequency at baseline (Model PA2b) did not substantially alter the results drastically. However, in the model adjusted for all selected covariates (Model PA3b), several associations were attenuated. Notably, Emerging caregivers remained significantly less likely to be physically inactive (OR=0.79, 95% CI: 0.69–0.91), while Temporary caregivers also showed reduced odds of physical inactivity (OR=0.91, 95% CI: 0.83–1.00). The associations for Long-term caregivers and those with Multiple caregiving transitions without current care became non-significant after full adjustment (OR=0.90, 95% CI: 0.72–1.11 and OR=0.95, 95% CI: 0.86–1.05, respectively). A marginally significant association emerged for Multiple transitions with current caregiving after full adjustment (OR=0.89, 95% CI: 0.80-1.00) while Former caregivers had the highest odds of physical inactivity in the adjusted model which was fully attenuated in the model adjusted for selected covariates. This shift in associations was mainly driven by sex and age suggesting that differences in physical inactivity between observed transition groups may be partially explained by confounding of sex and age.

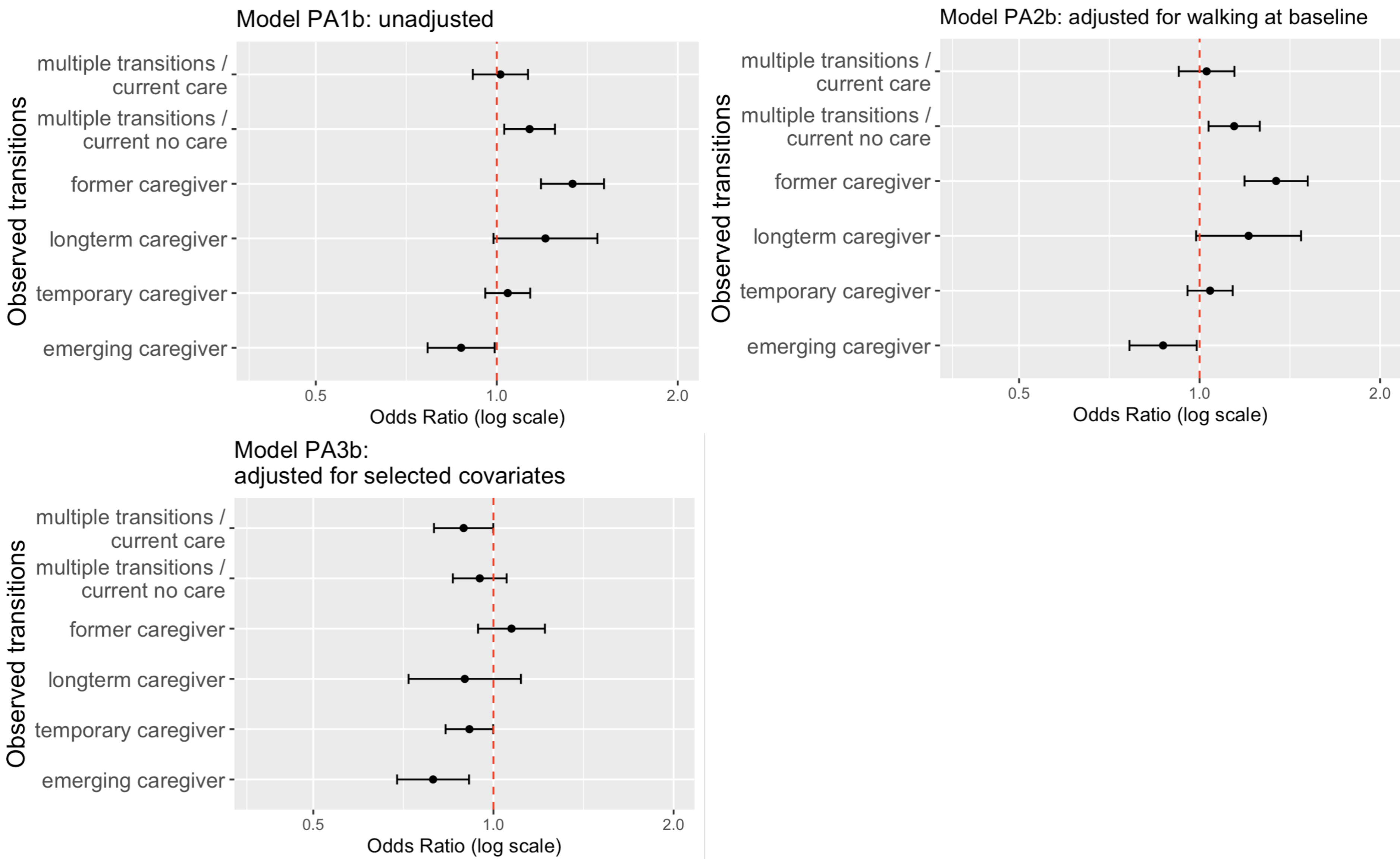


Figure 8.16 Regression for physical inactivity and Observed Transitions; odds ratios (log scale) for logistic regression models predicting physical activity across Observed Transition groups among UKHLS participants (n=25,049). Results are shown for three models: PA1b (unadjusted), PA2b (adjusted for walking at baseline), and PA3b (adjusted for selected covariates). The reference category is the 'non-caregiver' Observed Transition group. Estimates account for complex survey design, clustering at the household level, and multiple imputation (m=10).

Latent Class Analysis (LCA)

Figure 8.17 shows the regression models for physical inactivity and LCA. Recurrent caregiving was associated with lower odds of being physically inactive compared to Non-caregivers in the unadjusted (PA1a) and partially adjusted (PA2a) model (OR=0.80, 95% CI: 0.65-0.97 for both models). In the model adjusted for all selected covariates PA3a, this association became more pronounced with an OR of 0.65 (95% CI: 0.53-0.81). This suggests that Recurrent caregivers were significantly more active compared to Non-caregivers and that this relationship was suppressed by underlying confounding characteristics.

Besides, Former-long caregivers initially had the highest odds of inactivity in Models PA1a and PA2a (OR=1.41, 95% CI: 1.21-1.64; and OR = 1.43, 95% CI: 1.23-1.66, respectively), suggesting that ceasing caregiving may be linked to higher physical inactivity levels. However, this association was attenuated in the model adjusted for all selected covariates PA3a (OR=1.13, 95%: 0.96-1.33). Long-term caregivers also exhibited higher odds of inactivity in Models PA1a and PA2a (OR=1.16, 95% CI: 1.02-1.33; and OR = 1.17, 95% CI: 1.03-1.34), though this association was attenuated in the model adjusted for all selected covariates (OR=0.94, 95% CI: 0.81-1.08). Former-short caregivers had a similar trend as long-term caregivers.

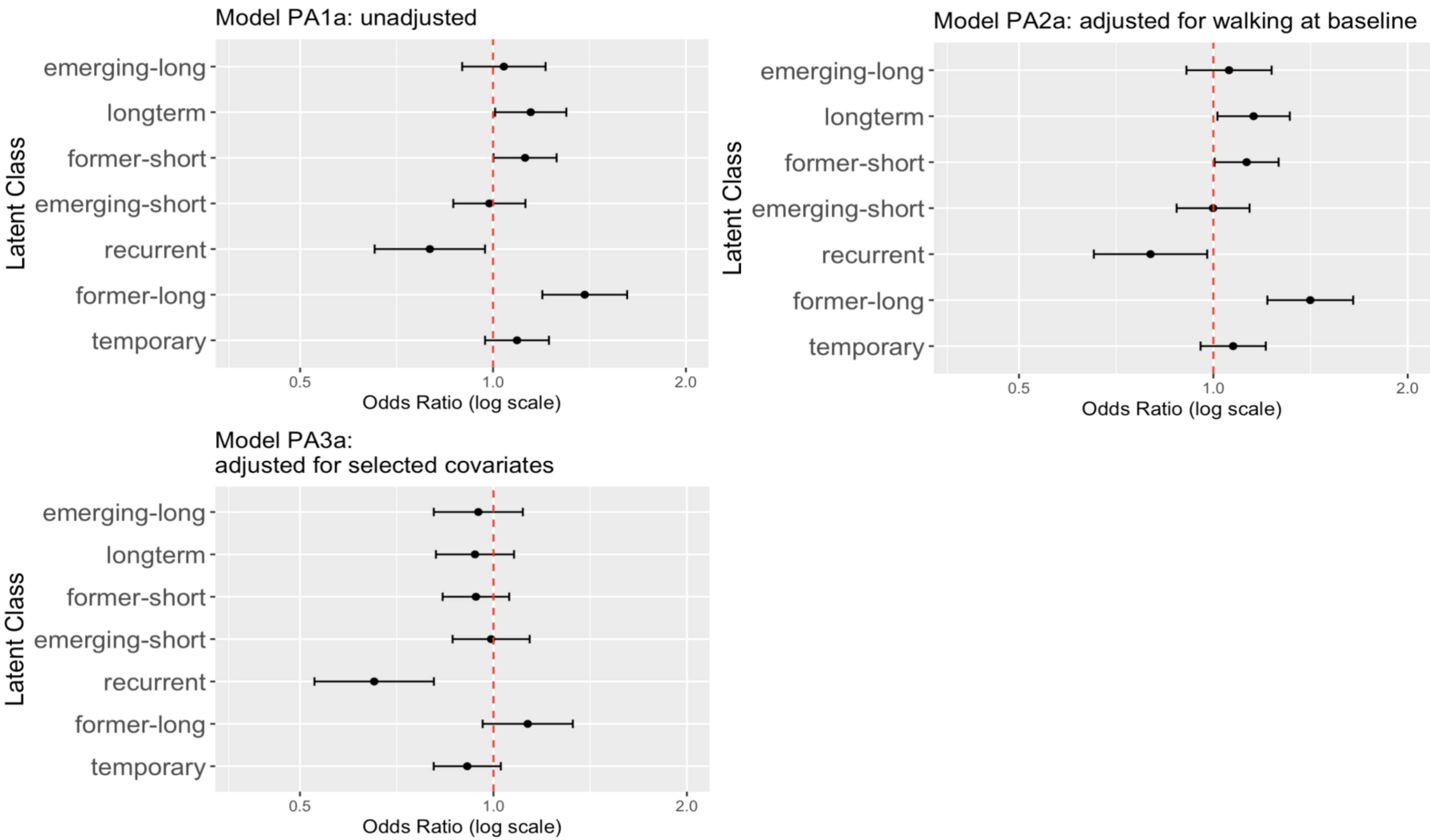


Figure 8.17 Regression for physical inactivity and latent classes; Odds ratios (log scale) for logistic regression models predicting physical inactivity across latent caregiving intensity classes based on the latent class analysis (LCA) solution. Results are shown for three models: PA1a (unadjusted), PA2a (adjusted for walking at baseline), and PA3a (adjusted for selected covariates). The reference category is the 'non-caregiver' latent class. Estimates account for complex survey design, clustering at the household level, and multiple imputation (m=10).

8.4.3.2 Fruit and vegetable consumption

Observed Transitions

Figure 8.18 shows the regression models for fruit and vegetable consumption and Observed Transitions. In the unadjusted model (Model DIET1b), former caregivers and those with Multiple caregiving transitions (both currently caregiving and no longer caregiving) reported significantly higher fruit and vegetable consumption compared to non-caregivers. Former caregivers had the largest positive coefficient (0.3, 95% CI: 0.1–0.4), followed by those with Multiple caregiving transitions who were no longer providing care (Coeff.=0.2, 95% CI: 0.1–0.3) and those with Multiple transitions and currently providing care (Coeff.=0.2, 95% CI: 0.1–0.3). Emerging, Temporary, and Long-term caregivers, however, did not show significant differences in fruit and vegetable intake compared to Non-caregivers.

After adjusting for baseline fruit and vegetable intake in Model DIET2b, the coefficients for all caregiving groups were slightly attenuated, although Former caregivers and those with Multiple caregiving transitions remained significantly associated with higher intake. In the model adjusted for all selected covariates (Model DIET3b), the small positive associations persisted for Former caregivers (0.1, 95% CI: 0.0–0.2) and Multiple transition caregivers (0.1, 95% CI: 0.0–0.2) but confidence intervals were crossing zero. This suggests that the higher consumption of fruits and vegetables of Multiple transition caregivers is explained by confounding of underlying characteristics.

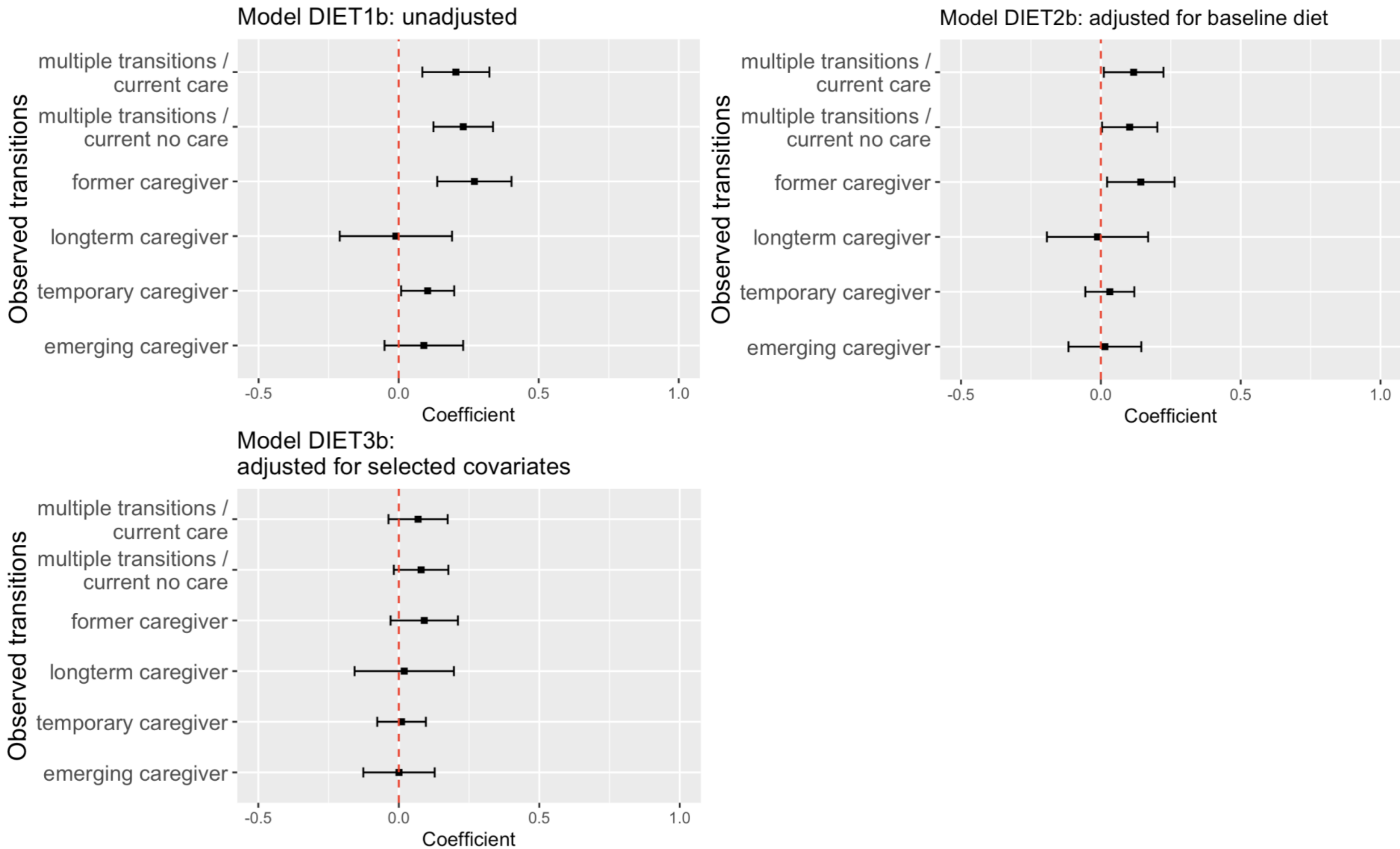


Figure 8.18 Regression for diet and Observed Transitions; linear regression models predicting average daily portions of fruit and vegetables across Observed Transition groups among UKHLS participants (n=25,049), showing pooled coefficient estimates from multiple imputation (m=10) and accounting for survey weights, clustering at the household level, and health behaviour outcomes. Results are shown for three models: DIET1b (unadjusted), DIET2b (adjusted for walking at baseline), and DIET3b (adjusted for selected covariates). The reference category is 'non-caregiver'.

Latent Class Analysis (LCA)

Figure 8.19 shows the regression model for fruit and vegetable consumption and latent caregiving classes. In the unadjusted model (DIET1a), all caregiving classes had a higher fruit and vegetable intake compared to Non-caregivers, but this was not significant for long-term and Emerging-long caregivers. These associations were attenuated when adjusting for fruit and vegetable consumption at baseline in model DIET2a and further in the adjusted model DIET3a, with confidence intervals crossing zero for most groups.

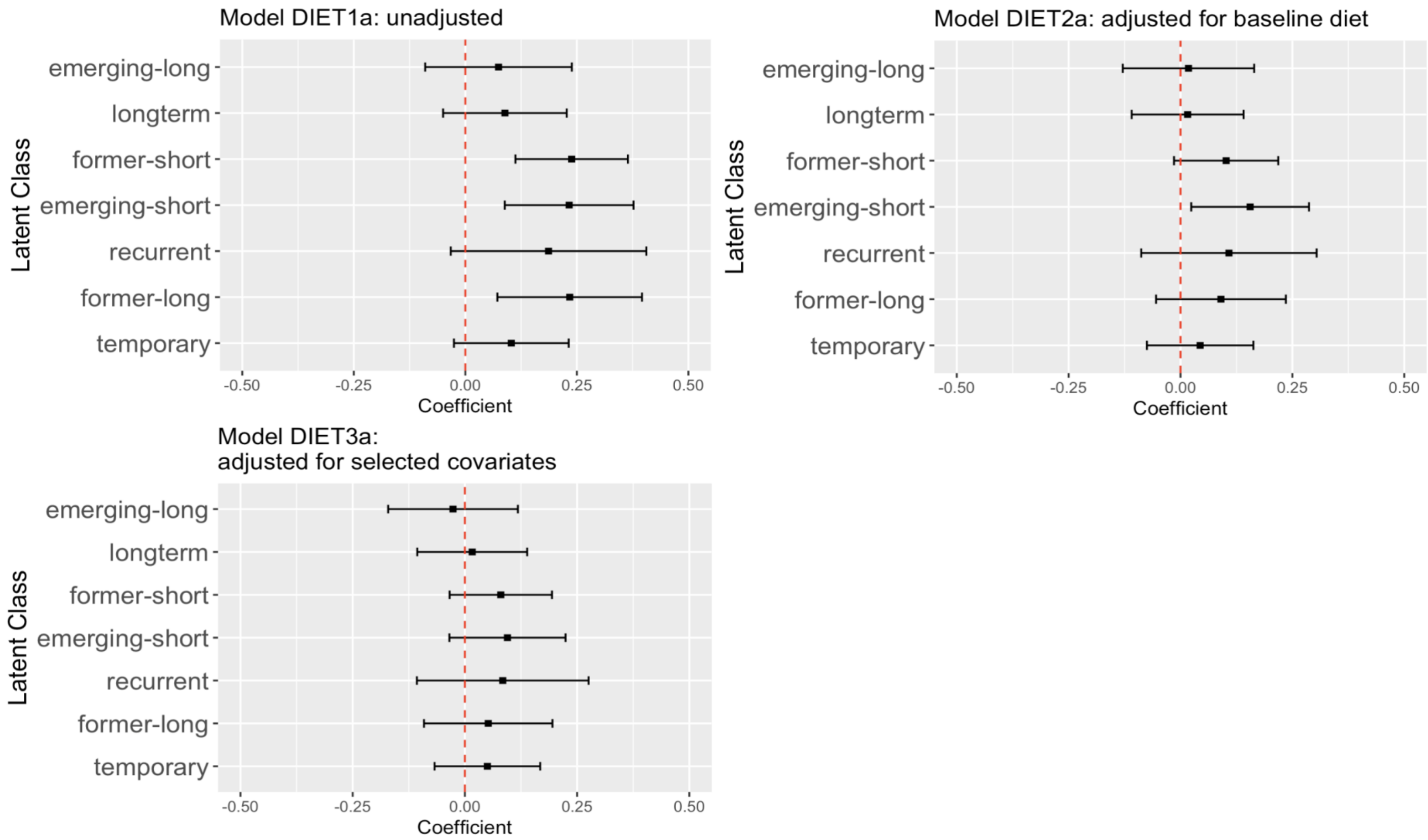


Figure 8.19 Regression for diet and latent classes; linear regression models predicting average daily portions of fruit and vegetables across latent caregiving intensity classes based on latent class analysis (LCA) among UKHLS participants (n=25,049), showing pooled coefficient estimates from multiple imputation (m=10) and accounting for survey weights, clustering at the household level, and health behaviour outcomes. Results are shown for three models: DIET1a (unadjusted), DIET2a (adjusted for walking at baseline), and DIET3a (adjusted for selected covariates). The reference category is the 'non-caregiver' latent class.

8.4.3.3 Problematic drinking

Observed Transitions

Figure 8.20 shows the regression models for problematic drinking and Observed Transitions. In the unadjusted model (Model ALC1b), Long-term caregivers (OR 0.80, 95% CI: 0.65–0.97), Former caregivers (OR=0.81, 95% CI: 0.71–0.91), and those with Multiple caregiving transitions (both currently caregiving and no longer caregiving) (OR=0.85, 95% CI: 0.76–0.94 and OR=0.85, 95% CI: 0.77–0.93, respectively) had significantly lower odds of problematic drinking compared to Non-caregivers. Emerging caregivers and Temporary caregivers did not show significant differences in alcohol consumption.

After adjusting for baseline alcohol intake in Model ALC2b, the associations became stronger, particularly for Former caregivers (OR = 0.71, 95% CI: 0.62–0.81) and those with Multiple caregiving transitions who were no longer caregiving (OR = 0.76, 95% CI: 0.68–0.85). In the model adjusted for all selected covariates (Model ALC3b), the previously significant associations weakened, with confidence intervals widening. Former caregivers (OR=0.87, 95% CI: 0.75–1.00) and those with Multiple caregiving transitions and current care (OR=0.87, 95% CI: 0.77–0.99) remained on the threshold of statistical significance, suggesting a potential but modest protective association of caregiving on problematic drinking. In contrast, Multiple transitions without current care was no longer associated with problematic drinking after full adjustment (OR=0.92, 95% CI: 0.82-1.04).

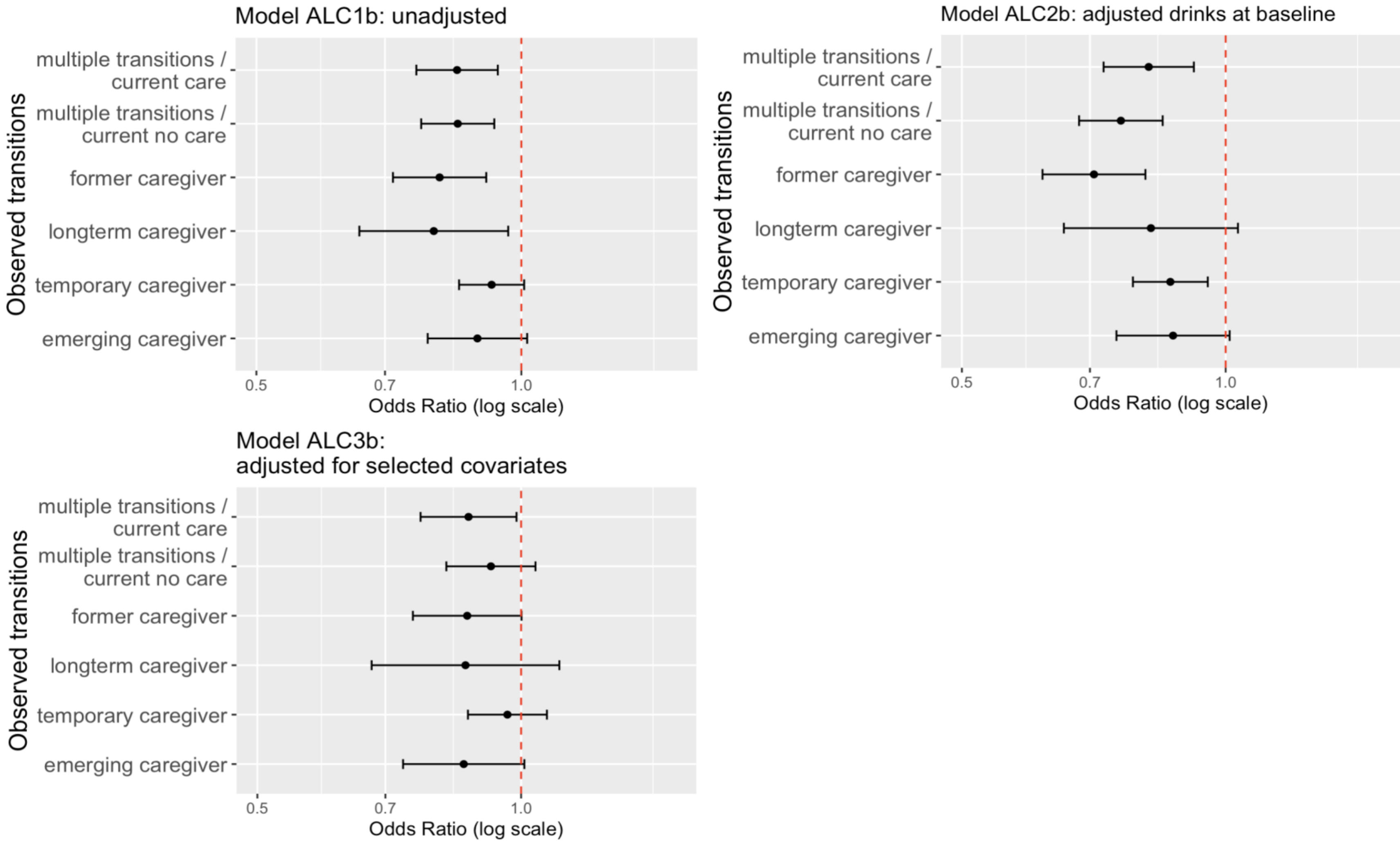


Figure 8.20 Regression for problematic drinking and Observed Transitions; Logistic regression models predicting problematic drinking across Observed Transition groups among UKHLS participants (n=25,049), showing pooled odds ratio estimates from multiple imputation (m=10) and accounting for survey weights, clustering at the household level, and health behaviour outcomes. Results are shown for three models: ALC1b (unadjusted), ALC2b (adjusted for walking at baseline), and ALC3b (adjusted for selected covariates). The reference category is 'non-caregiver'.

Latent Class Analysis (LCA)

Figure 8.21 shows the regression models for problematic drinking and LCA. Several caregiving classes showed lower odds of problematic drinking in the unadjusted model. Recurrent caregiving was associated with the lowest odds of problematic drinking compared to Non-caregiving in the unadjusted model ALC1a (OR=0.74, 95% CI: 0.61-0.89) and the magnitude of the association slightly increased after adjusting for drinks frequency at baseline in model ALC2a (OR=0.67, 95% CI: 0.54-0.83). After adjustment of covariates this association remained significant (OR=0.75, 95%CI: 0.59/0.94) which suggest that Recurrent caregiving is associated with lower odds of problematic drinking compared to Non-caregiving which is not explained by confounding of the underlying characteristics of Recurrent caregivers.

When comparing Recurrent caregivers to other caregiving groups, a similar trend is observed among Long-term caregivers, who also have reduced odds of problematic drinking in all models, though the association was attenuated in Model ALC3a. Temporary, Former long-term, and former-short caregivers show reductions in problematic drinking in earlier models, but these associations were partially or fully explained by confounding. Emerging-short and Emerging-long caregivers did not exhibit any significant differences from non-caregivers.

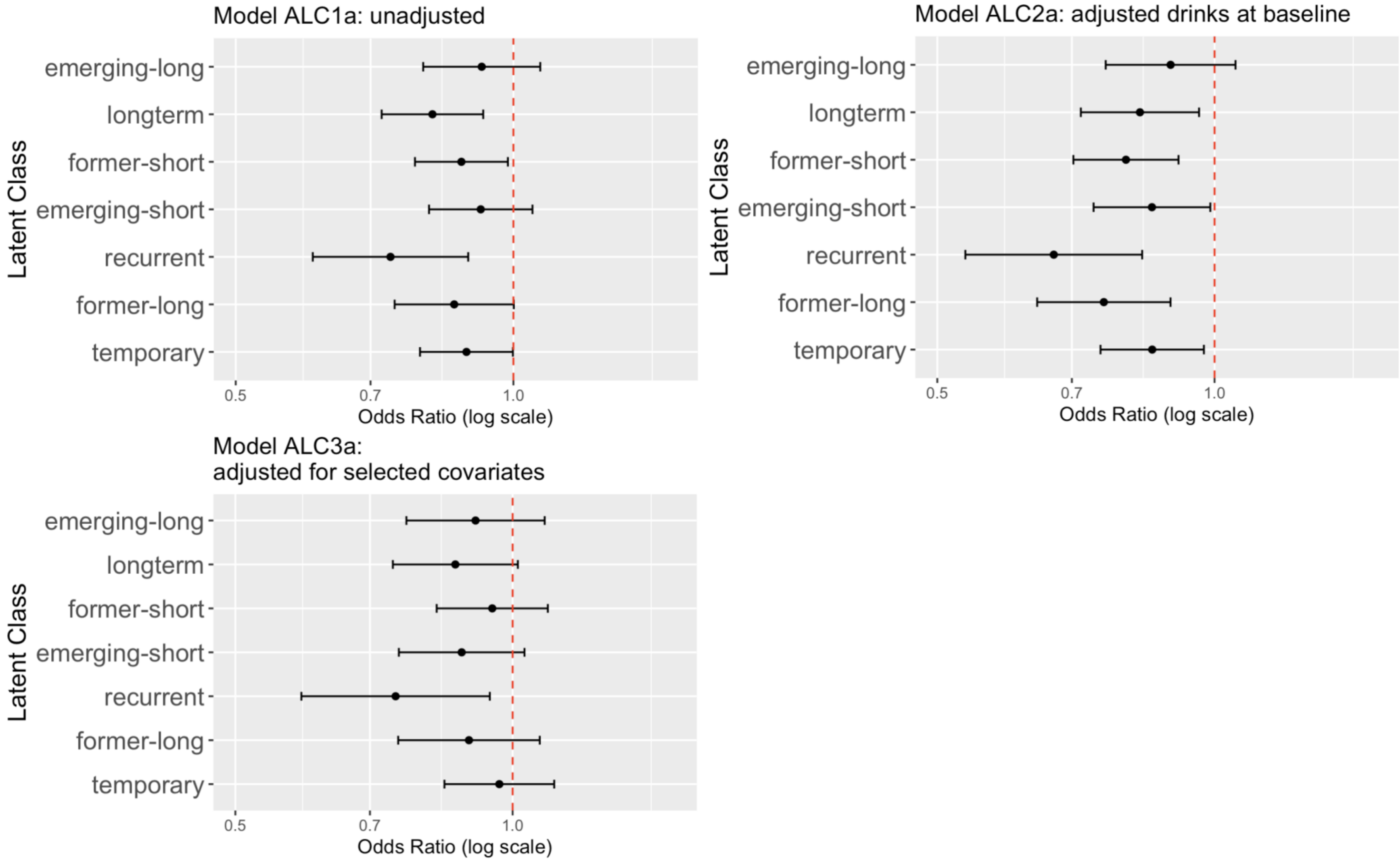


Figure 8.21 Regression for problematic drinking and latent classes; logistic regression models predicting problematic drinking across latent caregiving intensity classes based on latent class analysis (LCA) among UKHLS participants (n=25,049), showing pooled odds ratio estimates from multiple imputation (m=10) and accounting for survey weights, clustering at the household level, and health behaviour outcomes. Results are shown for three models: ALC1a (unadjusted), ALC2a (adjusted for walking at baseline), and ALC3a (adjusted for selected covariates). The reference category is the 'non-caregiver' latent class.

8.4.3.4 Smoking

Observed Transitions

Figure 8.22 shows the regression models for smoking and Observed Transitions. In the unadjusted model (Model SMOK1b), Long-term caregivers (OR=1.40, 95% CI: 1.08–1.83) and those with Multiple caregiving transitions who were currently providing care (OR=1.26, 95% CI: 1.08–1.47) had significantly higher odds of smoking compared to Non-caregivers. Other caregiving groups, including Emerging caregivers, Temporary caregivers, Former caregivers, and those with Multiple transitions but no longer providing care, did not show significant differences in smoking likelihood.

After adjusting for baseline smoking status in Model SMOK2b, the odds ratios for Long-term caregivers and Multiple transition caregivers who were currently providing care were attenuated and became non-significant (OR=1.15, 95% CI: 0.83–1.60 and OR = 1.19, 95% CI: 0.98–1.46, respectively). In the model adjusted for all selected covariates (Model SMOK3b), Multiple transition caregivers who were currently providing care exhibited significantly higher odds of smoking (OR=1.36, 95% CI: 1.10–1.67), suggesting that individuals experiencing multiple caregiving transitions while actively providing care were at higher odds of smoking. The association for Long-term caregivers further attenuated after full adjustment (OR=1.01, 95% CI: 0.70–1.43).

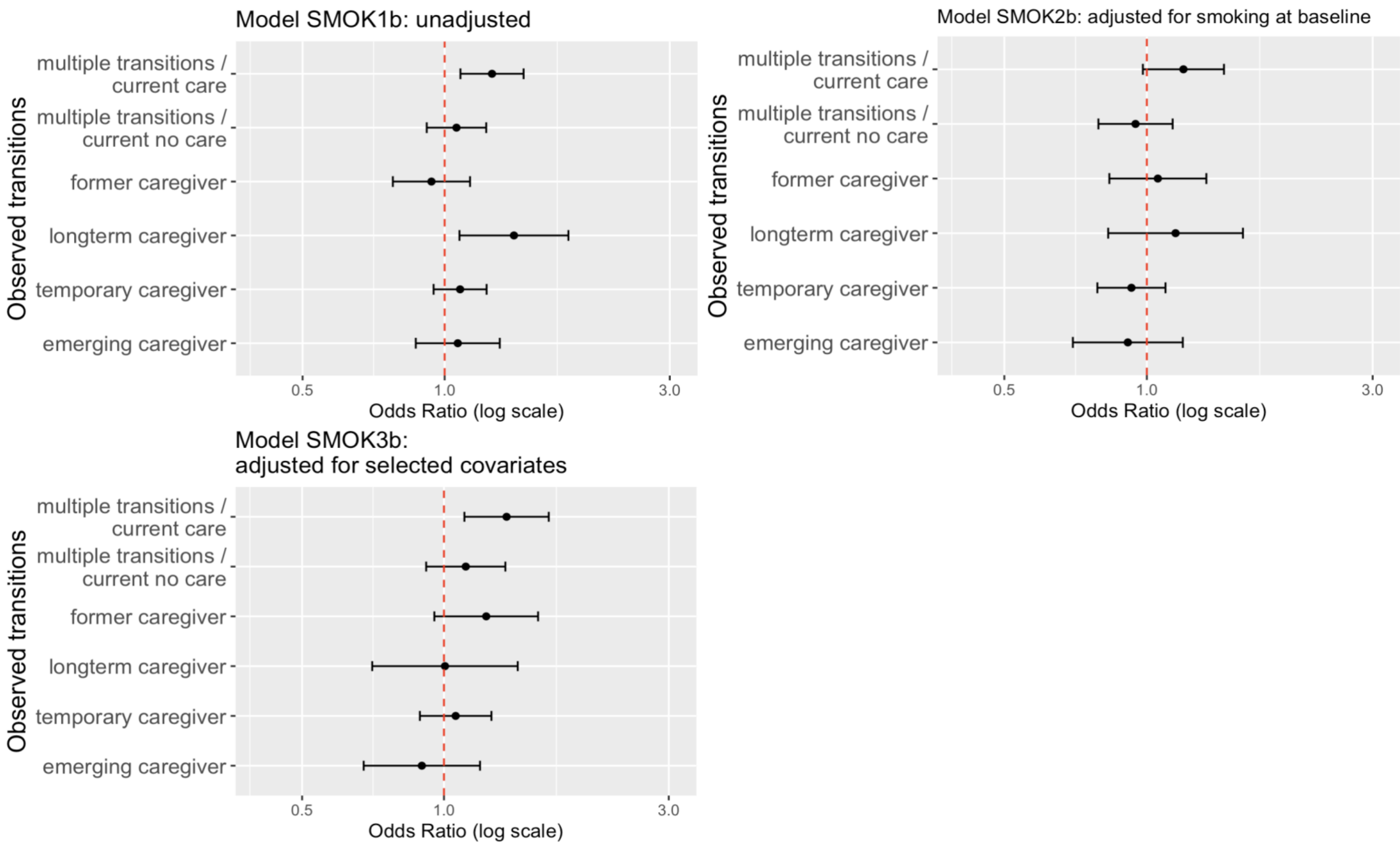


Figure 8.22 Regression for smoking and Observed Transitions; Logistic regression models predicting smoking status across Observed Transition groups among UKHLS participants (n=25,049), showing pooled odds ratio estimates from multiple imputation (m=10) and accounting for survey weights, clustering at the household level, and health behaviour outcomes. Results are shown for three models: SMOK1b (unadjusted), SMOK2b (adjusted for walking at baseline), and SMOK3b (adjusted for selected covariates). The reference category is 'non-caregiver'.

Latent Class Analysis

Figure 8.23 shows the regression model for smoking and LCA. In the unadjusted model SMOK1a, Recurrent caregiving was associated with higher odds of smoking compared to non-caregiving (OR=1.58, 95% CI: 1.22-2.04) which was slightly attenuated when adjusting for smoking status at baseline in model SMOK2a (OR=1.06-2.12). However, there remained a clear and significant association in the model adjusted for all selected covariates SMOK3a (OR=1.67, 95% CI: 1.17-2.40). This suggests that Recurrent caregiving is associated with higher odds of smoking which is not explained by smoking behaviour at baseline or confounding of covariates.

When comparing Recurrent caregivers to other caregiving groups, a clear distinction emerges. While Long-term caregivers also exhibit slightly higher odds of smoking, this association became non-significant after adjustment. Temporary, Former, and Emerging caregivers did not show any significant with smoking behaviour. This suggests that it was the recurrent nature of caregiving, rather than caregiving itself, that was particularly linked to an increased likelihood of smoking.

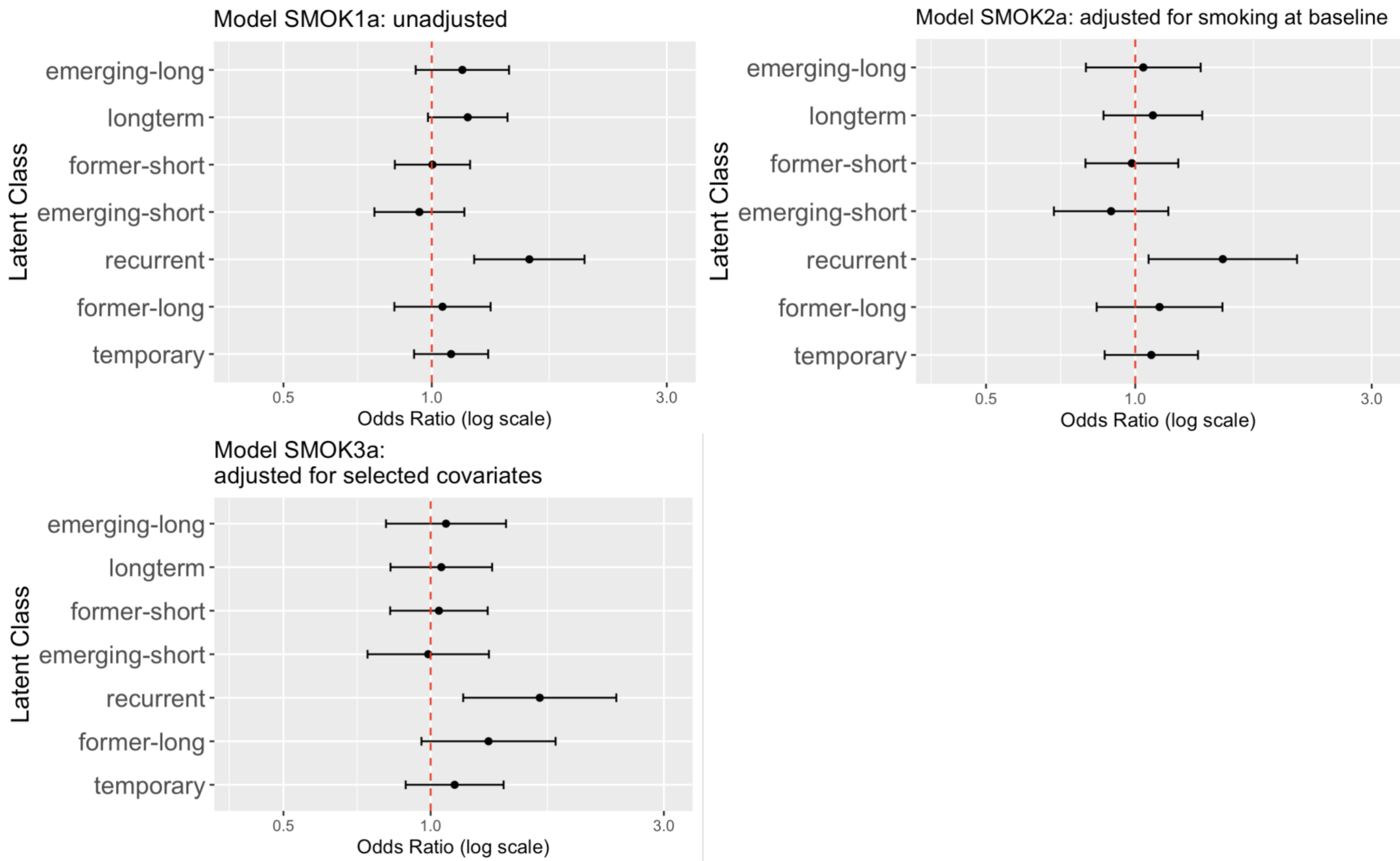


Figure 8.23 Regression for smoking and latent classes; logistic regression models predicting smoking status across latent caregiving intensity classes based on latent class analysis (LCA) among UKHLS participants (n=25,049), showing pooled odds ratio estimates from multiple imputation (m=10) and accounting for survey weights, clustering at the household level, and health behaviour outcomes. Results are shown for three models: SMOK1a (unadjusted), SMOK2a (adjusted for walking at baseline), and SMOK3a (adjusted for selected covariates). The reference category is the 'non-caregiver' latent class.

8.4.4 Interactions

Interaction terms were tested the relationship between sex, age group and the transition variable. The corresponding p-values for each interaction test are presented in **Table 8.9**. The interaction term for physical inactivity and sex was significant in the latent classes (p=0.05) but not for the Observed Transitions (p=0.30). In addition, the was evidence for an interaction between fruit and vegetable consumption and age group in the LCA (p=0.01) as well as the Observed Transitions (p=0.02) approach. Regarding smoking, there was evidence for an interaction between sex and the Observed Transitions variable (p=0.02). For problematic drinking, there was borderline evidence for an interaction between age groups and the Observed Transitions variable (p=0.06). Below, stratified results are presented for statistically significant interactions.

Table 8.9 Wald-test p-values for interaction terms between latent caregiving intensity classes and Observed Transition groups, predicting health behaviours among UKHLS participants (n=25,049). Estimates account for complex survey design, clustering at the household level, and multiple imputation (m=10).

	Latent class variable		**observed typology**	
	Sex	Age groups	Sex	Age groups
Physical inactivity	0.05	0.71	0.30	0.79
Fruit and vegetable consumption	0.74	0.01	0.68	0.02
Problematic drinking	0.88	0.44	0.71	0.06
Smoking	0.34	0.59	0.02	0.88

Physical inactivity and sex

The p-value for interaction between sex and latent class was marginally significant (p=0.05) and stratified results were presented in **Figure 8.24**. The results indicate that the associations between latent caregiving classes and physical inactivity differed by sex. Long-term caregiving was not significantly associated with physical inactivity in men (OR=1.14, 95% CI: 0.89, 1.44) but was linked to lower odds of physical inactivity in women (OR=0.83; 95% CI: 0.70, 0.98). Former-long caregiving, however, was associated with higher odds of physical inactivity in men (OR=1.44, 95% CI: 1.10, 1.87) but not in women (OR=0.96; 95% CI: 0.79, 1.16). Meanwhile, Recurrent caregiving showed a similar association for both men (OR=0.65, 95% CI: 0.48, 0.94) and women (OR=0.65, 95% CI: 0.50, 0.85), suggesting a consistent effect across sexes.

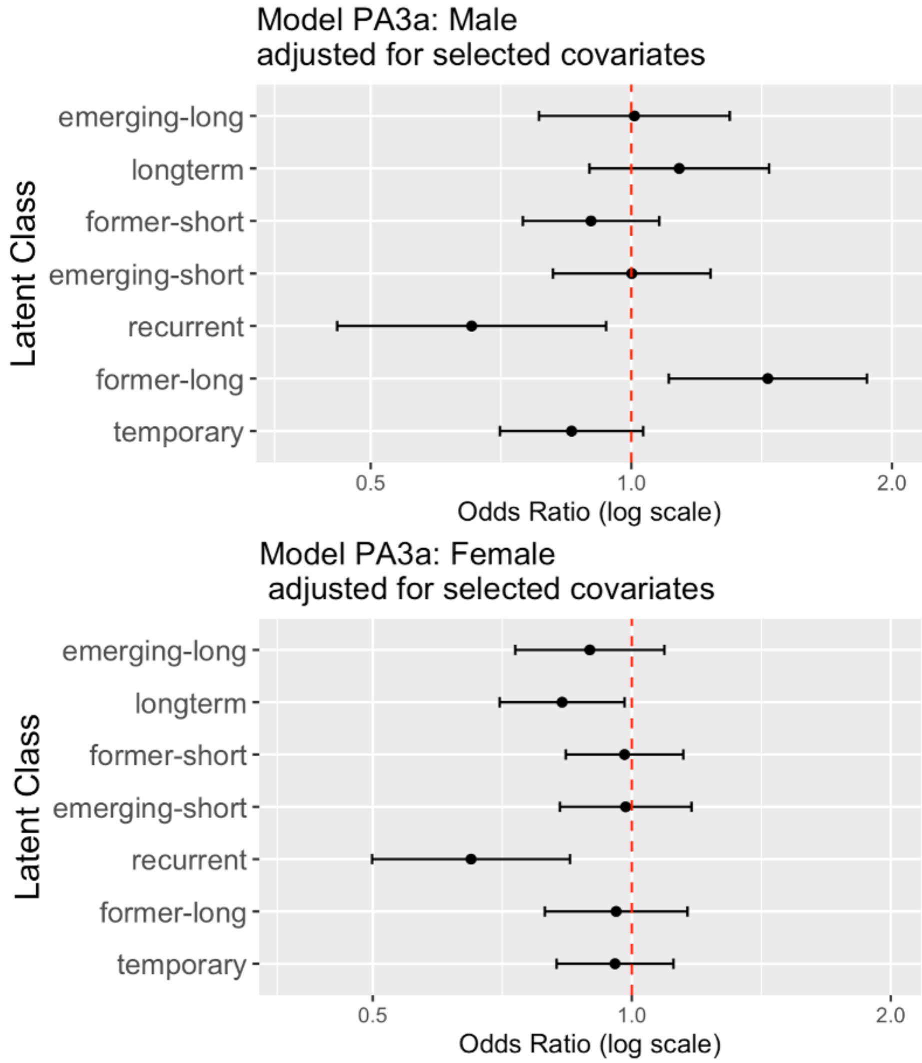


Figure 8.24 Physical inactivity stratified by sex (LCA); Sex-stratified logistic regression models predicting physical inactivity across latent caregiving intensity classes among UKHLS participants (n=25,049), showing pooled odds ratio estimates from multiple imputation (m=10) and accounting for survey weights, clustering at the household level, and selected covariates. Results are shown for males (Model PA3a) and females (Model PA3a). The reference category is the 'non-caregiver' latent class.

Fruit and vegetable consumption and age

For fruit and vegetable consumption, both the LCA and Observed Transitions approach agreed that there was a significant interaction between group membership and age group. The results from **Figure 8.25** suggest that the association between latent caregiving classes and fruit and vegetable consumption varies by age group. In early adulthood (16-29), most caregiving classes showed no associations with fruit and vegetable consumption apart from Emerging-long caregivers who had lower fruit and vegetable intake compared to non-caregivers (Coeff.=-0.6, 95% CI: -0.9/-0.2). In early mid-adulthood (30-49), some caregiving groups, particularly Former-long and Recurrent caregivers, had lower fruit and vegetable consumption, though confidence intervals crossed zero (Coeff.=-0.2, 95% CI: -0.5/0.1; and Coeff.=-0.2, 95% CI: -0.5/0.1, respectively). In late mid-adulthood (50-64), associations seemed to move to a different direction and many caregiving classes were associated with higher fruit and vegetable consumptions such as Recurrent caregiving (Coeff.=0.3, 95% CI: 0.0/0.6, p=0.05), Emerging-short (Coeff.=0.3, 95% CI: 0.0/0.5, p=0.03), Former-short (Coeff. = 0.2, 95% CI: 0.0/0.4, p=0.05), and Long-term caregiving (Coeff.=0.2, 95% CI: 0.0/0.4, p=0.04). However, in late adulthood (65+), only Recurrent caregiving and Former-long caregiving were associated with higher fruit and vegetable consumption compared to Non-caregiving (Coeff;=0.5, 95% CI: 0.01/1.0, p=0.03 and Coeff.=0.3, 95% CI: 0.0/0.6, p= 0.03, respectively).

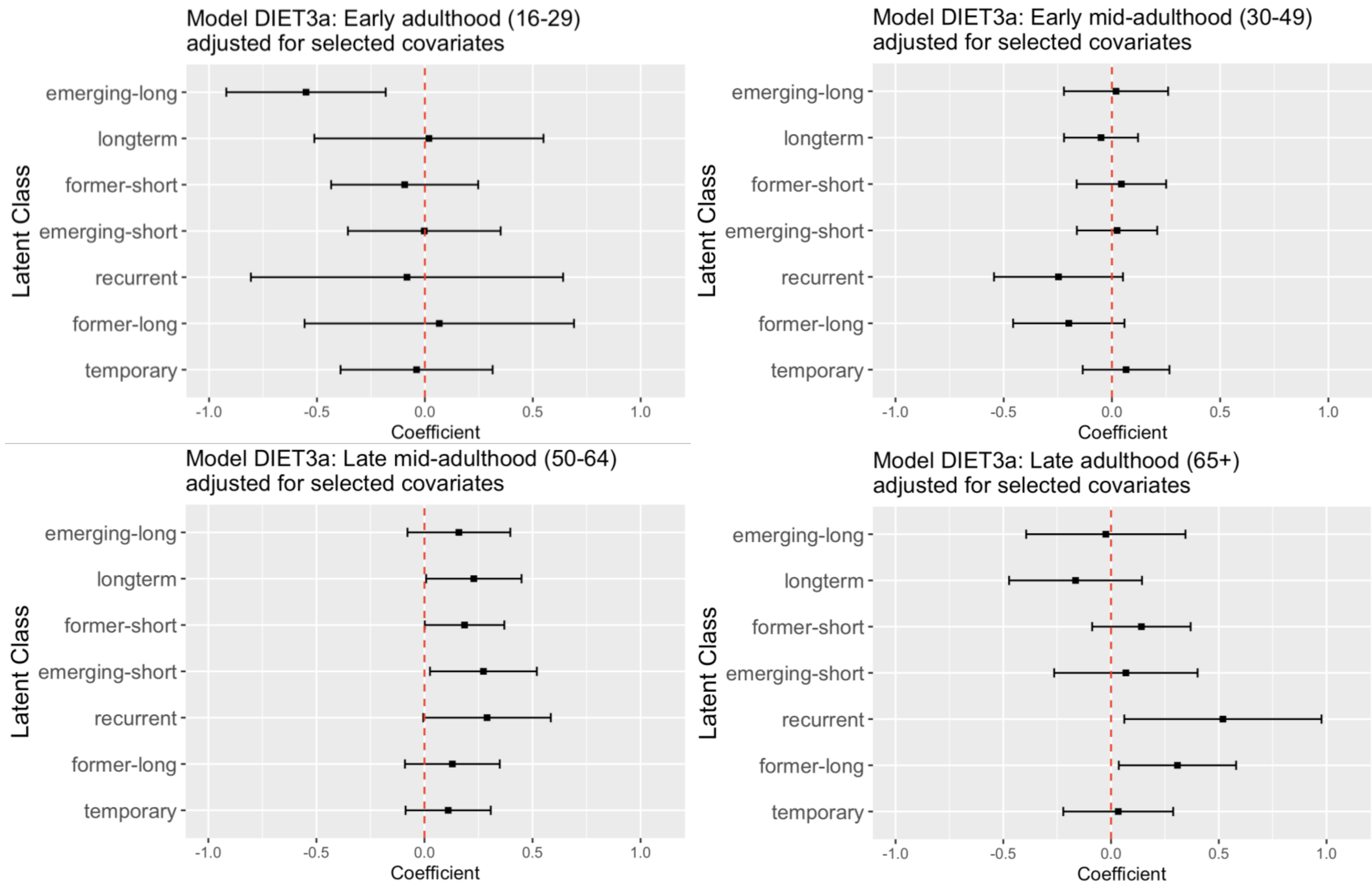


Figure 8.25 Diet stratified by age group (LCA); linear regression models predicting daily portions of fruit and vegetables across latent caregiving classes, stratified by age group among UKHLS participants (n=25,049). Results are shown for Model DIET3a, adjusted for selected covariates. The reference category is the 'non-caregiver' latent class. Estimates are pooled from multiple imputation (m=10) and account for survey weights, clustering at the household level, and health behaviour outcomes.

In contrast, the results from **Figure 8.26** show the age-stratified results for the Observed Transitions approach. In early adulthood (16-29), Multiple transitions with and without current caregiving was associated with lower fruit and vegetable consumption but this association was only significant for Multiple transition with current care (Coeff.=-0.4, 95%CI: -0.7/-0.1). In early mid-adulthood (30-49), most caregiving groups showed no association or confidence intervals crossing zero. In late mid-adulthood (50-64), Multiple caregiving transition were associated with higher fruit and vegetable consumption for participants with current care responsibilities (Coeff.=0.2, 95% CI: 0.0/0.4) as well as participants without current care responsibilities (Coeff;=0.3, 95% CI: 0.2/0.5). While these associations reached statistical significance for these two groups, other classes in this age group also showed positive point estimates of a similar magnitude, though their confidence intervals crossed zero in late adulthood (65+), Multiple caregiving transitions with current care was associated with higher fruits and vegetable consumption but this was statistically not significant (Coeff.=0.2, 95% CI: -0.1/0.5, p=0.15). These findings suggest that Multiple transitions or Recurrent caregiving was associated with worse fruit and vegetable consumption compared to young non-caregivers, whereas multiple caregiving transitions in later life may be linked to healthier eating patterns.

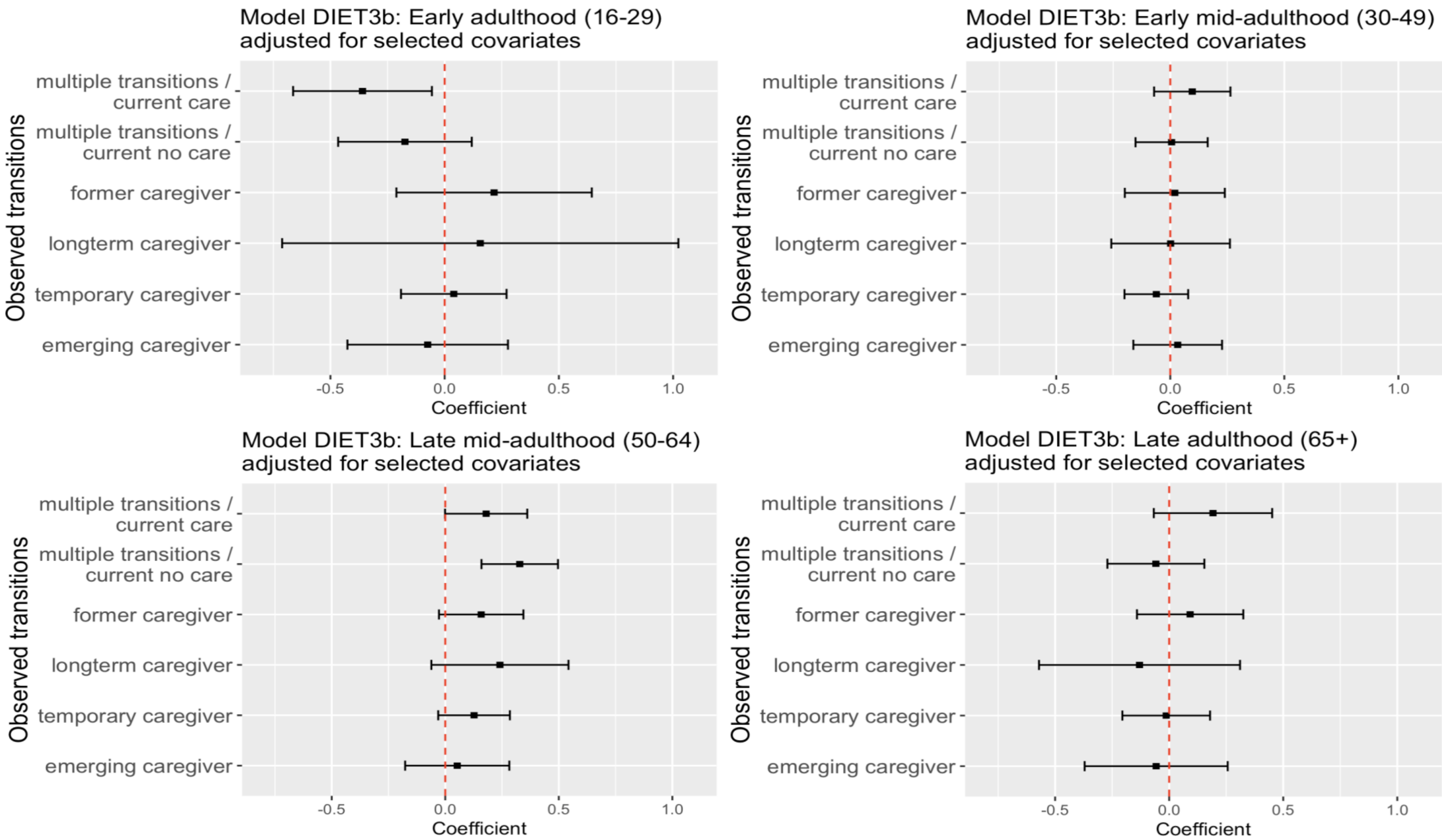


Figure 8.26 Diet stratified by age group ; linear regression models predicting daily portions of fruit and vegetables across Observed Transition groups among UKHLS participants (n=25,049), stratified by age group. Results are shown for Model DIET3b, adjusted for selected covariates. The reference category is 'non-caregiver'. Estimates are pooled from multiple imputation (m=10) and account for survey weights, clustering at the household level, and health behaviour outcomes.

Drinking and age

The interaction term for the Observed Transitions variable and age group was marginally not significant (p=0.06) and most results from the age-stratified show non-significant ORs that cross the confidence interval with a few exceptions as seen in **Figure 8.27**. Emerging caregiving in early adulthood (16-29) was associated with lower odds in problematic drinking compared to Non-caregivers of the same age (OR=0.59, 95% CI: 0.39/0.92). In early mid-adulthood Long-term caregiving and Multiple transitions with current care were associated with lower odds of problematic drinking (OR=0.59, 95% CI: 0.39, 0.88 and OR=0.76, 95% CI: 0.63, 0.93, respectively). In late mid-adulthood (50-64) and late adulthood (65+), there were no significant associations.

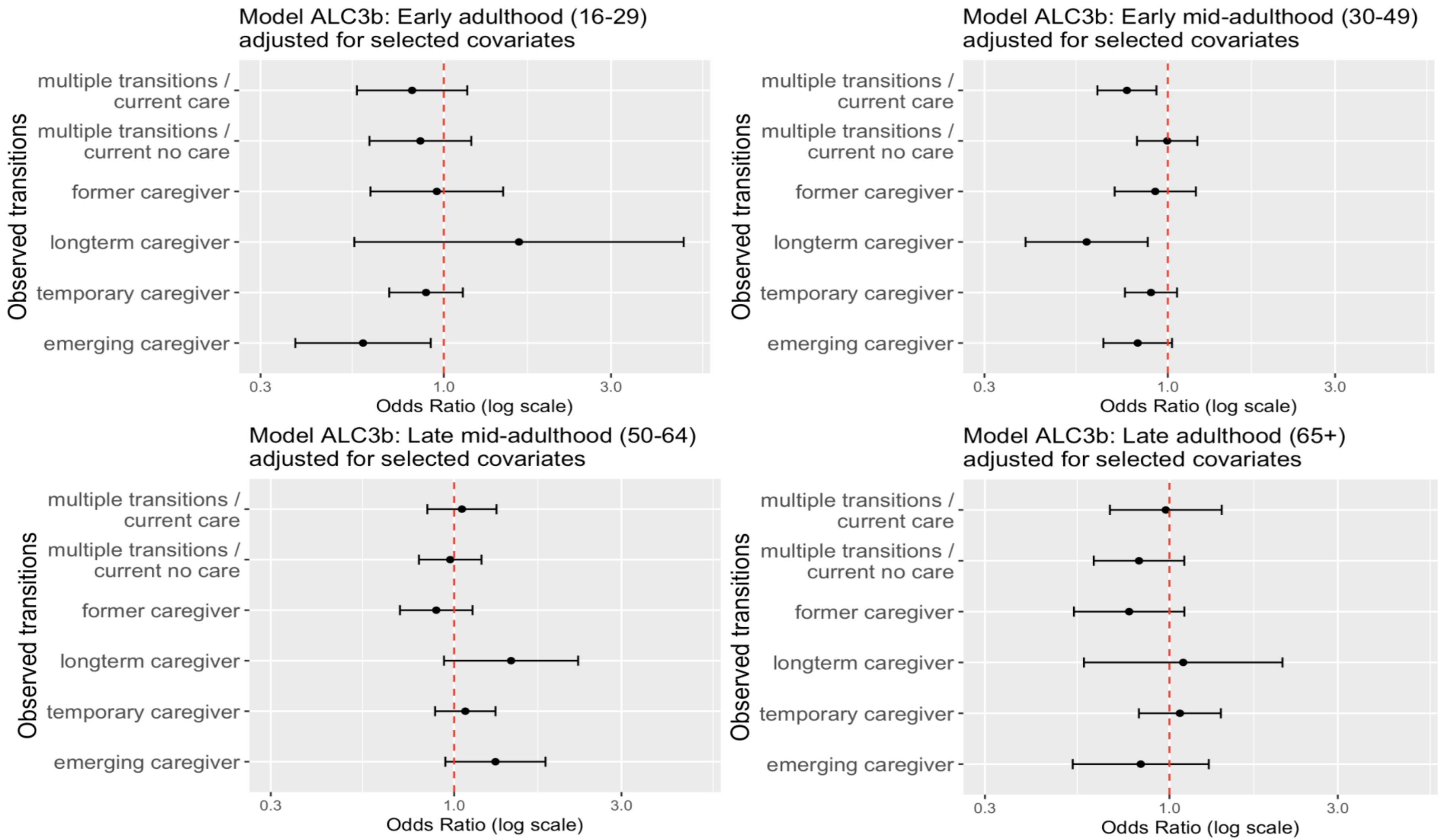


Figure 8.27 Problematic drinking stratified by age group; logistic regression models predicting problematic alcohol consumption across Observed Transition groups among UKHLS participants (n=25,049), stratified by age group. Results are shown for Model ALC3b, adjusted for selected covariates. The reference category is 'non-caregiver'. Estimates are pooled from multiple imputation (m=10) and account for survey weights, clustering at the household level, and health behaviour outcomes.

Smoking and sex

Figure 8.28 represents the stratified results for smoking by sex which suggest that the association between caregiving transitions and smoking differed by sex. Among men, Long-term caregiving was associated with a lower odd of smoking (OR=0.48, 95% CI: 0.22, 1.03, p=0.06) while it was associated with higher odds of smoking in women (OR=1.48, 95% CI: 0.98, 2.22, p=0.06) although both confidence intervals crossed one. Further, Multiple transition with current care as well as Former caregiving was associated with higher odds in smoking in women but not in men. These findings suggest that woman with caregiving responsibilities were more likely to smoke particularly when they experienced more sustained or recurrent caregiving episodes.

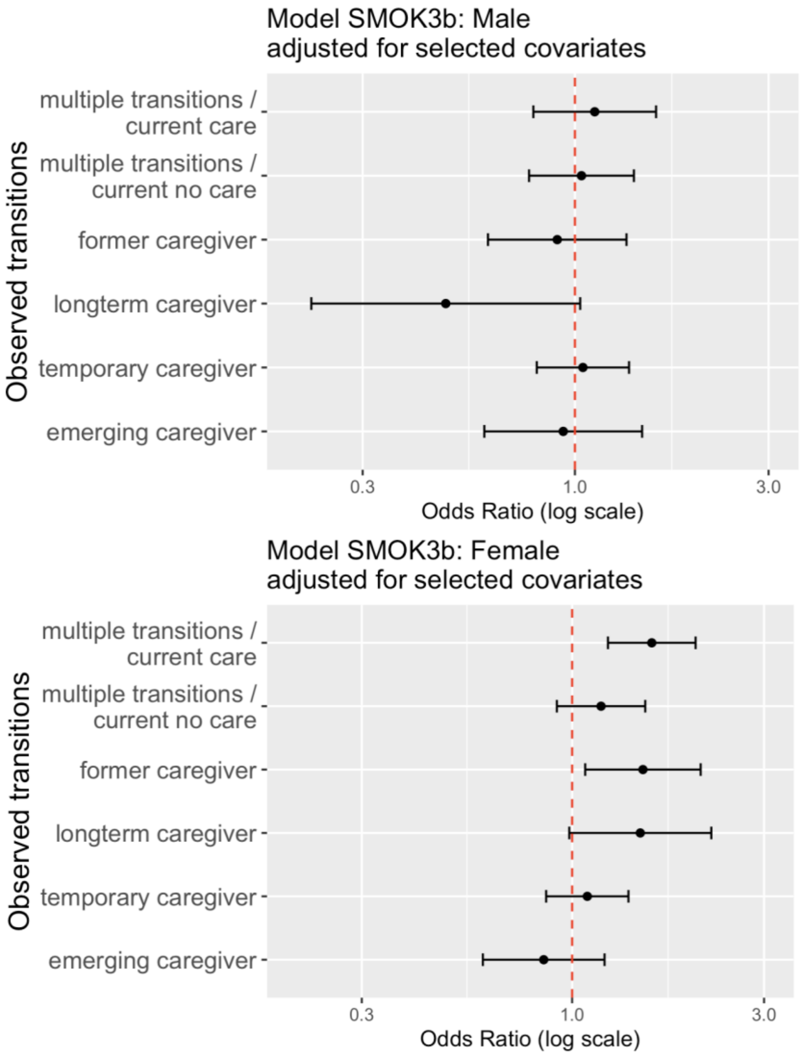


Figure 8.28 Regression of smoking by sex ; models predicting smoking status across Observed Transition groups among UKHLS participants (n=25,049), stratified by sex. Results are shown for Model SMOK3b, adjusted for selected covariates. The reference category is 'non-caregiver' Observed Transitions. Estimates are pooled from multiple imputation (m=10) and account for survey weights, clustering at the household level, and health behaviour outcomes.

8.5 Discussion

This chapter aimed to investigate the relationship between multiple caregiving transitions and changes in health behaviours, using two distinct methodological approaches: Observed Transitions and latent class analysis (LCA). The findings suggest that multiple caregiving transitions are common among caregivers but that the way they are classified influences their observed prevalence. Observed Transitions identified a relatively large group of caregivers who experienced multiple transitions, whereas LCA demonstrated that the number of transitions alone is not the primary determinant of transition patterns, rather, the stability of the caregiving trajectory played a more crucial role in classification.

The question must be asked which of these two approaches was superior in answering the research question of this chapter. The Observed Transitions and LCA approach offered distinct ways of capturing multiple caregiving transitions, with each method revealing different insights. It was striking that multiple transitions were relatively common in the Observed Transitions approach, while in the LCA approach, recurrent caregiver only consisted of a small group. Observed Transitions identified a relatively large group of caregivers experiencing multiple transitions, as it considered every recorded change in caregiving status over time, providing a potentially biased perspective as this approach neglects the duration of each caregiving or non-caregiving episode. In contrast, LCA classified caregivers based on the stability of their trajectory rather than the absolute number of transitions. This difference highlights how Observed Transitions captured the frequency of transitions but did not account for trajectory consistency, while LCA identifies caregiving patterns that remain stable over time. While Observed Transitions may be useful for understanding short-term fluctuations in caregiving, LCA may better capture sustained caregiving patterns that may have a lasting impact on caregiver's health behaviours.

When comparing the associations between caregiving transitions and health behaviours across the two approaches, several consistencies and inconsistencies emerged. In both methods, multiple caregiving transitions were associated with health behaviours in the same direction; however, the strength of these associations varied depending on how caregiving transitions were classified. The observed transitions approach highlighted that those who were still caregivers at the time the outcome was measured were less likely to be physically inactive, more likely to smoke, less likely to be problematic drinkers, and consumed more fruit and vegetables. However, most of these associations were weak or fully explained by confounding of third variables. There was evidence for a sex interaction in smoking, particularly pronounced among long-term care groups, with men less likely to smoke and women more likely to smoke.

In contrast, the LCA approach revealed more stable patterns, and although the recurrent caregiving class was small, it showed clearer and more statistically robust associations with health behaviours. Recurrent caregivers were more likely to be physical active, more likely to smoke and less likely to be problematic drinkers compared to non-caregivers even after adjusting for a wide range of selected covariates. This suggests that the way multiple caregiving transitions were conceptualised influenced interpretations about their impact on health behaviours.

Although recurrent caregivers were the smallest transition group in the LCA, it was the group that showed strongest association with health behaviours compared to non-caregivers. This finding may reflect a particular pattern of caregiving, where individuals who experience recurrent caregiving episodes develop distinct health behaviour adaptations in response to the caregiving role, which may be due to coping mechanisms or as a structured adjustment to ongoing responsibilities.[344,345] The fact that significant differences were found in this group underscores the importance of considering caregiving as a recurrent lifecourse experience rather than as an isolated event in someone's lifecourse.

8.5.1 Limitations

It must be acknowledged that each of the described approaches have their own limitations. For the Observed Transitions approach, the generated variable was based solely on transitions that were observed as forward filling of caregiving status was used if gaps between caregiving states were present. On the other hand, indicators of classification were borderline for the LCA approach which may suggest that some participants were misclassified. To address these limitations of both approaches, sequence imputation and sequence analysis (SA) was performed as sensitivity analysis which is presented in Appendix 8.2. The results from SA resembled results from LCA and similar transitions trajectories were found with recurrent caregivers being the smallest group. Regression of the clusters from SA was in line with LCA although some results were statistically not significant with the SA clusters.

Another approach to address the borderline classification statistic could have been to perform LCA on a sequence imputed data set which could improve entropy and average posterior probabilities. This was attempted in a sensitivity analysis in Appendix 8.3. However, the LCA on the sequence imputed data failed to resolve the concerns regarding the classification of classes as this approach only marginally improved entropy and average posterior probabilities. Besides, performing LCA on imputed data seems to be a relatively underexplored area which lacks clear methodological guidance.

Further, to understand multiple transitions more holistically, the question must be raised whether multiple caregiving transition are linked to turnover of care recipients or whether participants tend to re-transition to the same care recipient. The descriptive analysis of relationship changes and transition patterns in Appendix 8.4 highlights notable differences between caregiving groups. Overall, 61.2% of caregivers experienced no change in relationship to the care recipient while 8.6% experienced a change in the relationship with the care recipient and 30.3% changed the number of care recipients. However, this pattern varied across caregiving categories. Long-term caregivers in both Observed Transitions and LCA displayed the highest levels of stability, with fewer relationship changes but a substantial proportion experiencing changes in the number of care recipients suggesting that stability in caregiving role does not necessarily equate to stability in the individuals receiving care. Notably, multiple-transition caregivers demonstrated significant fluctuation, with high proportions reporting both relationship and care recipient changes. The recurrent group in LCA, while small, showed the highest percentage of changes in care recipients. This suggests that multiple transitions are linked with care recipient turnover.

It must be acknowledged that baseline weights were used for the analysis and that attrition could not be fully accounted for. This was justified because longitudinal weights would reduce sample size by a large margin and widen confidence intervals. The sensitivity analysis with longitudinal weights in Appendix 7.7 confirmed this and showed that the inference and direction of association remains the same across the models.

8.6 Chapter conclusion

This chapter had the aim to investigate the relationship between multiple caregiving transitions and health behaviour across the lifecourse. Two approaches were tested to identify transition pattern that characterise participants who transition into caregiving multiple times. The observed variable identified a large amount of caregivers and it suggest that multiple transitions occurred frequently amongst caregivers. In contrast, latent class analysis found that the absolute number of transitions were not the primary determinant to identify transition pattern but rather the stability of the trajectory.

Models from the analysis suggest that multiple caregiving transitions or recurrent caregiving was associated with positive health behaviours such as more physical activity, less problematic and potentially higher fruit and vegetable intake. However, multiple transitions were also associated with higher odds of smoking. It must be noted while associations went in the same direction in all analysis, however, their magnitude of association differed, and some associations were statistically not significant. It was also found that these associations differed by sex and age group. Male caregivers and caregiving in later life were generally associated with more positive health behaviour changes while caregiving in early adulthood and being female were generally associated with less favourable health behaviours.

9 Discussion & Conclusion

9.1 Introduction

Unpaid caregiving is a vital yet often underappreciated role, with significant implications for caregivers' health and well-being. This thesis aimed to investigate the relationship between caregiving transitions (entry, exit, changes in intensity, and multiple caregiving episodes) and health behaviours across the life course. By utilising longitudinal quantitative data from the UK Household Longitudinal Study, this research provides a nuanced understanding of how caregiving influences physical inactivity, smoking, alcohol consumption, and fruit and vegetable consumption.

The findings across the four analytical chapters reveal that caregiving impacts health behaviours in diverse and sometimes contradictory ways. While transitioning into caregiving was associated with increased physical activity, it was also associated with an increase in smoking rates. Exiting caregiving, on the other hand, was linked to increased physical inactivity but showed no substantial association on other health behaviours. Caregiving intensity emerged as a key factor, with high-intensity caregiving inside the household was associated with negative health behaviours, whereas caregiving outside the household appeared to have fewer detrimental effects. Recurrent caregiving transitions showed a more complex pattern, with some behaviours improving (reduced physical inactivity, reduced problematic drinking) while others worsened (increased smoking).

This chapter synthesises the findings from the four analytical chapters by health behaviour outcome, allowing for a clearer interpretation of the patterns and interactions observed. It will first examine how caregiving influences each health behaviour in turn, integrating insights from the different chapters. Following this, key moderating factors, including age, sex, and caregiving intensity, will be explored. The findings will then be contextualised within existing literature, highlighting consistencies, contradictions, and possible explanations. Finally, the chapter will outline the policy and practical implications of these results, discuss the strengths and limitations of the study, and suggest directions for future research. Through this discussion, the aim is to provide a comprehensive understanding of how caregiving transitions shape health behaviours across the life course, informing future research and policy efforts to better support unpaid caregivers.

9.2 Synthesis & discussion of key findings

9.2.1 Caregiving and physical Activity

It was found that entering caregiving was associated with a decrease in physical inactivity while exiting caregiving was associated with an increase in physical inactivity. In terms of caregiving intensity, participants who provided more intensive care over time were generally less physically active than those with lighter caregiving responsibilities. Additionally, those who moved in and out of caregiving roles repeatedly tended to become less physically inactive. This suggests a stronger relationship between physical activity and caregiving which could be explained by different pathways.

Firstly, physical activity of caregivers could be higher than in non-caregivers due to the physical elements of care-related tasks such as manual handling. The questionnaire in UKHLS asks participants how often they engage in moderate to vigorous PA for at least 10 minutes per occasion. They define moderate PA as an activity that requires *"moderate physical effort that makes you breath somewhat harder than normal and may include carrying light loads, bicycling at a regular pace or double tennis"*(University of Essex, p.272)[180] and they define vigorous PA as activities that "*make you breath much harder than normal and may include heavy liftin, aerobic or fast bicycling*" (University of Essex, p.269).[180] Hence, it is possible that caregivers perceive caregiving tasks that require physical strength as moderate to vigorous PA as defined in the questionnaire. However, if the increase in physical activity is the result of caregiving tasks, the question must be raised whether this increase in physical activity in caregivers also translates into better health outcomes in the long-term as it might differ from leisure time physical activity. This is because leisure physical activity such as sports has been shown to have a preventative effect on chronic diseases, mental health and mortality.[346–349] In contrast, occupational physical activity from work is associated with detrimental health outcomes such as physical disability, cardiovascular diseases and stress which is a phenomenon known as the 'physical activity paradox'.[163,165,166] Therefore, physical activity from caregiving tasks may be occupational physical activity and actually be harmful; however, more studies are needed to understand this paradox in the context of caregiving.

Secondly, an alternative explanation might be that caregivers engage in more physical activity relative to non-caregivers with the same characteristics as an attempt to seek respite from caregiving. A recent population-based ageing study in Europe found that caregivers were more likely to engage in volunteering activities and participate in community groups compared to non-caregivers, particularly when they provided less intense care.[350] This may seem counter intuitive given the time demands of caregiving but numerous studies have noted the positive influence of social participation of caregivers on quality of life.[351–353] Hence, it is possible that caregivers may engage in physical activity as respite from caregiving.

Another factor which seems to influence the relationship between physical activity and caregiving is the control group. In this study, it was found that caregivers were more physically active compared to non-caregivers which is consistent with other cross-sectional and longitudinal studies.[94,96,99,100,105,114,118,140] However, when comparing caregivers with each other, participants with high caregiving intensities were more likely to be physically inactive compared to low-intensity caregivers which is also consistent with other studies without non-caregiving control group which found that a higher care burden was associated with lower physical activity among caregivers.[119,146,149] This suggests that caregivers are more physically active than non-caregivers but, among caregivers, low intensity caregivers are more physically active than high-intensity caregivers. Possible explanations of these patterns might be that lower intensity caregivers have more time and flexibility to engage in structured physical activity or other forms of social participation.[354,355] In contrast, high -intensity caregivers may have limited opportunities, time resources and motivation due to engage in physical activity.[356,357] These patterns stress that caregivers are a heterogenous group and that caregiving intensity is a vital determinant of physical activity in caregivers.

Further, transitioning multiple times into caregiving was associated with lower odds of physical inactivity and it remains unclear why this was the case. One might argue it is because of the dominance of low-intensity caregivers in this group which tend to be more physical active compared to high intensity caregivers. However, this alone may not fully account for the finding, as other caregiving groups with similarly high proportions of low-intensity caregivers did not show a significant association.

Another explanation might be that people who transition multiple times into caregiving are influenced by lifecourse and structural factors. For example, recurrent caregivers may be part of social networks where more people require care, which increases their likelihood of re-entering caregiving.[358–360] Previous research, such as findings from the National Child

Development Study, has shown that women who have spent more time out of the workforce to care for children were more likely to subsequently care for parents.[361] Once an individual has taken on a caregiving role, they may feel more capable and be perceived by others as having the necessary skills and experience to provide care again.[362–364] Prior caregiving can also result in adjustments to employment, lifestyle and social roles, which in turn make future caregiving more feasible.[33,365,366] These repeated role transitions may influence health behaviours over time. These changes might be positive, such as increased physical activity or negative, such as increased smoking. Understanding these dynamics is important for identifying whether multiple caregiving episodes contribute to cumulative effects on health behaviours across the lifecourse.

It must be acknowledged that results from this thesis are based on a self-reported measure of physical activity that was dichotomised in line with definitions of adequate physical activity from the Chief Medical Officer for the UK.[181] Although this measurement is common in observational cohort studies, this comes with some limitations. Firstly, self-reported PA levels tend to correlate poorly with objectively measure PA levels especially for different demographics.[367] Secondly, the definition of PA from the IPAQ does not distinguish between different kind of physical activity such as occupational physical activity and leisure PA.[368] Consequently, it has been criticised for overestimating occupational PA.[369] Thirdly, in the physical activity questions of UKHLS, each occasion of PA had to be at least 10 minutes per occasion whereas new emerging evidence of pooled accelerometer data from six cohort studies found that even just a five minute increase in exercise-like PA was associated in improvements of systolic blood pressure.[370] Future longitudinal studies on physical activity in caregivers should consider using accelerometer data which is likely to become more mainstream and affordable over the next decade.

9.2.2 Smoking behaviour

Regarding smoking, findings from this thesis were fairly consistent. It was found that transitioning into caregiving was associated with higher probability of smoking while there was no association between cessation of caregiving and smoking behaviours. Higher intensity caregiving and recurrent caregiving were associated with higher odds of smoking. Hence, results from this thesis would support the hypothesis around maladaptive coping behaviours but do not support the hypothesis that caregiving creates teachable moments for behaviour change. Amng smokers, a transition into or out of caregiving was not associated with a change in the number of cigarettes they smoked.

Since UKHLS began in 2009, smoking rates have declined significantly, a trend consistent with broader research showing reductions in smoking prevalence in the UK due to policy interventions and shifting social attitudes.[371–373] Given this overall decline, the finding that caregivers had a higher probability of smoking raises the question of whether this association was primarily driven by increased smoking initiation, lower levels of smoking cessation, or a combination of both. A descriptive analysis of the propensity score-matched sample from Chapter 5 seen in Appendix 9.1 found that participants who transitioned into caregiving were more likely to continue smoking or start smoking but were a little less likely to quit smoking compared to those who remained non-caregivers ($p=0.003$). These findings suggest that transitioning into caregiving may not only serve as a stressor that triggers maladaptive coping mechanisms, such as smoking initiation, but also act as a barrier to smoking cessation. In this context, caregiving could reinforce existing smoking habits and reduce the likelihood of quitting, potentially due to increased stress, time constraints, or reduced access to cessation support.

A common explanation for higher smoking rates in caregivers is maladaptive coping mechanisms is response to burden or distress.[374,375] Psychological research suggests that psychological stress diminishes individuals self-control, leading to increased smoking behaviour as a means of coping.[376,377] Litzelman and colleagues[153] conducted a study with 1,483 cancer caregivers investigate coping style and its relation to health behaviours. They found that smoking in caregivers was associated with significantly higher score in, what was labelled as 'dysfunctional coping' compared to non-smokers. In this context, the classification of coping strategies as "dysfunctional" refers to their potential long-term ineffectiveness in addressing underlying stressors and their association with poorer health outcome. This suggest that smoking is associated with a tendency to engage in less effective coping strategies when dealing with stress or caregiver challenges.[153]

While transitioning into caregiving was associated with an increased probability of smoking, there was no association between exiting caregiving and smoking behaviours. This suggests that smoking behaviours persists even after caregiving ends. This may be because someone's smoking behaviour is influenced by multiple factors, including stress pathways, but the absence of distress does not necessarily lead to smoking cessation, as smoking is an addiction with physiological, psychological, and behavioural components.[378–380] Therefore, the finding that individuals who took on caregiving responsibilities were more likely to smoke, but did not become less likely to smoke after caregiving ends, has important public health implications. It highlights the need for targeted interventions that address both the stress-related drivers of smoking and the underlying mechanisms of nicotine dependence among caregivers. In addition, preventive efforts should focus on the early stages of the caregiving role to reduce the risk of smoking uptake before dependence develops.

That caregiving is associated with higher rates of smoking is consistent with some cross-sectional population-based studies from Spain and the USA.[86,94,96,99,100] In contrast, one population-based study from Australia found that caregiving was associated with lower odds of smoking while some[90] population-based cross-sectional studies from Spain, USA and Germany found no difference.[85,93,95] The evidence for longitudinal population-based studies is sparse and restricted to two studies of ageing which found that caregiving was associated with a decrease in smoking in a European sample, excluding the UK[104] or no difference in an Japanese study.[101]

This raises the question of why the associations observed in this study differ from findings in other population-based longitudinal studies. One possible explanation is the inclusion of younger participants, specifically those in early adulthood (16–29) and early mid-adulthood (30–49). The findings in this thesis suggest that age modified the relationship between transitioning into caregiving and smoking, with individuals aged 16–49 were more susceptible to an increased probability of smoking compared to those over 50. In contrast, no significant association was found between transitioning into caregiving and smoking probability in late mid-adulthood (50–64) or late adulthood (65+). This pattern aligns with findings from a large population-based cross-sectional study in Spain, which reported that caregiving was associated with smoking only among individuals aged 18–44, but not among caregivers aged 45 and older.[94] These results suggest that younger caregivers may be particularly vulnerable to smoking-related coping mechanisms, potentially due to differences in stress management, life-stage pressures, or access to cessation support.

9.2.3 Problematic drinking

In this thesis, it was found that transition into care was associated with slightly higher odds of problematic drinking for participants who transition into higher intensity care in early mid-adulthood (30-49) or lower intensity care in late adulthood (65+) in the fixed effect models, these findings could not be replicated in the piecewise growth curve models. In contrast, transitioning into higher-intensity caregiving was associated with a decreased probability of problematic drinking in the post-transition period. There was no association between caregiving exit and problematic drinking whereas high intensity caregiving inside the household and recurrent caregiving were associated with lower odds of problematic drinking.

This suggests a more complex relationship between caregiving and problematic drinking that is modified by the intensity of care provided. One possible explanation for these variations can be drawn from role theory. Caregivers may initially experience increased stress and challenges as they adjust to their new caregiving role at lower intensities of caregiving. This added stress in combination with sufficient time resources and enough opportunities might give low-intensity caregivers higher prospects to engage in problematic drinking as a coping mechanism. This aligns with numerous studies that have highlighted caregivers' elevated risk for problematic drinking behaviours, particularly when burden and emotional stress are high.[89,94,134,142,159,222]

In contrast, higher and more sustained caregiving demands could act as a deterrent to problematic drinking. This is because caregivers providing intensive care may need to remain consistently vigilant, reducing their opportunities for alcohol consumption. Additionally, high-intensity caregivers may experience fewer social interactions, further limiting social drinking opportunities.[96,125] These aspects of role theory could also explain why high-intensity caregiving was not associated with increased risk of problematic drinking but other coping mechanisms such as smoking.

Although the identified association make sense from a theoretical perspective, questions should be raised as to why findings are inconsistent with findings from population-based longitudinal studies from Europe[104] and Japan[101] which both found that that caregivers were at higher risk of heavy drinking[101] or that caregiving was associated with increase in alcoholic drinks.[104] Firstly, one should note that measures were different. The Japanese study by Tanigushi and colleagues[101] used a binary variable of heavy drinking that was defined as consuming more three drinks of Japanese sake (around 540ml) which is equivalent of 60g of ethanol or a comparable amount of alcohol per day whereas this threshold was halved for women. Besides, The European study by Hiyoshi and colleagues[104] assessed drinking habits by asking participants how often they consumed alcoholic beverages in the last three months. Participants who reported drinking less frequently than 'once or twice a week' were classified as non-regular drinkers while the remaining individuals were classified as 'regular drinkers'. In contrast, this thesis used the validated Audit-C tool which consists of three questions regarding drinks frequency, number of drinks per occasion and binge drinking frequency. This variation in measurements and definitions might explain variations in the results.

Another explanation of difference might be cultural differences. In Japan, the culture of alcohol consumption tends to embody a more collective approach, where social drinking is integral to both business and personal interactions, particularly among men. For women, however, drinking patterns are more varied and often shaped by different social norms and expectations, including family responsibilities and traditional gender roles.[381–383] Further, there are difference within Europe how alcohol is consumed and scholars have argued that in the UK alcohol is often consumed in a more harmful context such as binge drinking while Mediterranean countries tend to consume moderate levels of alcohol alongside food.[384–386]

Notably, the prevalence of problematic drinking in this study was relatively high at around 50% in some groups. This was despite using a cut-off for Audit-C scoring that were used in other studies who measured alcohol consumption in caregivers.[103,125,134] A comparative study using data from the UK Household Longitudinal Study (UKHLS) to examine differences in alcohol consumption between the US and UK found that, in the UK, 23% of adults consumed more than four drinks per week and 16.6% engaged in weekly heavy drinking episodes during the period following the COVID-19 pandemic. The study did not utilise the full AUDIT-C scoring system but instead analysed individual AUDIT-C questions separately.[387]

Nevertheless, the cut-points of 4 for men and 3 for women have been challenged in a recent cross-sectional multi-national study of the army population.[388] Authors of this study argued that the typical cut-off Audit-C scores heavily inflated the prevalence of problematic drinking among soldiers and veterans and they advocate for higher cut-off points for men and women.[388] Future studies should investigate the most suitable cut-points to detect problematic drinking within the UK adult caregiving and non-caregiving population.

However, it should be noted that not all findings from the current study differed from those reported in the cohort studies conducted in Europe[104] and Japan.[101] Specifically, results from the fixed-effect models demonstrated some alignment with these studies. Furthermore, other analyses presented in this thesis, such as trajectories of caregiving intensity and recurrent caregiving, investigated aspects not addressed in either the European[104] or Japanese[101] cohort studies.

9.2.4 Fruit and vegetable consumption

In this thesis, there was no evidence that entering or exiting caregiving was associated with fruit and vegetable intake while high intensity caregiving inside the household was associated with lower fruit and vegetable consumption and recurrent caregiving was associated with higher fruit and vegetable consumption. The magnitude of the effect observed for fruit and vegetable consumption was relatively small, raising the question of whether these differences are strong enough to substantially influence caregiving policy or intervention strategies. While statistical associations were found, the actual differences in fruit and vegetable consumption between caregivers and non-caregivers were minimal.

In this thesis, fruit and vegetable consumption was treated as a continuous variable. This was possible because fruit and vegetable consumption approximated normal distribution and did not have excess zeroes which suggests minimal censoring to the left. Some studies used non-daily fruit and vegetable consumption as cut-point for a dichotomous variable[104,122] but this would not have been appropriate in this sample because the prevalence of non-daily fruit and vegetable consumption was only around 1% in this sample. It would have been possible to use the definition of fruit and vegetable consumption by the WHO which recommends at least five portions of fruits and/or vegetables per day. However, it was seen as the superior approach to retain and analyse fruit and vegetable consumption on continuous scale.

This raises the question whether there are truly no differences in fruit and vegetable consumption between caregivers and non-caregivers, or whether dietary habits are particularly difficult to measure accurately. Dietary reporting is often prone to social desirability bias and recall errors, which may obscure small but meaningful changes in consumption patterns[389,390]. While diet diaries are often considered the standard method, they are time-consuming and can place a considerable burden on respondents.[391] More objective measures, such as dietary biomarkers (e.g. blood or urine assays for nutrient levels)[392] should be considered for capturing differences in dietary patterns between caregivers and non-caregivers.[167,393]

The conceptual framework hypothesised several pathways linking caregiving with dietary health. Due to increased time demands, perceived stress, and the hidden costs of caregiving,[394] caregivers may have fewer resources and less opportunity to prepare healthy meals containing fruit and vegetables.[87,122,395] Chronic stress and emotional strain can further promote emotional or comfort eating as coping mechanisms.[74,396] Conversely, caregiving can sometimes create 'teachable moments,' such as when caregivers witness the direct impact of diet-related health conditions in the care recipient,[152,259,397] for example managing diabetes. These experiences can prompt caregivers to actively seek improvements in their own diets,[398] such as increasing fruit and vegetable intake or reducing high-fat and processed foods, as a preventive measure for both themselves and their care recipient. Thus, capturing changes in fast food or comfort eating might best reflect dietary deterioration related to stress and time constraints, while changes in fruit and vegetable consumption could better indicate deliberate improvements or healthier eating motivated by caregiving responsibilities.

This raises the question of whether fruit and vegetable consumption was a suitable measure to capture dietary changes arising from distress and limited resources. Nevertheless, fruit and vegetable intake was frequently been used as an indicator of dietary quality in previous caregiving studies[85,93,94,100,103,104,122,142,152,158] and was readily available within the nutrition module of the UKHLS dataset. However, future caregiving research should consider additionally assessing unhealthy eating habits, such as the frequency of fast-food consumption or snacking, to better reflect stress-induced or resource-limited dietary patterns.

When comparing results from this thesis with other studies that measured fruit and vegetable consumption, some differences emerge. Cross-sectional studies have frequently reported that caregiving was associated with lower fruit and vegetable consumption compared to non-caregivers[85,103,122,158] while some cross-sectional population-based studies found that lower intensity caregiving was associated with higher odds of fruit and vegetable consumption.[93,94] Only one population-based study with a European sample investigated dietary patterns of caregivers longitudinally which found that non-daily fruit and vegetable increased in men who became caregivers compared to men who remained non-caregivers.[104] However, it must be considered that this study was restricted ton adults aged 50 years and older and was limited to a measure of non-daily fruit and vegetable consumption.[104]

9.2.5 Role of care characteristics

The work of this thesis found that caregiving characteristics modified the relationship between caregiving and health behaviours. It was found that the hours of care and also the place of care were indicators of caregiving intensity, with participants who reported higher hours in caregiving or reporting caregiving inside the household were considered as higher intensity categories. Hence, caregivers were found to be a heterogenous group and associations for low-intensity caregivers and high-intensity caregivers differed. In particular, higher intensity caregiving was associated with lower physical activity, higher smoking rates but less problematic drinking while lower intensity caregiving was associated with more physical activity.

This supports evidence that low-intensity caregiving may have beneficial effects on health, whereas high-intensity caregiving could be detrimental. This could be explained by role enhancement and role strain theories. Role enhancement theory states that caregivers can derive personal growth and fulfilment from their roles, particularly when they feel a sense of agency and choice in their caregiving activities[399,400] with low-intensity caregiving may provide purpose, social connection, and moderate physical activity, all of which contribute to better health and well-being.[401] This is because when caregiving demands are relatively low, individuals are more likely to retain a sense of autonomy and balance with other life roles, enabling them to engage in activities that support good health, such as regular exercise, healthy eating, and maintaining social connections. In this way, the responsibilities associated with low-intensity caregiving can act as a source of purpose and social integration, which in turn may help sustain beneficial health behaviours.[258,402]

In contrast, the role strain hypothesis suggests that high-intensity caregiving may diminish the opportunity and motivation to engage in such behaviours. High-intensity caregiving often entails substantial emotional strain, significant time constraints, and heavy physical demands, which can increase stress and the risk of role overload.[278,403] These pressures can limit available time, physical energy, and mental capacity for self-care, while reducing motivation to maintain healthy routines, ultimately leading to poorer diet, reduced physical activity, or trigger adverse health behaviours like smoking and alcohol consumption..[355,404–406]

This aligns with existing literature on unpaid work, such as volunteering, which has been shown to follow a reversed U-shaped relationship with health outcomes.[407–409] In this research, low-to-moderate engagement in unpaid roles provided social, emotional, and cognitive benefits, whereas excessive involvement leads to role overload, stress, and negative health effects.[409] In the case of volunteering, research has found that moderate engagement enhances well-being by fostering social integration and a sense of purpose,[410,411] but excessive volunteering can become burdensome, particularly for individuals with other competing responsibilities.[412,413] It is possible that similar pathways could explain difference between low- and high-intensity caregivers although it must be acknowledged that while volunteering and caregiving are both forms of unpaid work, they fulfil different societal and personal needs which influence the perspective and experience of those engaged with them.[138,139]

Thus, these findings reinforce the idea that the intensity and demands of unpaid roles, such as caregiving, are crucial determinants of whether such roles enhance or harm health. Policies and interventions should therefore focus on supporting caregivers to maintain sustainable caregiving roles, mitigating the adverse effects of high-intensity caregiving, and promoting moderate engagement in unpaid activities for optimal well-being. However, this makes it problematic to conceptualise caregiving as a binary variable because caregivers are not a homogenous group.

An interesting finding from the latent class analysis in Chapter 7, which examined caregiving intensity and changes in health behaviours, was that providing care inside the household was associated with negative health behaviour changes, and this was observed not only among those with high care hours but also among those with medium and low care hours. For example, even caregivers in classes characterised by low-intensity care inside the household had higher odds of physical inactivity, higher odds of smoking and lower odds of problematic drinking compared to those providing low-intensity care outside the household. This may suggest that caregivers inside the household underestimate their time spent caregiving or caregiving inside the household comes with additional burden due to the need to remain vigilant to the care-recipient's needs.[414,415] This is consistent with a Swedish study that identified that particularly female caregivers underestimated their time spend caring for someone within the household.[416] This highlights the unique challenges of caregiving inside the household, where the blurred boundaries between caregiving and daily life may contribute to both underreporting of caregiving hours and increased strain which ultimately shapes their experience in ways that differ from those providing care outside the household.

For caregivers providing intensive support of more than 35 hours per week, the UK government offers financial assistance through Carer's Allowance, a non-contributory benefit established in 1976. To qualify, caregivers must be over 16, spend at least 35 hours weekly caring for someone receiving specific disability benefits, and meet certain income and residency criteria.[417] As of April 2025, the allowance is £83.30 per week.[418] However, results from this thesis suggest that changes in health behaviour due to caregiving already occur even if less than 35 hours of care are provided. This is supported by other studies which found that caregivers providing 10 to 20 hours of care per week experience significant deterioration of their physical and mental health.[17,419] Given these findings, it is recommended that the UK government reevaluate the eligibility threshold for Carer's Allowance to support caregivers providing fewer than 35 hours of care per week. Lowering the threshold could offer necessary financial assistance to a broader range of caregivers, potentially mitigating adverse health outcomes and acknowledging the substantial impact of caregiving responsibilities on individuals' well-being.

This thesis could be criticised for not investigating more variables in relation of the care characteristics such as the care tasks provided, care-recipient characteristics or the relationship between caregiver and care recipient. The focus of this thesis was on hours and place of care because this information was available for both caregivers inside as well as outside the household. With regard to the relationship between caregiver and care recipient, it was not an emerging theme in the literature review from Chapter 2 that the relationship type was a strong predictor of health behaviours. The quality of the relationship and the level of reciprocity between caregiver and care recipient tend to be more important than the actual relationship types. Studies have highlighted that higher quality interactions between caregiver and recipient that are characterised by mutual support and understanding, are linked to lower perceived stress and caregiving burden.[420,421] Evidence also emphasises the influence of reciprocity on caregiver wellbeing. Caregivers who feel that their contributions are recognised and appreciated often report better mental health outcomes and greater satisfaction with their role.[422–424] Therefore, studies investigating the relationship between caregiver and care-recipient in relation to health behaviours should consider measuring the quality aspects of the relationship or reciprocity rather than the relationship type.

9.2.6 Role of sex

It was found in this thesis that male caregivers showed generally worse health behaviours than female caregivers apart from physical activity. While male caregivers were more physically active, they tended to eat fewer fruit and vegetables, had higher probabilities of problematic drinking and higher rates of smoking compared to female caregivers. These patterns are consistent with broader population-level gender differences in health behaviours, where men typically have higher levels of physical activity but less healthy dietary patterns and greater engagement in risky health behaviours such as smoking and excessive alcohol consumption compared to women.[425–427] However, not much statistical evidence could be found that would support the hypothesis that sex modifies the relationship between caregiving transition and health behaviours. This might be seen as a surprising finding given that woman in this study engaged more often higher intensity caregiving.

In this thesis, most sex-differences could be found when examining caregiving trajectories and multiple transitions in Chapter 8. In this particular analysis, males were more physically inactive when providing long-term care compared to male non-caregivers while female caregivers who provided long-term care were more physically active compared to female non-caregivers. A speculative explanation might be that men, who are generally more physical active compared to women,[428,429] lose opportunities to engage in physical activity due to their long-term care commitments. In contrast, females might be more likely to engage in physical activity as a form of respite from caregiving as studies found that women are more likely to access respite services compared to men.[430]

Further, one contrasting finding revealed lower odds of smoking in men but higher odds of smoking in women when providing long-term care compared to non-caregivers of the same sex. This might support the hypothesis that male and female participants develop generally different coping mechanism in response to caregiving. However, fewer studies explore caregiving from a male perspective. A scoping review by Robinson and colleagues[43] investigated empirical research on men as unpaid caregivers of people with dementia. They found that male caregivers often associated their role with traditional masculine traits, such as being a provider or protector. The authors argue that many men took a task-focused, problem-solving approach to caregiving, reinforcing ideals of strength and control. This helped them manage their responsibilities while maintaining their sense of control. To cope with challenges, men tended to suppress emotional responses and preferred discussing their experiences with others in similar caregiving roles rather than with peers who had not shared the same experience.[43]

In contrast, the literature suggests that women adopt different coping styles and that they prefer emotion-orientated coping methods.[431,432] One strategy is described as seeking social support. Such support networks provide practical assistance, emotional understanding and shared experiences to mitigate feeling of isolation and stress.[433] Therefore, differences in coping styles may help explain sex differences in health behaviours observed across studies. While this thesis found fewer sex differences, future research should aim to adjust for sex, stratify analyses accordingly, or test for interactions to better understand potential variations.

The lack of sex-difference contrast with other population-based longitudinal studies which, in fact, identified differences between caregiving women and men. The European study, using the SHARE data set, led by Hiyoshi and colleagues[104] found that caregiving inside the household was associated with non-daily fruit and vegetable consumption for men but not for women. Besides, caregiving outside the household was associated with an increase in problematic drinking and an increase in physical activity for men but not for women.[104] Further, the study by Taniguchi and colleagues[101] reported that caregiving 20 hours of more care per week was associated with lack of exercise in women but not in men. It was also observed that men were more likely to be heavy drinkers if they provided less intense care while they had higher odds of smoking when they provided more intense care.[101] However, this in contrast to results from this thesis which could not find any evidence that caregiving intensity trajectories were modified by sex.

The nature of the relationship between sex, caregiving and health behaviours is likely influenced by gender role stereotypes, cultural norms around caregiving and the way health behaviours are expressed. Cultural and social constructs often place women in caregiving roles.[44,434] Although societal norms evolve and there is a shift in cultural opinion regarding gender roles, traditional gender roles seem to persist.[38,435] This might be one of the reasons that caregiving research often focuses on female caregivers which is evident from some studies who used a female only sample in their study.[108,109,112,117,118,123,124] For this reason, it is not surprising that findings across samples and nations might differ and each study has to be viewed within their cultural context and the characteristics of the sample.

However, it is important to acknowledge that in this thesis, sex was conceptualised as a binary construct, shaped by prevailing gender norms and societal roles. A key limitation is the exclusion of non-binary perspectives, which were not explored in this thesis.

9.2.7 Role of lifecourse stage of caregiving

This thesis found that the lifecourse stage at which caregiving occurs influences caregivers' health behaviours in various ways. The association between caregiving transitions and physical activity was most pronounced in later adulthood (65+), where transitioning into caregiving was linked to increased physical activity, while exiting caregiving was associated with decreased physical activity. Problematic drinking declined most notably among those who took on high-intensity caregiving after age 65, whereas exiting caregiving was linked to reduced problematic drinking in late mid-adulthood (50–64). Smoking was more prevalent among caregivers in early and early mid-adulthood (16-29 and 30-49, respectively). No evidence suggested that the effect of caregiving intensity on health behaviours varied by lifecourse stage. Lastly, caregiving transitions were associated with lower fruit and vegetable consumption in early adulthood, while some older age groups exhibited higher consumption, though not all results were statistically significant.

This can be explained with lifecourse theory and the fact that caregiving likely affects people differently at each lifecourse stage.[25,436] One explanation lies in the fact that unpaid caregiving in later life might be seen as more normative compared to unpaid caregiving in early life. Lifecourse theory argues that non-normative, unexpected and undesired transitions are more stressful than desired or normative lifecourse transitions such as becoming a parent.[437–439]

Caregiving in earlier adulthood might have a profound impact in a caregiver's ability to engage in education and the employment market. Early caregiving roles frequently impose significant constraints on the educational attainment and employment opportunities.[439] In the UK context, longitudinal population-based studies have found that caregiving in early adulthood was associated with a lower likelihood of obtaining a degree or entering employment market compared to non-caregivers of the same age[440] and that caregiving in early adulthood has been associated with a decrease in the number of friends.[441] In early mid-adulthood, many individuals begin raising a family and research has shown that simultaneously providing both childcare and elder care can have a negative impact on physical and mental health.[419]

In contrast, caregiving in later life has been associated with health benefits. Scholars have argued that the better health in older caregivers could be explained by reverse causation, or the "healthy caregiver" effect, whereby those in better health are more likely to take on or continue in caregiving roles.[258] While the healthy caregiver effect is supported in some areas such as cognitive function[225,442] and mortality,[226] but findings are inconsistent across other health domains and populations.[11,258] Healthier individuals may self-select into caregiving, so causality remains uncertain.

Another possible explanation is that retirement may facilitate positive outcomes by reducing competing demands and enabling engagement in meaningful roles that enhance health and well-being.[443,444] Further, it has been argued that caregiving can trigger stimulating cognitive engagement which is vital for maintaining mental health and preventing age-related cognitive decline.[257,445] However, this is challenged by other evidence which suggests that caregiving burden in later life might exacerbate existing health problems of the ageing caregivers.[446,447] It can be concluded that the impact of caregiving varies depending on the caregiver's stage in the lifecourse, which may also help explain differences in health behaviours across age groups.

It is difficult to compare results with other longitudinal studies because the only other known population-based longitudinal studies of caregiving and health behaviours were on participants aged 50 or older.[101,104] However, results from this thesis are in line with other cross-sectional population-based studies that stratified by age group. For example, younger caregivers (≤45) were more likely to engage in risky behaviours, such as hazardous alcohol consumption[103] and smoking among young men.[94] In contrast, older caregivers (≥65) showed healthier behaviours, including lower smoking rates.[96] Physical activity patterns also varied, with younger caregivers sometimes being more active than non-caregivers[94] though this advantage diminishes with age.[96] Alcohol consumption trends are mixed, with older caregivers generally drinking less,[103] though some studies suggest higher intake compared to non-caregivers.[94] Caregiving in later life is also linked to better dietary habits.[94]

These findings suggest caregiving impacts health behaviours differently by age, with younger caregivers exhibiting more risks and older caregivers adopting healthier habits. This is supported by studies that focus on caregivers in early adulthood. A population-based US study of adults aged 18-25 found that caregivers had a higher smoking prevalence compared to non-caregivers but that there was no difference[97] Besides, a study of school-aged adolescence (10-18 years) found that caregiving in adolescence was associated with an unbalanced diet but they were no differences found regarding physical activity between caregiving and non-caregiving youth.[84]

While there were no population-based longitudinal studies that investigate caregiving and health behaviours in people below the age of 50, studies which investigated physical and mental health outcomes in young caregivers highlight the disproportionate burden of caregiving on people in youth, early adulthood and early midlife. A systematic review by Lacey and colleagues found that caregiving in early life was associated with the worse mental and physical outcomes.[448] More recently, evidence from the UK suggests that caregiving in early adulthood was associated with lower life satisfaction as well as worsening physical and mental health trajectories.[441,449]

9.3 Strengths and Limitations

9.3.1 Limitations

In this thesis, methodological limitations have been discussed in each analytical chapter and specific limitations of the measures have been discussed in the discussion sections above. Therefore, this section will focus on the general limitations and strengths of the findings from this thesis.

The findings from this thesis have several limitations. Firstly, while the specific limitations of each health behaviour measure have been discussed in the synthesis above, all measures share a common limitation: they rely on self-reported data provided by participants. Although this limitation is common in large, longitudinal, population-based studies, it must be acknowledged that self-reports may introduce measurement bias related to social desirability, inaccurate reporting, and recall errors. Consequently, the potential for these biases should be considered when interpreting the findings.

Second, caregiving was measured using ‘objective indicators’ such as caregiving hours and place of caregiving. Although these measures represent quantifiable features of the caregiving experience and provide standardised, comparable data, they still rely on participants' self-reports. Therefore, they are not objective and may be influenced by individual interpretations of caregiving intensity and setting, as well as recall bias and social desirability. It must be acknowledged that these measures of caregiving intensity do not capture the subjective experience of caregiving such as the quality aspects of caregiving, reciprocity, and the perceived rewards from caregiving. Therefore, whilst these measures offer valuable insights into caregiving activities, their limitations must be acknowledged when interpreting the findings.

Third, the findings presented in this thesis are based exclusively on participants from the UK, limiting the generalisability to caregiving populations in other countries or contexts. Caregiving is a unique experience, strongly shaped by cultural norms, social expectations, and the structure of welfare and support systems, all of which vary significantly across different settings. Therefore, caution should be exercised in extending these findings beyond the UK context, as differences in these determinants may substantially influence caregiving experiences and associated health behaviours.

Fourth, as with other longitudinal studies, panel conditioning might be an important methodological consideration when interpreting findings from this thesis on caregiving and health behaviours. It occurs when repeated participation in surveys influences participants' responses or behaviours over time. For example, caregivers may become increasingly reflective or self-aware regarding their health behaviours, such as physical activity, fruit and vegetable consumption, drinking and smoking, potentially altering these behaviours simply due to ongoing assessment. Additionally, repeated assessments can contribute to survey fatigue, which may result in careless responses or dropout. Attrition related to panel conditioning can bias findings, particularly if those who continue in the study systematically differ from those who drop out. Although all analyses presented in this thesis are longitudinal, it was not possible to fully account for participant attrition in every instance. Specifically, in Chapter 5 (Entering caregiving) and Chapter 6 (Exiting caregiving), a propensity score-matched sample was utilised, resulting in a sample no longer representative of the original population and thus rendering the use of weights inappropriate. Conversely, in Chapter 7 (Intensity change) and Chapter 8 (Multiple transitions), baseline weights were applied, and the rationale for this choice was thoroughly outlined in Chapter 7. Nevertheless, it must be acknowledged that even this approach does not completely address attrition, potentially introducing bias and limiting the generalisability of the findings.

Fifth, although studies from this thesis utilised a large population-based samples, certain subgroups, such as caregivers in early adulthood or, may have been underpowered to detect statistically significant differences. This limitation is likely attributable to the relatively small magnitude of associations with health behaviours within these groups, which reduces the likelihood of achieving statistical significance despite consistent patterns observed in the overall sample.

Lastly, despite employing analytical methods commonly applied in causal inference research, this study remains observational in nature. Consequently, causal relationships cannot be assumed from the findings presented. Additionally, although efforts were made to control for potential confounders through techniques such as propensity score matching, residual confounding due to unmeasured or inadequately measured factors may still persist. Thus, caution is necessary when interpreting associations identified in this thesis, as they do not necessarily indicate causation.

9.3.2 Strengths

Despite these limitations, this thesis has several notable strengths that enhance the validity, reliability and originality of its findings. Firstly, to the author's knowledge, this study represents the first longitudinal analysis of caregiving and health behaviours focusing specifically on individuals in early adulthood and early mid-adulthood. Moreover, it is the first population-based study conducted in the UK investigating how transitions of unpaid caregiving influence health behaviours which addressed a substantial gap in the literature.

Secondly, the robustness and novelty of the findings are underpinned by the application of advanced quantitative methods. Techniques such as propensity score matching and latent class analysis were employed to control for selection bias and identify distinct caregiving patterns. Additionally, substantial efforts were made to reduce bias further by carefully adjusting for confounders identified through directed acyclic graphs (DAGs) and triangulating results to ensure consistency and reliability.

Thirdly, this research adopted a comprehensive approach by explicitly incorporating a lifecourse perspective. This methodological choice enabled a nuanced exploration of caregiving, highlighting critical variations by sex, life stage at caregiving onset, and their intersectionality. As such, the analysis provides deeper insights into how caregiving responsibilities might differently affect health behaviours depending on individual characteristics and timing within the lifecourse.

Finally, a notable strength of this thesis is its innovative consideration of diverse caregiving transitions beyond the commonly examined initiation of caregiving. By systematically investigating transitions such as exiting caregiving roles, changes in caregiving intensity, and multiple caregiving transitions, the research offers a richer, more holistic understanding of the caregiving experience. This broader perspective significantly advances current knowledge, providing valuable insights for both researchers and policymakers seeking to address the complex dynamics between caregiving and health behaviours.

9.4 Policy Implications

Findings from this thesis have several implications and recommendations for policy. Firstly, interventions which target individual behaviour change for unpaid caregivers should include targeted smoking cessation interventions because caregiving was associated with an increased likelihood of smoking but not cessation. Interventions that target physical activity of caregiver should not only focus to increase leisure physical activity in caregivers but also provide training to caregivers how to engage in occupational physical activity such as manual handling to minimise the risk of harmful physical activity from caregiving.

Secondly, systems support should be targeted towards caregivers who provide higher hours of care and those who provide care within the household. It should be the aim of the system of support to provide temporary relief from competing family roles and responsibilities in the form of respite care[450,451] and offering flexible working schemes[452–454]. Besides, longer-term and more sustained forms of support are equally necessary. These may include accessible formal care services, financial support, and workplace policies that enable caregivers to balance their responsibilities more effectively.[322,455,456] Evidence from the European studies indicates that countries with robust state support tend to have higher rates of participation in unpaid caregiving. However, caregivers in these countries typically provide fewer hours of care and experience fewer negative health impacts.[195,457–459] This is consistent with the findings of this thesis, which show that high-intensity caregiving is associated with poorer health behaviours. Therefore, policies that enable individuals to provide care at lower levels of intensity should be prioritised.

Third, the government should consider decreasing the ‘35 hour per week threshold’ to qualify for Carer’s Allowance because findings from this thesis suggest that caregiving influences health even below the 35 hours threshold required to qualify for financial support from the government. The government should also commission or fund research that aims to identify policy solution for the challenges unpaid caregivers face.

Fourth, it was found in this thesis that transitioning multiple times into caregiving is relatively common among caregivers. Therefore, the policy framework should recognise and address the phenomenon of multiple caregiving transitions across the lifecourse. Repeatedly transitioning into and out of caregiving roles not only affects individual health but also has wider socio-economic implications.[44,460] These transitions influence how individuals establish themselves within society, shape their career progression, affect their capacity to accumulate wealth over time, and impact their own decisions about starting a family. Recognising these broader impacts in policy would help ensure caregivers receive adequate support, protecting their long-term social and economic wellbeing.

Fifth, caregiving during early adulthood and mid-adulthood demonstrated the strongest association with changes in negative health behaviours. This finding underscores the importance of developing robust mechanisms for identifying caregivers at these critical life stages. Early identification would enable the timely provision of targeted training, practical advice, and support strategies to help caregivers balance their caregiving responsibilities with other competing demands, such as family obligations and paid employment.[17,461] Proactive interventions during these stages could not only mitigate potential negative health outcomes but also support sustained participation in the workforce and overall wellbeing throughout the lifecourse.

9.5 Methodological implications

Findings from this thesis highlight the challenges of accurately capturing changes in health behaviours in large longitudinal studies that are prone to desirability and reporting bias, such as physical activity, fruit and vegetable consumption and problematic drinking. However, as technologies are evolving and becoming more affordable, designers of longitudinal studies should consider including objective measures such as data from accelerometers (e.g. smart watches) and biomarkers (e.g. glucose, cholesterol, triglycerides).[462–464]

If the application of objective measures is not feasible, designer of longitudinal studies should consider better distinguishing between leisure time physical activity and occupational physical activity. For healthy eating, researchers should consider alternative ways to measure diet in caregivers and their controls. For example, measuring fast food intake or snacking frequency might be more suitable to measure changes in caregivers' diet that may be related to the stress pathways.

When conducting quantitative research on caregiving, researchers should be aware of the heterogeneity among caregivers and that the variations in intensity, duration and place of care complicate the analysis. Therefore, using binary caregiving variables is not ideal in all scenarios and all analyses. Future research should take advantage of advanced methodological tools that allow for a finer distinction between different caregiving trajectories such as latent class analysis or sequence analysis.

Further, findings from this thesis highlight that caregivers below the age of 50 constitute a substantial yet often overlooked cohort. Therefore, longitudinal studies focusing on early life and early adulthood should systematically incorporate questions about unpaid caregiving roles. Integrating caregiving data into such studies would enable researchers to accurately capture and evaluate the short- and long-term impacts of caregiving during these formative life stages, facilitating meaningful comparisons across different cohorts. This enhanced understanding could subsequently inform targeted policy interventions and resource allocation to better support younger caregivers.

Lastly, longitudinal studies should consider incorporating not only objective indicators of caregiving, such as the number of caregiving hours provided, specific caregiving tasks performed, and the place of care, but also subjective indicators. These subjective measures should include perceived rewards from caregiving, the sense of reciprocity within the caregiving relationship, and the overall quality of the relationship between caregiver and care recipient. Incorporating these dimensions would provide a more comprehensive understanding of the caregiving experience, highlighting not just the burdens but also the emotional and relational factors that influence caregiver wellbeing and outcomes over time.

9.6 Future research directions

While this thesis provided important insights into caregiving transitions and associated health behaviours, stratified by caregiving intensity, sex, and lifecourse stage of caregiving, further subgroup analyses are necessary. Future research should specifically explore caregiving transitions in relation to socioeconomic position, ethnicity, and engagement in paid employment. Conducting detailed subgroup analyses based on these characteristics would reveal additional layers of intersectionality and help to identify whether specific groups of caregivers face heightened vulnerabilities or distinct protective factors. Such research would ultimately facilitate the development of targeted interventions and policies that effectively address inequalities within caregiving populations.

Additionally, developing research that models and evaluates different policy solutions would be valuable. For instance, future research should employ simulation methods to identify optimal eligibility thresholds for caregiving allowances. Such simulations would enable policymakers to better understand the potential economic and social impacts of varying thresholds, helping ensure that allowances effectively target caregivers most in need of support. This approach would contribute to more evidence-informed policymaking, ultimately enhancing both the efficiency and fairness of caregiving support systems.

In addition, conducting cross-national comparisons would allow researchers to explore how societal norms and differing policy contexts influence the relationship between caregiving and health behaviours. By comparing caregiving experiences across countries with diverse cultural attitudes towards caregiving, varying welfare structures, and different policy provisions, researchers could gain deeper insights into the role these contextual factors play. Such comparisons would facilitate the identification of best practices and effective policy interventions, ultimately informing more contextually sensitive strategies to support caregivers internationally.

Further research is needed to clarify whether the observed increase in physical activity among caregivers is primarily driven by leisure-time physical activity or occupational-related physical activity. Additionally, it is important to investigate whether these changes in physical activity translate into tangible improvements in caregivers' physical health outcomes. Longitudinal structural equation modelling or other advanced mediation analysis methods would be particularly suitable approaches for addressing these questions, as they allow researchers to disentangle the pathways linking caregiving, physical activity behaviours, and subsequent physical health. Such analyses would significantly enhance understanding of the mechanisms behind health behaviour changes observed in caregivers.

More research is needed to fully understand the impact of caregiving undertaken during early life and early adulthood, periods which are critical for personal, social, and economic development. Investigating caregiving in these stages could reveal long-term implications for mental and physical health, educational attainment, career trajectories, and family formation. Such research would contribute significantly to identifying vulnerable groups and periods, informing targeted interventions, and shaping policies that provide adequate support to young caregivers during these formative years.

Future research should focus on qualitative research to gain a better understanding of the possible pathways and mechanisms between caregiving and health behaviours in the UK context. For example, qualitative research could explore why high intensity caregivers were less likely to be problematic drinkers. This would help to inform and strengthen health behaviour theory within caregiving.

Lastly, while this thesis attempted to capture multiple caregiving transitions, the best way to measure multiple caregiving transition throughout the lifecourse remains an understudied area and more research is needed to gain a better understanding on the lifecourse associations of individuals who transition several times into caregiving throughout their life.

9.7 Conclusion

This thesis aimed to investigate the relationship between unpaid caregiving transitions and health behaviours across the lifecourse. Utilising comprehensive data from the UK Household Longitudinal Study, the research applied advanced quantitative methods, including propensity score matching, piecewise growth curve models, and latent class analysis. The findings reveal a complex picture, demonstrating that caregiving transitions are linked with both positive and negative changes in health behaviours, influenced by factors such as the type of caregiving transition, caregiving intensity, and the lifecourse stage at which caregiving occurs.

Among positive health behaviour changes, transition into caregiving was associated with increased physical activity, although further research is necessary to clarify if this change translates to better health in the caregiver. Conversely, fruit and vegetable consumption showed minimal or no significant associations with caregiving transitions. It is possible that measuring fruit and vegetable intake was not the most suitable measure to capture changes in diet, highlighting a need for additional research into dietary impacts within caregiving contexts.

Regarding alcohol consumption, while it was inconclusive whether transitioning into caregiving was associated with higher odds of problematic drinking, findings across chapters consistently indicated that higher-intensity caregiving was linked with reduced problematic drinking. While seemingly beneficial, this may reflect increased caregiving responsibilities and the associated necessity for heightened vigilance rather than a purely positive health outcome. However, more research is needed to understand the presence of this association fully.

In contrast, smoking behaviours consistently emerged as a concern, with caregiving transitions associated with a higher likelihood of smoking. This finding carries significant implications for designing targeted public health interventions aimed at promoting smoking cessation among caregivers.

Efforts to positively influence caregivers' health behaviours should extend beyond individual-level interventions, encompassing systemic changes, such as improved access to supportive resources, flexible working arrangements, and financial assistance for caregivers providing varying levels of care intensity.

Overall, this thesis contributes original insights into the relationship between unpaid caregiving and health behaviours from a lifecourse perspective, particularly highlighting caregiving during early adulthood and early mid-adulthood. By addressing these under-researched life stages within the UK context, this research closes significant gaps in the existing literature and offers valuable directions for future studies and policy interventions.

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Appendices

Table of content for appendix

List of tables for appendix

List of figures for appendix

Appendix Chapter 2: Literature review

Appendix 2.1: Search terms and Data base

CINAHL

***Concept of informal caregiving with proximation N3**

S1: TI (((informal or unpaid or families or family or relative* or spouse* or elder*) N3 ("care giv*" OR caregiv* or caregiver* or carer*))) OR AB (((informal or unpaid or families or family or relative* or spouse* or elder*) N3 ("care giv*" or caregiv* or caregiver* or carer*))) // 4371

***global search term for health behaviour**

S2: (TI ((“Health behavio*” or “Health promot*” or “health-related behavio*” or “health risk* behavio*”)) OR AB ((“Health behavio*” or “Health promot*” or “health-related behavio*” or “health risk* behavio*”)) OR ((MH "Health Behavior") OR (MH "Health Promoting Behavior (Iowa NOC)") OR (MH "Health Behavior (Iowa NOC)") OR (MH "Health Knowledge and Behavior (Iowa NOC)")) **// 13,140 results**

***individual health behaviours**

S3: (MH "Physical Activity") OR TI (physical n1 activ* OR exercise* OR leisure N1 activ* OR physical N1 inactive*) OR AB (physical n1 activ* OR exercise* OR leisure N1 activ** OR physical N1 inactive*)**OR**((MH "") OR (MH "Nutrition")) OR (TI (diet OR nutrition OR fruit N2 vegetable intake OR soda N2 intake OR "fast food" N2 intake OR sugar N2 intake) OR AB (diet OR nutrition OR fruit N2 vegetable intake OR soda N2 intake OR "fast food" N2 intake OR sugar N2 intake))**OR**((MH "Smoking") OR (MH "Electronic Cigarettes") OR (MH "Tobacco Products") OR (MH "Tobacco")) OR (TI (smok* OR tobacco OR cigarett* OR nicotine OR vape OR vaping) OR AB (smok* OR tobacco OR cigarett* OR nicotine OR vape OR vaping)) **OR** (MH "Alcohol Drinking") OR TI ((alcohol* OR drink*) AND (abuse OR misuse OR consum* OR intake)) OR AB ((alcohol* OR drink*) AND (abuse OR misuse OR consum* OR intake)) **OR** (MH "Sleep") OR (TI (sleep* AND (quality OR length OR disturb* OR duration OR habit* OR behavio* OR hour*)) OR AB (sleep* AND (quality OR length OR disturb* OR duration OR habit* OR behavio* OR hour*))) // 77,508

***combined global term and individual health behaviours**

S4: S2 OR S3 // 85,337

***combined with AND: informal caregiving plus health behaviour outcomes**

S5: S1 AND S4

S6 restricted to published between 2002 and 2025 and English language

Medline + Embase + Psychinfo (Ovid)

1 ((informal or unpaid or families or family or relative* or spouse* or elder*) adj4 ("care giv*" or caregiv* or caregiver* or carer*)).tw.

2 ("health behavio*" or "health promot*" or "health-related behavio*" or "health risk* behavio*").tw.

3 ((physical adj2 activ*) or exercise* or (leisure adj2 activ*) or (physical adj2 inactive*)).tw.

4 (diet or nutrition or (fruit adj2 vegetable intake) or (soda adj3 intake) or ("fast food" adj3 intake) or (sugar adj3 intake)).tw.

5 (smok* or tobacco or cigarett* or nicotine or vape or vaping).tw.

6 ((alcohol* or drink*) and (abuse or misuse or consum* or intake)).tw.

7 2 or 3 or 4 or 5 or 6

8 1 and 7

9 limit to English language

10 limit 9 to dt=20220903-20250223

Web of Science

1: (TI=(((informal OR unpaid OR families OR family OR relative* OR spouse* OR elder*) NEAR/4 ("care giv*" OR caregiv* OR caregiver* OR carer*))) OR AB=(((informal OR unpaid OR families OR family OR relative* OR spouse* OR elder*) NEAR/4 ("care giv*" OR caregiv* OR caregiver* OR carer*)))

2: (TI=(("health behavio*" OR "health promot*" OR "health-related behavio*" OR "health risk* behavio*"))) OR AB=(("health behavio*" OR "health prompt*" OR "health-related behavio*" OR "health risk* behavio*"))

3: (TI=(((physical NEAR/2 activ*) OR exercise* OR (leisure NEAR/2 activ*) OR (physical NEAR/2 inactive*)))) OR AB=(((physical NEAR/2 activ*) OR exercise* OR (leisure NEAR/2 activ*) OR (physical NEAR/2 inactive*)))

4: (TI=((diet OR nutrition OR (fruit NEAR/2 "vegetable intake") OR (soda NEAR/3 intake) OR ("fast food" NEAR/3 intake) OR (sugar NEAR/3 intake)))) OR AB=((diet OR nutrition OR (fruit NEAR/2 "vegetable intake") OR (soda NEAR/3 intake) OR ("fast food" NEAR/3 intake) OR (sugar NEAR/3 intake)))

5: (TI=((smok* OR tobacco OR cigarett* OR nicotine OR vape OR vaping))) OR AB=((smok* OR tobacco OR cigarett* OR nicotine OR vape OR vaping))

6: (TI=(((alcohol* OR drink*) AND (abuse OR misuse OR consum* OR intake)))) OR AB=(((alcohol* OR drink*) AND (abuse OR misuse OR consum* OR intake)))

8: #2 OR #3 OR #4 OR #5 OR #6

9: #1 AND #8

10: #9 yr=2022-2025

Scopus

S1: TITLE-ABS-KEY((informal OR unpaid OR families OR family OR relative* OR spouse* OR elder*) W/4 ("care giv*" OR caregiv* OR caregiver* OR carer*))

S2: TITLE-ABS-KEY("health behavio*" OR "health promot*" OR "health-related behavio*" OR "health risk* behavio*")

S3: TITLE-ABS-KEY((physical W/2 activ*) OR exercise* OR (leisure W/2 activ*) OR (physical W/2 inactive*))

S4: TITLE-ABS-KEY(diet OR nutrition OR (fruit W/2 "vegetable intake") OR (soda W/3 intake) OR ("fast food" W/3 intake) OR (sugar W/3 intake))

S5: TITLE-ABS-KEY(smok* OR tobacco OR cigarett* OR nicotine OR vape OR vaping)

S6: TITLE-ABS-KEY((alcohol* OR drink*) AND (abuse OR misuse OR consum* OR intake))

S7: #2 OR #3 OR #4 OR #5 OR #6

S8: #1 AND #8

S9: "limit 8 to yr="2023 - 2025""

S10: "limit 19 to english"

Appendix 2.2: Sleep and caregiving

Sleep was the outcome of interest in 33 included studies of which 23 studies used a cross-sectional design while 7 were longitudinal and 3 were reviews. Some 10 studies used self-reported subjective measures with validated scales.[98,465–473] The most frequent subjective measured used were the Pittsburgh Sleep Quality Index (PSQI)[474] which is a 19-item self-reported questionnaire using Likert-type and open question that measures several sleep-related variables such as sleep quality, sleep duration, sleep medication, sleep latency and sleep disturbance. Additionally, two studies[475,476] assessed the chances of falling asleep in eight everyday situations using Epworth Sleepiness Scale (ESS).[477] The score ranges from 0 to 24 and a score of 110 or more indicates excessive daytime sleepiness.[477] Around 8 studies used general questions about sleep duration or quality that were not based on a specific scale.[84,106,142,159,175,478–480] However, 12 studies utilised objective sleep measures in which sleep was recorded via polysomnography[475,481,482] or the less invasive wrist-actigraphy.[112,476,483–489]

Reviews

Three reviews, of which one performed a meta-analysis, were identified and all of this reviews targeted caregiving of dementia or cancer patients. The first review included 18 studies about sleep in dementia caregivers. Authors found depressive symptoms aggravates sleep problems in caregivers but studies reported conflicting results in view of other factors that are associated with sleep such as age, sex and education.[490] The second review included 10 studies about sleep in cancer caregivers. They described that caregivers overestimate the amount of sleep they have achieved.[491] Despite differences in target population, both reviews reported consistently a higher prevalence of sleep disturbance in caregivers compared to non-caregivers.[490,491]

The review with meta-analysis reviewed 35 studies but only included 5 studies in the meta-analysis to analyse sleep time and 10 studies to explore sleep quality. They found that caregivers had significantly reduced sleep time and poorer sleep quality compared to non-caregivers. However, researchers stressed that the majority of published evidence is limited in view of sample size, measurement of caregiving and non-representative samples.[492]

Cross-sectional studies without control group

Out of the 23 cross-sectional studies, 14 had no control group and most were based on a small sample of dementia or cancer caregivers.[112,153,159,465–468,470–472,479,483,487,488]. These studies found a high level of caregiving burden and care-recipient characteristics, such as problematic behaviour, and limited physical functioning, were associated with poor sleep quality in caregivers.[175,465,465,468,479,487,488]

Cross-sectional studies with control group

These findings were confirmed with the nine cross-sectional studies that had a control group.[84,175,473,475,478,480–482,485] Across different sub-groups of caregivers, it was consistently reported that caregiving is associated with poorer sleep quality or quantity in caregivers compared to non-caregivers.[475,480,485] One representative youth survey with a larger sample found that that this relationship was moderated by ethnicity: white youth caregivers were more likely to experience insufficient sleep compared to black youth caregivers and non-caregiving youth.[84] Other studies reported that age, sex and depressive symptoms modified the association between caregiving and sleep. The result from these studies suggest that caregivers who were depressed, older and male had the highest odds of sleep problems.[175,478,482]

Longitudinal studies

In view of evidence from longitudinal studies, a smaller study with 33 dementia caregiving dyads investigated the association of respite care on sleep measures of caregivers. They found that caregivers clearly arranged their sleep routine around the needs of the care-recipients and that the provision of respite care alleviated sleep problems in caregivers in the short-term. However, these effect could not be sustained after this respite period.[476] Other longitudinal studies, some of which with a larger population-based sample found that transitioning into caregiving was associated with a decline in subjective and or objective sleep quality. [98,106,484,486]

In contrast, when caregivers ceased caregiving, results from different studies were less consistent. Hajek and Koenig reported that transitioning out of the role of the caregiver was not associated with changes in sleep quality in men and women[98] whereas Sacco and colleagues found that ceasing caregiving was associated with reduced sleep disturbance.[469] A large cross-national representative study of aging reported that caregiving was indeed associated with decrease in sleep-problems in caregivers but stressed that caregivers failed to reach the sleep quality prior to caregiving and defined this as the 'legacy of caregiving'.[106] The reason for the termination of caregiving might be influential for caregivers sleep as studies reported that sleep quality of caregivers decreases as the death of the patient approaches[486] and that male caregivers still reported worse subjective three months after the death of the care recipient.

In conclusion, despite the variety in populations studied and subjective as well as objective measures used, the evidence is fairly consistent and suggests that caregiving is associated with worst sleep quality due to burden/stress and the demands of caregiving during the night. Gaps in the insisting evidence include that there is no study with a population-based sample in the UK and that the longitudinal studies are based on older populations or caregivers in employment. However, there are overall fewer gaps in evidence compared to other health behaviour outcomes. Future studies should focus on younger samples and ideally incorporate subjective and objective sleep measures as this seems to be the gold standard when investigating sleep quality.

Summary

Studies measuring sleep were more consistent and highlighted the negative association between caregiving and sleep. This finding is consistent with other reviews that synthesised the evidence of sleep outcomes in caregivers which reported that caregiving is linked with poor sleep.[490–492] This could be explained through different pathways, First, caregivers may act as the main caregivers for 24 hours a day and attempt to remain vigilant during the night-time. For example, a review by Malty and colleagues found that caregivers are less likely to take sleeping tablets due to fear this might negative impact their performance as a caregiver.[491] Second, stress and higher burden have been linked to poorer sleep in caregivers even if they were not residing with the care-recipient.[470] As a result of the available evidence, there are fewer gaps in the literature on caregiving and sleep.

Appendix 2.3: Sure checklists

Specialist Unit for Review Evidence (SURE)

Questions to assist with the critical appraisal of cross-sectional studies[1]

Citation: *Are there other companion papers from the same study?*	
	Yes/ Can't tell/ No
1. Is the study design clearly stated?	
2. Does the study address a clearly focused question? Consider: Population; Exposure (defined and accurately measured?); Outcomes.	
3. Are the setting, locations and relevant dates provided? Consider: recruitment period; exposure; data collection.	
4. Were participants fairly selected? Consider: eligibility criteria; sources & selection of participants.	
5. Are participant characteristics provided? Consider if: sufficient details; a table is included.	
6. Are the measures of exposures & outcomes appropriate? Consider if the methods of assessment are valid & reliable.	
7. Is there a description of how the study size was arrived at?	
8. Are the statistical methods well described? Consider: How missing data was handled; were potential sources of bias (confounding factors) considered/controlled for.	
9. Is information provided on participant eligibility? Consider if following provided: number potentially eligible, confirmed eligible, entered into study	
10. Are the results well described? Consider if: effect sizes, confidence intervals/standard deviations provided; the conclusions are the same in the abstract and the full text.	
11. Is any sponsorship/conflict of interest reported?	
12. Finally…Did the authors identify any limitations and, if so, are they captured above?	
Summary *Add comments relating to areas of concern that were avoidable and a statement indicating if the results are reliable and/or useful.*	

This checklist should be cited as: Specialist Unit for Review Evidence (SURE) 2018. Questions to assist with the critical appraisal of cross-sectional studies. Available at: http://www.cardiff.ac.uk/insrv/libraries/sure/checklists.html

[1] Devised with reference to the STROBE consideration and elaboration article: Vandenbroucke JP, von Elm E, Altman DG, Gøtzsche PC, Mulrow CD, et al. (2007) Strengthening the Reporting of Observational Studies in Epidemiology (STROBE): Explanation and Elaboration. PLoS Med 4(10): e297. doi:10.1371/journal.pmed.0040297

Figure A2.1 SURE checklist for cross-sectional studies

Specialist Unit for Review Evidence (SURE)

Questions to assist with the critical appraisal of cohort studies[1]

Citation: *Are there other companion papers from the same study?*	
	Yes/ Can't tell/ No
1. Is the study design clearly stated?	
2. Does the study address a clearly focused question? Consider: Population; Exposure (defined and accurately measured?); Comparator/Control; Outcomes.	
3. Are the setting, locations and relevant dates provided? Consider: recruitment period; exposure; follow-up & data collection.	
4. Were participants fairly selected? Consider: eligibility criteria; sources & selection of participants; method of follow-up; for matched studies – details of matching criteria and number of exposed or unexposed.	
5. Are participant characteristics provided? Consider if: sufficient details; a baseline table is included.	
6. Are the measures of exposures & outcomes appropriate? Consider if the methods of assessment are valid & reliable.	
7. Was bias considered? e.g. recall or selection bias	
8. Is there a description of how the study size was arrived at?	
9. Are the statistical methods well described? Consider: How missing data was handled; were potential sources of bias (confounding factors) controlled for; How loss to follow-up was addressed.	
10. Is information provided on participant flow? Consider if following provided: flow diagram; numbers of participants at each stage; details of drop-outs; details of missing participant data; follow-up time summarised; numbers of outcome events.	
11. Are the results well described? Consider if: effect sizes, confidence intervals/standard deviations provided; the conclusions are the same in the abstract and the full text.	
12. Is any sponsorship/conflict of interest reported?	
13. Finally...Did the authors identify any limitations and, if so, are they captured above?	
Summary *Add comments relating to areas of concern that were avoidable and a statement indicating if the results are reliable and/or useful.*	

This checklist should be cited as: Specialist Unit for Review Evidence (SURE) 2018. Questions to assist with the critical appraisal of cohort studies. Available at: http://www.cardiff.ac.uk/insrv/libraries/sure/checklists.html

[1] Devised with reference to the STROBE consideration and elaboration article: Vandenbroucke JP, von Elm E, Altman DG, Gøtzsche PC, Mulrow CD, et al. (2007) Strengthening the Reporting of Observational Studies in Epidemiology (STROBE): Explanation and Elaboration. PLoS Med 4(10): e297. doi:10.1371/journal.pmed.0040297

Figure A2.2 Sure checklist for cohort studies

Appendix 2.4: Theories and concepts used

Table A2.1 Summary of theories used in reviewed literature

First Author, year	Caregiving theories	Health behaviour theories	Life course theories	Other theories
Cross-sectional				
Armstrong-Carter, 2022 [84]				Parentification theory
Cutbert, 2017 [116]	Model of cancer family caregiving			
Dionne-Odom 2017 [127]		Pendler's health promotion model Riegel's middle range theory of self-care of chronic diseases		
Etkin, 2008 [128]		Transtheoretical Model of PA Social cognitive theory		Stress and coping framework
Parker, 2015 [126]	Caregiver activation theory			
Rabinowity, 2004 [124]	Model of health effects of caregiving			Stress process model
Reeves, 2012 [100]	Caregiver Stress Process Model			
Ross, 2020 [129]		Pendler's Health Promotion Model		
Tang, 2002 [132]		Health Promotion Model		
Tung, 2005 [133]		Transtheoretical Model of PA		
Yamashita, 2018 [102]			Life course Theory Third age Theory	
Son, 2023 [131]		Pender's Health Promotion Model		

Hernandez Chilatra [134]				Transactional model of coping and stress (Lazarus model)
Keller, 2024 [123]				Individual and family self-management theory
Longitudinal				
Ellis, 2017 [135]				Interdependence theory
Kearns et al, 2017 [125]	Role theory (in discussion)			Adaptive and Maladaptive coping
Zan, 2022 [114]				SLOTH Model of time allocation
Hiyoshi, 2023 [104]	Caregiving stress process			
Reviews				
Ross, 2013 [130]		Health Belief Model		

Appendix 2.5: Caregiving measures

Zarit Burden Interview

The Zarit Burden Interview (ZBI) is a 22-item questionnaire on a 5-point Likert scale and a total score ranging from 0 to 88 (higher scores indicate higher burden) [136,493]. The subscales for the ZBI include the burden in the relationship, emotional well-being; social and family life, finances, and loss of control over one's life.

Caregiver Burden Inventory

Another example of a scale is Caregiver Burden Inventory (CBI). The CBI depicts caregiving burden as a five dimensional phenomenon, consisting of (1) time-dependence burden which can be conceptualised as the perceived impact of caregiving on the caregiver's time; (2) developmental burden which is the extent to which caregivers compare their situation with their peers without caregiving responsibilities; (3) physical burden which aims to measure the extent of fatigue due to caregiving; (4) social burden which refers to the role conflict between caregiving, work and family roles; and (5) emotional burden which reflects negative feelings towards the care-recipient such as resentment or embarrassment [494].

Caregiver Reaction Assessment

Further, the Caregiver Reaction Assessment (CRA) is a 24-item questionnaire on a five-point Likert scale that aims to measure positive as well as negative aspects of caregiving on the caregiver. It consist of five subscales: (1) Impact on Schedule; (2) Caregiver's esteem; (3) Lack of family support; (4) Impact on health; and (5) Impact on finances [495].

Caregiver Strain Index

The caregiver strain index is a questionnaire comprising of 13 items of which each represents a burden with binary responses "Yes" and "No". The questionnaire includes burdens in relation to the domains of employment, finances, physical, social and time burdens. The total score ranges from 0 to 13, where a score of 7 or higher indicates a high level of stress of burden.[144]

Cost of Care Index

Cost of Care Index is a case management tool that was developed to support professionals to detect perceived or actual problems in relation to the care of elderly relatives. It is a 20-item questionnaire on a 4-point likert scale and consist of the dimensions personal and social restrictions, physical and emotional health, feeling of worthiness of providing care and the care-recipient as a provocateur and economic cost. The score can range between 0 to 80 with higher scores suggesting higher cost of care and, therefore, risk.[496]

Pearling Role Overload Scale

Pearling Role Overload Scale is a 4-item instrument using self-report to measure various stressors experienced by caregivers such as exhaustion, not having time for oneself, having more things to do than one can handle and feeling not to make progress despite hard work [26].

Appendix 2.6: Summary of included studies

Table A2.2 Summary of results from the literature review on unpaid caregiving and health behaviours

First author, year	Country	Sample Size	Population	age range or Mean age (SD) or age groups	Control group	Risk of bias	Key findings
				Cross-sectional studies			
Aggarwal, 2008 [145]	USA	263	Caregivers of patients hospitalised with cardiovascular disease	20-78	N	some	Caregiving was associated with less PA
							High caregiving strain associated with higher saturated fat intake, depression, BMI and lower levels of social support. Relationship between caregiving strain and obesity mediated by depression
Armstrong, 2022 [84]	USA	10,880	Representative youth risk behaviour survey in Florida	10-18	Y	high	Caregiving youth associated with unbalanced diet, age was moderator and association remained significant for older youth caregivers but not for younger youth carers
							There was no difference in PA between caregiving and non-caregiving youth
Bailey, 2018 [108]	USA	33 dyads	Veterans with functional disability and their caregivers	IQR: 54-80	N	high	High care burden positively associated with PA
Bailey, 2019 [158]	Australia	144	caregivers of mentally ill patients	18-38: 4.2% 35-54: 20.4% 55-74: 64.8% 75+: 10.6%	N	high	Caregivers in work more likely to report less physical activity compared to caregivers who are not employed
							Caregivers had low rate of achieving recommended fruit and vegetable intake
							Male caregivers more likely to engage in harmful drinking
							Smoking rate of caregivers was 11.8%
Beesley et al, 2011[152]	Australia	101	ovarian cancer caregivers	22-84	N	high	More than half of caregivers describe negative changes in overall health behaviours since becoming a caregiver.
							Majority of caregivers do not meet Australian guidelines for PA 14% of caregivers reported an increase in PA since becoming a caregiver
							Caregivers report less alcohol consumption since becoming caregiver

First author, year	Country	Sample Size	Population	age range or Mean age (SD) or age groups	Control group	Risk of bias	Key findings
							Few caregivers reported changes in smoking behaviour since cancer diagnosis of family member
							Caregivers had low rate of achieving recommended fruit and vegetable intake
Buckinx, 2023[115]	Belgium	90	Caregiving and non-caregiving participants of an online survey	70.0 (3.8)	Y	High	Caregivers had significantly lower amount of physical activity minutes compared to their peers.
Carpenter, 2020[160]	USA	44	Dementia/Alzheimer caregivers	57.5 (7.9)	N	high	Caregivers were mostly sedentary
Castro, 2007 [85]	USA	1,234	Racially representative to regional area (3 states) with caregivers and non-caregivers from rural areas in Missouri, Arkansas and Tennessee	18-98	Y	some	no difference in smoking behaviour between caregivers and non-caregivers.
							no difference in PA between caregivers and non-caregivers
							Caregivers reported less fruit and vegetable intake compared to non-caregivers
Cavusoglu and Yurtsever, 2022[154]	Turkey	107	cancer caregivers	19-40: 35.5% 41-60: 51.4% 61+: 13.1%	N	high	Better lifestyle behaviour scores if caregiver is single, university educated, has higher income and lives in nuclear family
							Exercise least practiced health behaviour in dementia caregivers
Cho and Ra, 2015[148]	Korea	153	dementia caregivers	28-78	N	high	Family burden negatively correlated with overall preventative health behaviour.
Cuthbert, 2017 [116]	Canada	153	Cancer caregivers	60-84	N	high	Caregiver had higher levels of adequate physical activity compared to the population average
Denham et al, 2019[103]	Australia USA Canada New Zealand UK	384	caregivers of all categories and ages 18+	18-45: 22.9% 45-65: 56.8% 65+: 20.3%	N	high	Caregivers in the UK had the highest proportion of overall negative health behaviour compared to caregivers from Australia, Canada, New Zealand and the USA
Denham, 2019 [103]	Australia USA Canada	384	caregivers of all categories and ages 18+	18-45: 22.9% 45-65: 56.8% 65+: 20.3%	N	high	99% of participants did not meet recommendations for PA
							Young age caregiving associated with higher odds of hazardous alcohol consumption. Highest rates of drinking in the UK.

First author, year	Country	Sample Size	Population	age range or Mean age (SD) or age groups	Control group	Risk of bias	Key findings
	New Zealand UK						Smoking rate of caregivers 12.4% with highest proportion of smokers in cancer caregivers.
							Most caregivers did not meet recommended portions of fruit and vegetables a day
Diaz, 2020 [92]	USA	102,486	Nationally representative parents of children with disabilities and healthy children	37.3 (10.2)	Y*	low	Parents of children with down syndrome were more likely to be physically inactive compared with parents of typical children and parents of children with other special health needs
Dionne-Odom [127]	USA	294	Caregivers of cancer patients with poor prognosis	65.5 (12.7)	N	high	Caregivers scores lowest for PA out of all measured health behaviours
							Caregivers scored low on sub-scale for nutrition
							low scores self-care associated with worse wellbeing of caregiver and poorer performance of caregiving
Etkin, 2008 [128]	USA	208	Family caregivers (mainly elderly care)	60.8 (12.4)	N	some	Caregiver attitudes and perception of self-care more important indicator of PA than caregiving characteristics
Farrugia, 2019 [117]	Australia	157	Caregiving and non-caregiving women over 50	50-54: 37.6 % 55-59: 21.5 % 60-64: 17.2% 65-70: 12.9% 70+: 10.8	Y	high	Caregiving associated with lower frequency in physical activity compared to non-caregivers. Less PA if no respite services for caregivers were available.
Fredman, 2006 [118]	USA	1069	Sub-sample of female caregivers and non-caregivers from osteoporosis study	80.5 (3.1)	Y	some	Elderly female caregivers reported less leisure-time exercise than non-caregivers but were not less physically active, which may be explained by activity during caregiving tasks
Fuchs, 2023[93]	Germany	22,464	Representative survey of caregiving and non-caregiving adults aged 18+	18-44: 38.8% 45-64: 35.1% 65+ 26.0%	Y	Some	Intense caregivers were less physical active compared to non-caregivers but this was not significant in the regression models.
							Less intense (<10 hours) caregivers less likely to have non-daily fruit and vegetable consumption (better diet), but no statistical difference
							No difference between caregivers and non-caregivers

First author, year	Country	Sample Size	Population	age range or Mean age (SD) or age groups	Control group	Risk of bias	Key findings
							Intense caregivers had highest prevalence of smoking compared to non-caregivers and low-intensity caregivers, but this was statistically not significant.
Garcia-Mayor ey al, 2020[94]	Spain	44,755	Nationally representative household survey with non-caregiving controls	Female: <20hrs: 50 (12) >20hrs: 57 (13) Male: <20hrs: 51 (13) >20hrs: 57 (15)	Y	some	Providing care for <20h/week is associated with lower odds of having a high sum of risk factors. Age-stratified analysis: caregiver over 45 of age at lower odds of having a high sum of risk factors
							Caregivers who performed <20h of caregiving per week had lower odds of non-daily fruit and vegetable consumption compared to non-caregivers
							Women at higher odds of drinking; Men at higher odds of drinking if providing <20 hours care per week
							Male and female caregivers have higher odds of smoking compared to non-caregivers, this difference was more pronounced in female caregivers
							Female caregiver <20h care per week had lower odds of being physically inactive
Gonzales-de Paz [95]	Spain	2518	Sub-sample from Spanish Representative Health Survey with matched non-caregivers	17-96	Y	some	no difference in PA between caregivers and non-caregivers
							no difference in drinking habits between caregivers and non-caregivers
							No difference in smoking habits between caregivers and non-caregivers.
Gottschalk, 2020 [96]	USA	59,183	Nationally representative sample with dementia caregivers, non-dementia caregivers and non-caregiving controls	56.1 (15.5)	Y	low	Lower odds of insufficient physical activity for caregivers compared to non-caregivers. No difference for dementia caregivers vs. non-caregivers
							Dementia and non-dementia caregivers are at lower odds of binge drinking compared to non-caregiving controls
							Higher odds of smoking of caregivers compared to non-caregivers. No difference in odds of smoking for dementia-caregivers compared to non-caregivers.
Grenard, 2020[97]	USA	17,606	Nationally representative sample from Behavorial Risk	18-20: 59% 21-25: 41%	Y	some	Current cigarette smoking more prevalent among caregivers compared to non-caregivers but no difference between caregivers and expectant caregivers.

First author, year	Country	Sample Size	Population	age range or Mean age (SD) or age groups	Control group	Risk of bias	Key findings
			Factor Surveillance System 2015-2017.				No association between caregiving status amnd binge drinking, heavy drinking and smoking of e-cigarettes.
Hernandez Chilata, 2024[134]	USA	453	Caregivers of people with alzheimers or dementia	51.6 (14) Range: 38.3-65.5			18.1% of Alzheimer caregivers screened positive for hazardous drinking (17% national average). Difficulties in emotional regulation and avoiding coping styles associated with higher odds of hazardous drinking
Hipolito, 2020[149]	Portugal	50	Caregivers of patients with COPD	62.7 (9.8)	N	some	Caregivers with higher levels of psychological distress reported lower levels of PA
Hirano, 2010[119]	Japan	50	Elderly dementia/Alzheimer caregivers	72.3 (4.2)	N	high	higher caregiving burden associated with lower PA
Hoffman et al, 2012[86]	USA	18,629	Representative for California's "baby boomer" generation (born between 1946-1964) with non-caregiving controls	45-63	Y	low	Caregivers have greater odds of overall negative health behaviour compared to non-caregivers. Among caregivers, being a stressed spouse, the duration of caregiving role and hours spent caregiving not associated with negative health behaviour Caregiving not associated with sedentary behaviour Caregivers had greater odds of soda and fast food consumption compared to non-caregivers Caregivers had greater odds of smoking compared to non-caregivers
Horner-Johnson, 2015 [87]	USA	2872	Representative to Oregon area	50.8 (SE 1.02)	Y	some	Caregiver at higher odds of experiencing food insecurity and hunger (despite adjustment for household income) compared to non-caregivers
Jacob, 2020 [105]	LMIC	204,315	Representative adults from 38 low and middle income countries	18-44: 67.3% 45-64: 23.8% 65+: 8.9%	Y	low	Caregivers ere at lower odds of low physical activity. The more caregiving activities, the lower the odds of low PA.
Keller, 2024[123]	USA	1,478	Sub-sample of all female, all Afro-American caregivers from representative survey	18-24: 11.9% 25-44: 34.9% 45-64: 40.8% 65+: 12.4%	N	High	53.9% of Afro-American female caregivers did not meet PA recommendations. Age above 65 associated with lower odds of meeting PA guidelines. Education and health insurance associated with PA.
Kilmer, 2024[99]	USA	445,703	Two cross-sectional samples from representative survey (2015-16 vs. 2021/22)	2015/16: 18-29: 18.0% 30-39: 14.4%	Y	some	Prevalence of physical inactivity decreased for caregivers and non-caregivers, but the decrease was more pronounced for caregivers

First author, year	Country	Sample Size	Population	age range or Mean age (SD) or age groups	Control group	Risk of bias	Key findings
				40-49: 17.8% 50-59: 21.9% 60-69: 16.9% 70-79: 8.3% 80+: 2.9% 2021-22: 18-29: 13.3% 30-39: 14.5% 40-49:15.9% 50-59: 21.0% 60-69: 19.8% 70-79: 11.3% 80+: 4.3%			No difference between caregivers and non-caregivers. Prevalence of smoking decreased for caregivers and non-caregivers, but caregivers remained to have a higher smoking prevalence compared to non-caregivers.
Koponen, 2021 [120]	Finland	125	Caregivers with carers allowance	74.6 (7.3)	N	high	Nutrient intake is lower in caregivers than recommended levels
Lee, 2009 [109]	USA	77	All female, all spousal caregivers (urban vs. rural)	71.4 (7.4)	N	High	Diet was one of the least practiced health behaviour in rural and urban caregivers PA least practices health behaviour in caregivers No statistical difference for overall health behaviour between rural and urban female spousal caregivers
Litzelman, 2018 [153]	USA	1,482	cancer caregivers	20-50 (27.2%) 51-60 (28.5%) 61-70 (24.1%) 71+ (20.1%)	N	high	Caregivers who reported binge drinking scores low for emotional coping but high for dysfunctional coping Higher score in dysfunctional coping if caregiver reported current smoking Problem-focused coping style associated with greater PA levels in caregivers
Marques, 2012 [121]	USA	72	Elderly dementia caregivers and elderly non-caregiving controls	68.1 (9.1)	Y	high	Only few non-significant differences found
Mochari-Greenberg, 2012 [146]	USA	423	Caregivers who live with care recipient suffering from cardiovascular disease	48.7 (13.5)	N	high	Upsetting behaviour of care recipient and financial strain associated with lower odds of PA if caregiving >4 days a week

First author, year	Country	Sample Size	Population	age range or Mean age (SD) or age groups	Control group	Risk of bias	Key findings
							time demands, disturbed sleep, feeling overwhelmed, upsetting behavioiur and financial strain associated with lower odds of low saturated fat intake
Nedim, 2023 [140]	Turkey	64	Caregivers of children with physical disability and caregivers of children with typical development	42.1 (6.2)	Y	High	No difference in physical activity and sitting scores between caregivers of children with physical disability and typically developing children.
Parker, 2015 [126]	USA	44	dementia caregivers (doctoral thesis)	18-44 (15.8%) 45-64 (31.9%) 65+ (52.2%)	N	high	Caregiver activation not associated with PA caregiver activation negatively associated eating habits Caregiving activation not associated with drinking habits in dementia caregivers
Puranem, 2014 [168]	Finnland	99 dyads	Alzheimer/Dementia patients and their caregivers	75.2 (7.0)	N	High	Being a male caregiver was associated with lower nutrient and lower energy intake
Rabinowitz, 2004[124]	USA	257	All female, Caucasian and Latina dementia caregivers	57.3 (13.8)	N	high	higher levels of self-efficacy for obtaining respite, and controlling upsetting thoughts were predictive of reduced cumulative health risk
Reeves, 2012 [100]	USA	10,015	caregiving and non-caregiving women of age ³ 41 (4 states from women health module of national health behaviour survey)	55.9 (0.3)	Y	some	Caregiving associated with higher odds of being physical active in whites but not in non-whites Caregiving was not associated with fruit and vegetable intake No significant association Female caregivers had increased odds of smoking compared to non-caregivers.
Rha, 2015 [141]	South Korea	1135	cancer caregivers age- and sex matched non-caregiving controls selected from representative health behaviour survey	46.6 (12.0)	Y	high	Caregiving associated with lower PA levels compared to matched controls Caregivers were more likely to consume less alcohol compared to controls No differences in smoking habits observed between caregivers and matched non-caregivers
Rospenda, 2010 [89]	USA	998	Representative of employed caregivers in Chicago metropolitan area	42.1 (10.1)	N	some	Caregiving with high emotional or social burden predicted alcohol use. Time-dependence, physical or developmental burden did not predict alcohol use in caregivers.

First author, year	Country	Sample Size	Population	age range or Mean age (SD) or age groups	Control group	Risk of bias	Key findings
Ross et al, 2020[129]	USA	129	Cancer caregivers	48.6 (11.8)	N	high	Caregiver age and mutuality (strength of family relationship) positively correlated with health behaviour scores on the HPLP-II scale Caregiver Reaction Assessment negatively correlated with health behaviour scores on the HPLP-II scale.
							Caregivers report decreased PA since caregiving. PA least practices health behaviour compared to other health dimensions.
							Diet worse since started role as caregiver
Savela, 2023 [122]	Finland	125	Caregivers of people aged over 65	74 (8)	N	high	20% of caregivers were at risk of malnutrition. Caregivers who experienced subjective poverty were less likely to consume at least two portions of fruit and vegetables a day.
Son, 2011 [111]	South Korea	500	Caregivers of patients with advanced cancer post-surgery and age- and sex matched controls	54.6 (9.8)	Y	some	No difference in PA levels between caregivers and matched controls
							No difference for problematic drinking between caregivers and controls.
							Proportion of smokers small in caregivers compared to non-caregivers but it was only marginally statistically significant
Son, 2023[131]	USA	124	Caregivers of people receiving cancer treatment	49.0 (11.7)	N	High	Higher caregiving burden, perceived stress and lower self-efficacy was associated with lower practice of health promoting behaviours.
Stacey, 2019 [90]	Australia	1788	Representative sub-sample from population-based cohort study with caregivers and non-caregivers over the age of 40	40-59: 48.2% 60+: 51.8%	Y	some	Caregivers more likely to undertake insufficient levels of PA
							Caregiving was associated with lower alcohol intake compared to controls.
							Caregivers were less likely to be current smokers compared to non-caregivers
Tang and Chen, 2002[132]	Taiwan	134	Caregivers of stroke survivors	21-90	N	high	In caregivers, positive health promotion behaviour was associated with less disability, higher education, greater satisfaction with resources and social support
Tough, 2020 [142]	Switzerland	133	caregivers and their partners with spinal cord injury	50.2 (10.1)	N	high	Subjective caregiving burden associated with less physical activity

First author, year	Country	Sample Size	Population	age range or Mean age (SD) or age groups	Control group	Risk of bias	Key findings
							no significant association between subjective or objective burden and fruit and vegetable intake
							Higher subjective burden associated with more alcohol consumption.
							Caregivers reporting higher subjective burden smoked to greater intensity compared to caregivers with lower subjective burden.
Tung, 2005 [133]	Taiwan	108	Caregivers of patients with mental illness	52.2 (15.4)	N	high	older people more likely to be in action/maintenance stage of PA. Most common PA reported were house cleaning, walking, farming, biking, gardening, taking care of small children or ill adults
Valero-Cantero, 2022 [147]	Spain	75	Caregivers of patients with terminal cancer	62.7 (12.8)	N	High	Most caregivers performed PA in line with WHO guidelines although caregivers >65 years performed lower moderate-to-vigorous PA compared to younger carers. Compliance with WHO recommendation on PA was associated with lower Quality of Life but strength of association was limited.
Vu, 2022 [159]	USA	200	dementia/Alzheimer caregivers	IQR: 32-47	N	high	54.4% of caregivers physical active
							35.5% of caregivers reported increased alcohol use to alleviate stress from caregiving
							35.5% reported increased marihuana use to alleviate stress from caregiving
White, 2016 [91]	USA	861	Adults above 66 from diverse neighbourhoods in Washington area	75.4 (6.8)	N	some	Caregiving was associated with sedentary behaviour, but this was not further explored in multivariate model as association was not significant
Willette-Murphy, 2009 [112]	USA	68	Caregivers of cancer patients at the initiation of radiotherapy	Inactive CG 65.5 (8.3) Active CG 62.8 (9.3)	N	high	Inactivity in caregivers associated with comorbidities

First author, year	Country	Sample Size	Population	age range or Mean age (SD) or age groups	Control group	Risk of bias	Key findings
Yamashita, 2018 [102]	USA	1210	Sub-sample of caregivers and non-caregivers aged 65 years or older from nationally representative time-use survey	72.2 (6.0)	N	some	Caregivers reported less PA compared to non-caregivers on weekdays but there was no difference on weekends between caregivers and controls in view of PA
Yücel, 2025[143]	Uzbekistan	155	Caregivers of people with disabilities	39.5 (12)	N	High	There was no correlation between burden and overall health behaviour but some correlation in some of the sub-scales.
Zalewski, 2011 [113]	USA	20 dyads	Stroke survivors and their caregivers	68.1 (7.0)	N	some	Caregivers on average physically inactive. Main barriers to PA for caregivers was lack of willpower and lack of time.
				Longitudinal studies			
Ellis, 2017 [135]	USA	484 dyads	Patients with advanced cancer and their caregivers	26-95	N	high	Social support mediates the relationship between caregiving and PA in caregivers. Better patient PA at baseline associated with better PA in caregivers in subsequent waves
							Individuals previous behaviour was a strong predictor of their future behaviour. No association between caregiver and recipient diet at any time point.
Hiyoshi, 2023 [104]	Europe	57,962	Representative sample from Survey of Health, Ageing and Retirement in Europe (SHARE) including 17 countries from 2004-2017	65 (9.5)	Y	Low	Providing out-of-home care associated with lower odds of physical inactivity compared to non-caregivers but no significant association between co-resident caregiving and physical activity
							Higher odds of non-daily fruit and vegetable intake in male caregivers but not female caregivers compared to non-caregivers
							Caregivers at higher odds of problematic drinking in male and female, especially in in individuals with lower education and Nordic countries
							Smoking decreased among caregivers compared to non-caregivers.
Hossain, 2021 [88]	USA	1674	Representative to working age Whites and Africans in Baltimore	52.5 (8.8)	Y*	some	rather negative association
Kearns, 2017 [125]	USA	124	Caregivers of ICU survivors	47.8 (13.6)	N	high	Caregiving burden and actual time spent caregiving not associated with problem drinking. Caregivers who underestimated time spent for caring at higher risk of problem drinking.

First author, year	Country	Sample Size	Population	age range or Mean age (SD) or age groups	Control group	Risk of bias	Key findings
Roddy, 2020 [162]	USA	22	caregivers of early-stage lung cancer patients following surgery	64.4 (4)	N	high	Most caregiver continued smoking (13.6% caregiver were smoker at baseline and 9.1% still smoked at 6-months follow up).
							Self-efficacy in caregivers at baseline associated with greater levels of PA
Snyder, 2020 [110]	USA	239	Caregiving spouses of dementia/Alzheimer patient and matched non-caregiving spouses	71.7 (8.9)	Y	some	Indirect mediating effect of hours of care on CG status with PA
							NCG greater increase in meet dietary guidance
Tanigushi, 2025 [101]	Japan	30,530	Representative sample from survey of middle-aged and older adults from 2005-2019	Median: 55 IQR: 52-57	Y	Low	Caregiving was associated with higher odds pf physical inactivity
							Caregiving associated with deteriorating heavy drinking.
							No difference (OR 95% CI: 1.00-1.26)
Zan, 2022 [114]	USA	9,173	Representative sample from Health and Retirement Study (HRS) from 2004-2016	71	Y	Some	Providing spousal care was associated with an increase initiation of moderate to vigorous PA.
				Reviews			
Ayre, 2025 [167]		22	Cancer caregivers				Great variation how dietary intake and quality was measured. Overall inconclusive because evidence on the dietary quality and intake of cancer caregivers is dominated by small cross-sectional studies with conflicting findings
Hazzan, 2024[174]		5	Dementia caregivers in the USA				Studies used a variety of methodological approaches to define alcohol misuse. Generally challenging to draw conclusion but evidence suggests that caregivers may be less likely to misuse alcohol compared to non-caregivers.
Horne, 2021 [107]		3	Caregivers in the UK				No study reported prevalence of PA in caregivers in the UK; Some barriers and facilitators for PA were identified

First author, year	Country	Sample Size	Population	age range or Mean age (SD) or age groups	Control group	Risk of bias	Key findings
Lindsay, 2021 [161]		77	International caregivers of all categories				Inconsistent evidence but trend suggests PA levels in caregivers are lower than global average. Some studies did not distinguish between leisure time PA, exercise PA and PA from caregiving
Ross, 2013 [130]		8	Cancer caregivers				Conflicting or inconclusive results for PA
							Conflicting or inconclusive results for diet
							Conflicting or inconclusive results for alcohol consumption
							Conflicting or inconclusive results for smoking

Appendix Chapter 4: Data & measures

Appendix 4.1: Variable codes

Table A4.1 Variable codes for all included variables in the study, providing a reference for the operational definitions and corresponding codes used throughout the analysis.

Variable	Description	Type	Label
carebi	Caregiving status	Binary	0 = no caregiver 1 = Caregiver
carehrs	Caregiving hours	Categorical	0 = No caregiver 1 = <20 hours/week 2 = >20 hours/week
careecat	Caregiving categories	Categorical	0 = No caregiver 1 = non-residential caregiver 2 = household caregiver 3 = non-residential & household caregiver
pabi	Physical inactivity	Binary	0 = Active 1 = inactive
meandiet	Number of portions of daily fruit and vegetable consumption	Continuous	
smok	Smoking status	Binary	0 = non-smoker 1 = smoker
alc	Problematic drinking	Binary	0 = No 1 = Yes
sex	Sex of participants	Binary	0 = Male 1 = female
age	Age at interview	Continuous	
cage	Age centred at the mean	Continuous	
cages	Age centred squared	Continuous	
agecat	Age ctageories	Ordinal categorical	0 = 15 - 35 years 1 = 36 - 50 years 2 = 51- 65 years 3 = 66+ years
married	De-facto marital status	Binary	0 = single or not cohabiting with partner 1 = married or cohabiting with partner
hhsize	Household size	Count	
hhgroup	Household size groups	Ordinal categorical	0 = 1 household member 1 = 2 household members 2 = 3 - 4 household members 3 = 5+ household members
oclass3	Occupational class	Categorical	0 = Management / professional 1 = intermediate 2 = routine 3 = not employed
edu	Highest educational attainment	Ordinal categorical	0 = no qualification 1 = A-level, GCSE, other qualification 2 = Degree or other higher education qualification
workbi	Working status	Ordinal catgeorical	0 = full-time employed 1 = part-time employed 0 = not in paid employment

iwealth	Quintiles of equivalised household income	Ordinal categorical	1-5
ghq	Score from General Health Questionnaire	Continuous	
cghq	Mean centred GHQ score	Continuous	
ghealth	General self-rated health	Binary	0 = excellent / very good / good 1 = fair / poor
sf12p	Physical component of SF12 scale	Continuous	
csf12p	Mean centred SF12P score	Continues	
nmis	Complete case	Binary	0 = complete case 1 = case with at least 1 item missing
indscui_xw	longitudinal weight		
pidp	Cross-wave person identifier		
hidp	household identifier		
strata	strata		
psu	PSU		

Appendix 4.2: STROBE checklist

Table A4.2 STROBE checklist; for observational studies, detailing the essential items required for reporting in epidemiological research[79].

	Item No	Recommendation
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found
Introduction		
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported
Objectives	3	State specific objectives, including
Methods		
Study design	4	Present key elements of study design early in the paper
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection
Participants	6	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up
		(*b*) For matched studies, give matching criteria and number of exposed and unexposed
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group
Bias	9	Describe any efforts to address potential sources of bias
Study size	10	Explain how the study size was arrived at
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding
		(*b*) Describe any methods used to examine subgroups and interactions
		(*c*) Explain how missing data were addressed

		(*d*) If applicable, explain how loss to follow-up was addressed	
		(*e*) Describe any sensitivity analyses	
Results			
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	
		(b) Give reasons for non-participation at each stage	
		(c) Consider use of a flow diagram	
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	
		(b) Indicate number of participants with missing data for each variable of interest	
		(c) Summarise follow-up time (eg, average and total amount)	
Outcome data	15*	Report numbers of outcome events or summary measures over time	
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	
		(*b*) Report category boundaries when continuous variables were categorized	
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	
Discussion			
Key results	18	Summarise key results with reference to study objectives	
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	
Generalisability	21	Discuss the generalisability (external validity) of the study results	
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	

Appendix 4.3: Directed Acyclic Graph

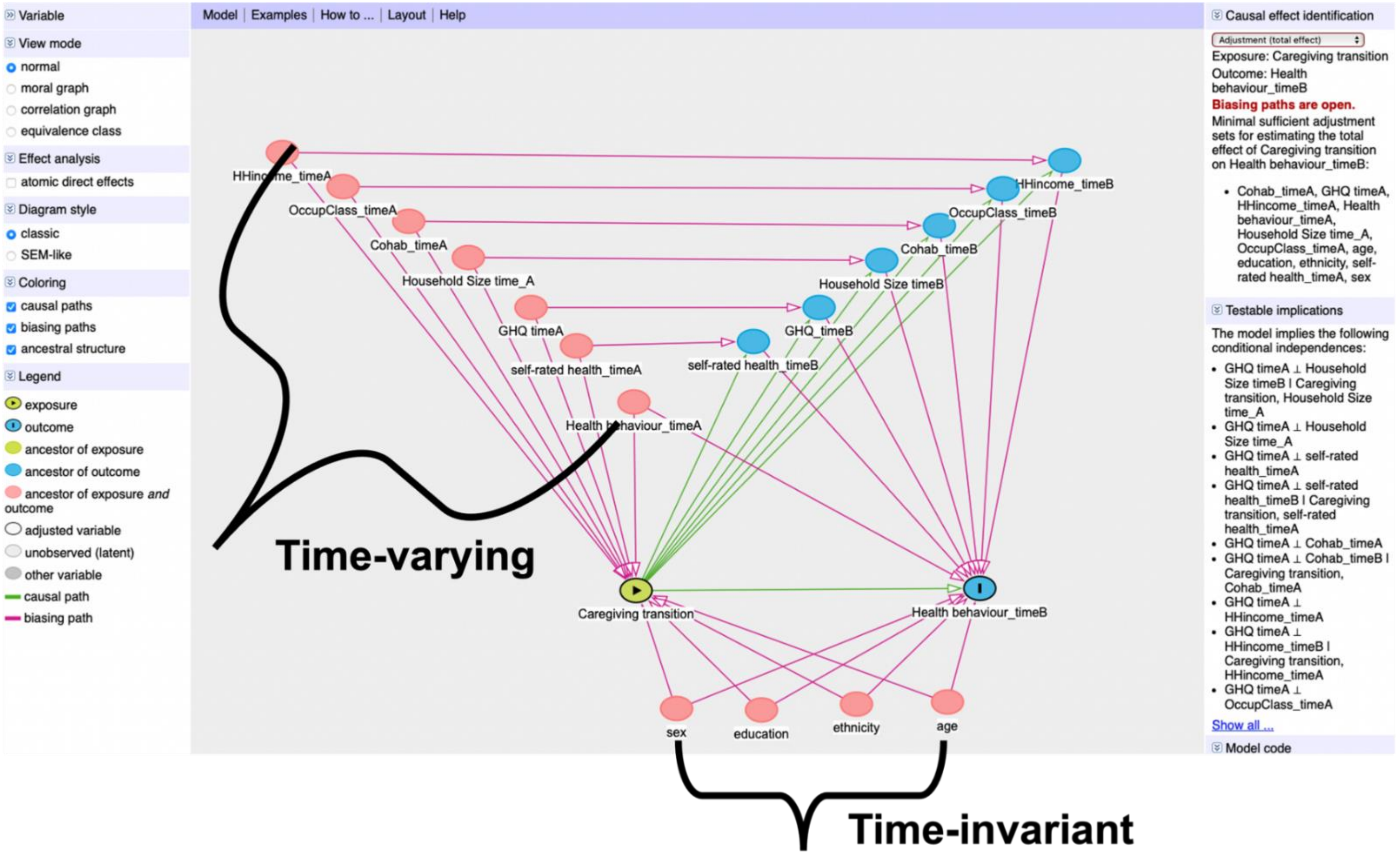


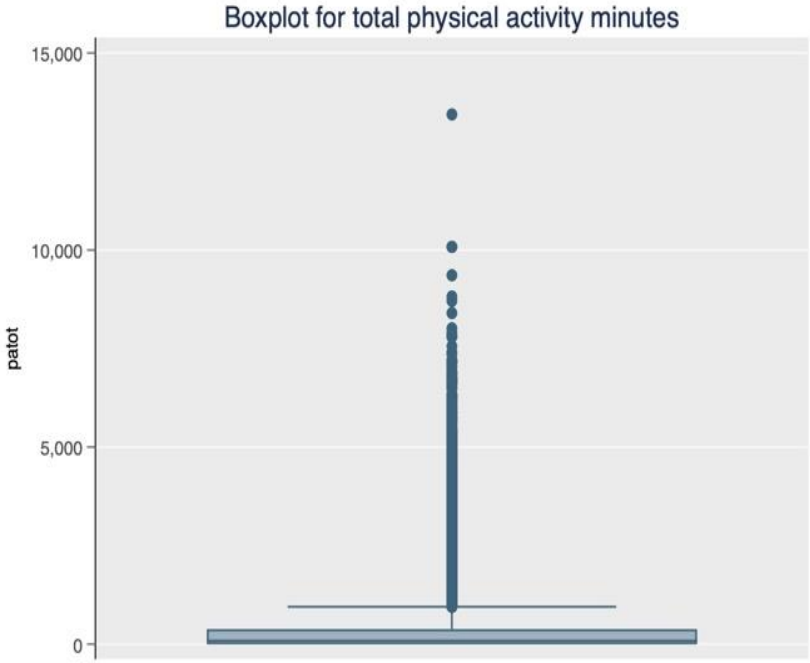
Figure A4.1 Directed Acyclic Graph (DAG) illustrating the relationship between caregiving transitions and health behaviours over time. The graph depicts time-varying variables at two time points (timeA and timeB), including exposure (caregiving transition), outcomes (health behaviour), and control variables (e.g., socioeconomic factors, self-rated health, etc.). Arrows represent causal paths, with colours indicating the relationship between variables and their ancestors. The diagram highlights the temporal aspect of caregiving transitions and their effects on health behaviours.

Appendix 4.4: Code for DAG

```
dag {
bb="-0.5,-0.5,0.5,0.5"
"Caregiving transition" [exposure,pos="-0.061,0.276"]
"GHQ timeA" [pos="-0.165,-0.115"]
"Health behaviour_timeA" [pos="-0.063,0.016"]
"Health behaviour_timeB" [outcome,pos="0.279,0.273"]
"Household Size timeB" [pos="0.182,-0.180"]
"Household Size time_A" [pos="-0.227,-0.184"]
"self-rated health_timeA" [pos="-0.120,-0.062"]
"self-rated health_timeB" [pos="0.055,-0.068"]
Cohab_timeA [pos="-0.286,-0.234"]
Cohab_timeB [pos="0.239,-0.228"]
GHQ_timeB [pos="0.120,-0.115"]
HHincome_timeA [pos="-0.411,-0.329"]
HHincome_timeB [pos="0.363,-0.318"]
OccupClass_timeA [pos="-0.351,-0.282"]
OccupClass_timeB [pos="0.302,-0.279"]
age [pos="0.247,0.430"]
education [pos="0.063,0.441"]
ethnicity [pos="0.157,0.433"]
sex [pos="-0.021,0.439"]
"Caregiving transition" -> "Health behaviour_timeB"
"Caregiving transition" -> "Household Size timeB"
"Caregiving transition" -> "self-rated health_timeB"
"Caregiving transition" -> Cohab_timeB
"Caregiving transition" -> GHQ_timeB
"Caregiving transition" -> HHincome_timeB
"Caregiving transition" -> OccupClass_timeB
"GHQ timeA" -> "Caregiving transition"
"GHQ timeA" -> GHQ_timeB
"Health behaviour_timeA" -> "Caregiving transition"
"Health behaviour_timeA" -> "Health behaviour_timeB"
"Household Size timeB" -> "Health behaviour_timeB"
"Household Size time_A" -> "Caregiving transition"
"Household Size time_A" -> "Household Size timeB"
"self-rated health_timeA" -> "Caregiving transition"
"self-rated health_timeA" -> "self-rated health_timeB"
"self-rated health_timeB" -> "Health behaviour_timeB"
Cohab_timeA -> "Caregiving transition"
Cohab_timeA -> Cohab_timeB
Cohab_timeB -> "Health behaviour_timeB"
GHQ_timeB -> "Health behaviour_timeB"
HHincome_timeA -> "Caregiving transition"
HHincome_timeA -> HHincome_timeB
HHincome_timeB -> "Health behaviour_timeB"
OccupClass_timeA -> "Caregiving transition"
OccupClass_timeA -> OccupClass_timeB
OccupClass_timeB -> "Health behaviour_timeB"
```

```
age -> "Caregiving transition"
age -> "Health behaviour_timeB"
education -> "Caregiving transition"
education -> "Health behaviour_timeB"
ethnicity -> "Caregiving transition"
ethnicity -> "Health behaviour_timeB"
sex -> "Caregiving transition"
sex -> "Health behaviour_timeB"
}
```

Appendix 4.5: Distribution of physical activity minutes



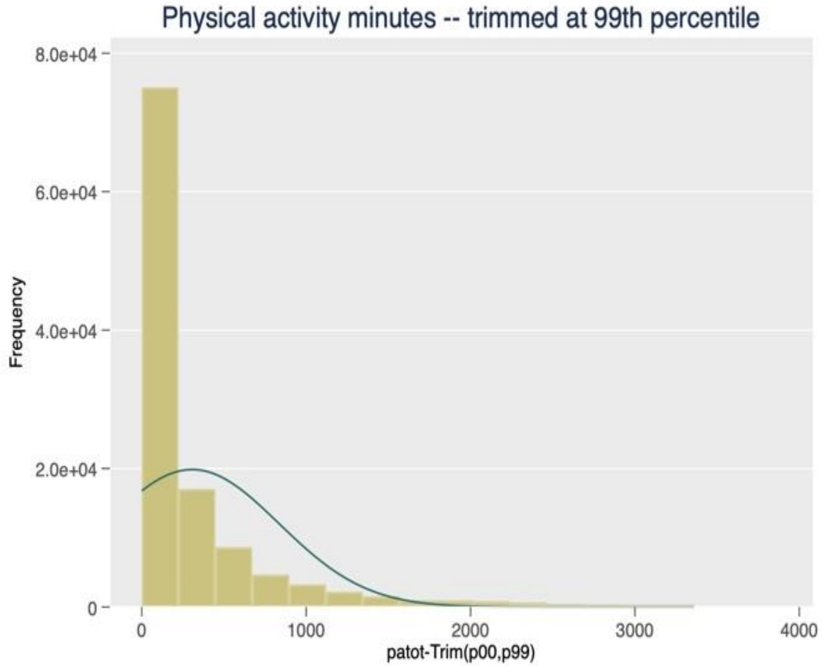


Figure A4.2 Distribution of physical activity minutes; (Left) Boxplot showing total physical activity minutes across participants in the study. The boxplot highlights the distribution, including outliers in the data; (Right) Histogram of physical activity minutes, with values trimmed at the 99th percentile to remove extreme outliers. The plot shows the distribution of activity minutes after outlier adjustment.

Appendix 4.6: Distribution of fruit and vegetable consumption

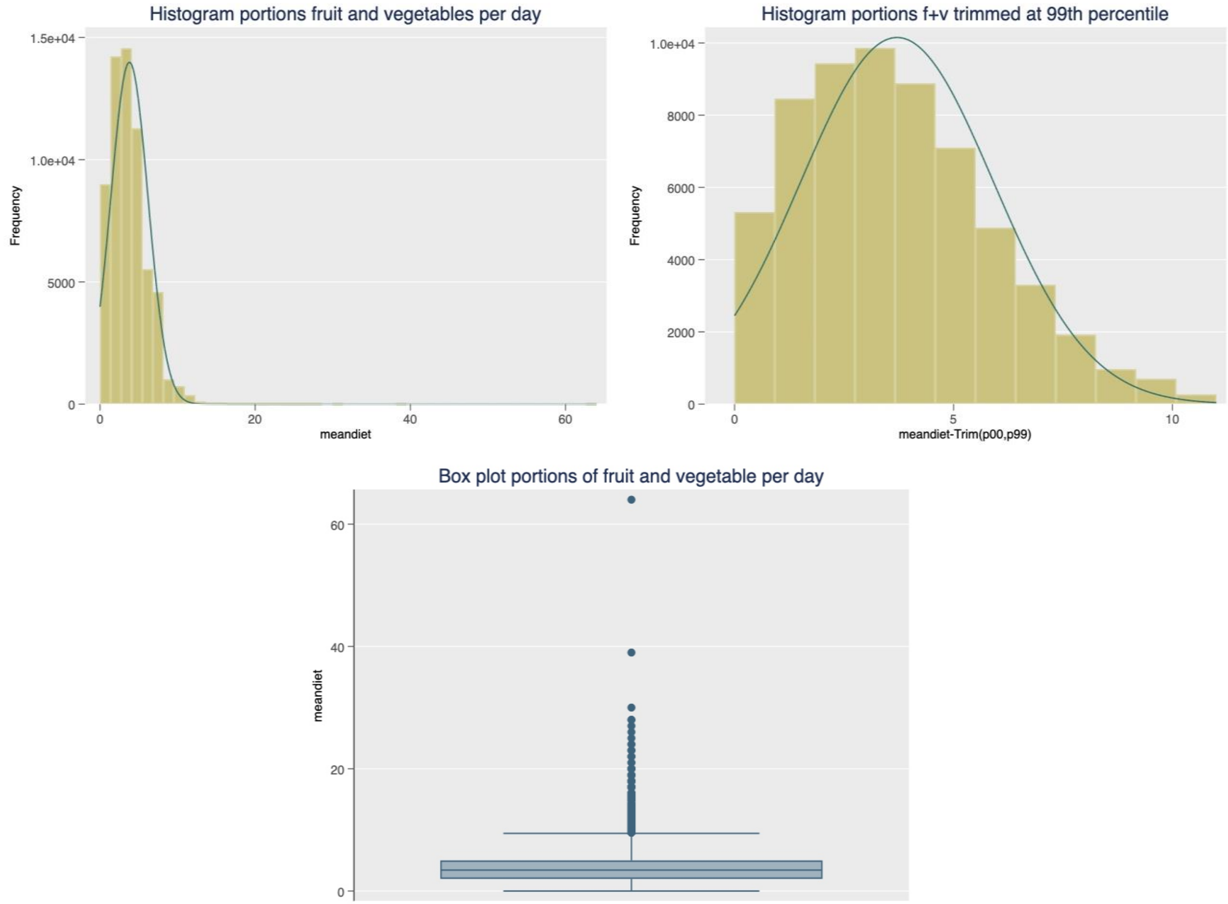


Figure A4.3 Distribution of daily portions fruit and vegetable; (Top Left) Histogram showing the distribution of fruit and vegetable portions per day across participants, with raw data including extreme values; (Top Right) Histogram of fruit and vegetable portions per day, with values trimmed at the 99th percentile to remove extreme outliers, showing the adjusted distribution; (Bottom) Boxplot of fruit and vegetable portions per day, illustrating the spread of data and highlighting outliers before trimming.

Appendix 4.7: Distribution of number of cigarettes

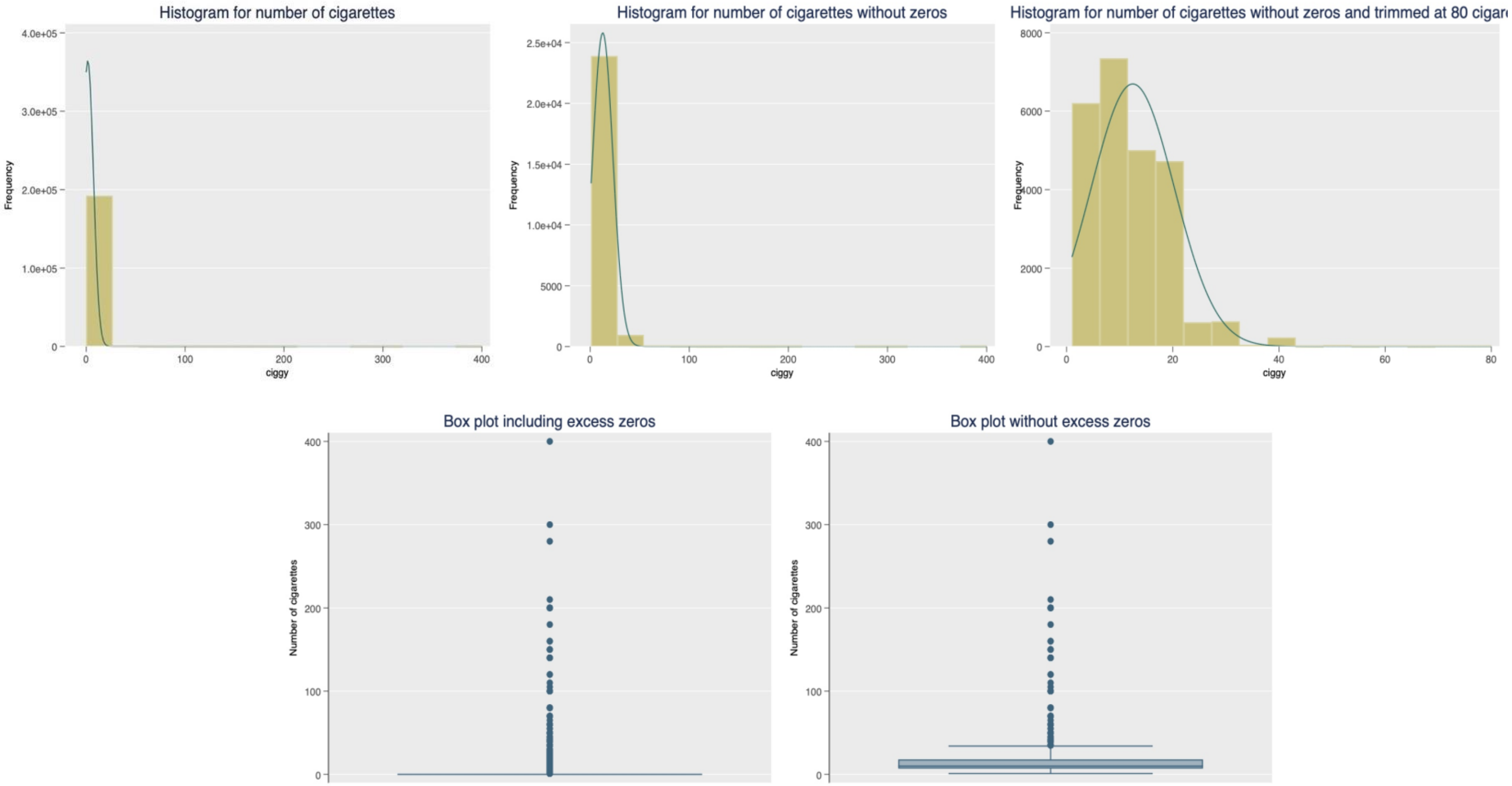


Figure A4.4 Distribution of numbers of cigarettes smoked per day; (Top Left) Histogram showing the distribution of the number of cigarettes smoked per day, including all participants; (Top Middle) Histogram showing the number of cigarettes smoked per day, excluding participants who reported zero cigarettes smoked; (Top Right) Histogram of the number of cigarettes smoked per day, excluding zeros and trimming values above the 80th percentile (capped at 80 cigarettes); (Bottom Left) Box plot of the number of cigarettes smoked per day, including participants with zero cigarettes smoked; (Bottom Right) Box plot of the number of cigarettes smoked per day, excluding participants who reported zero cigarettes smoked

Appendix Chapter 5: Transition into caregiving

Appendix 5.1: Sample size flowcharts (transition into caregiving)

Fixed effect models

Fruit and vegetable consumption

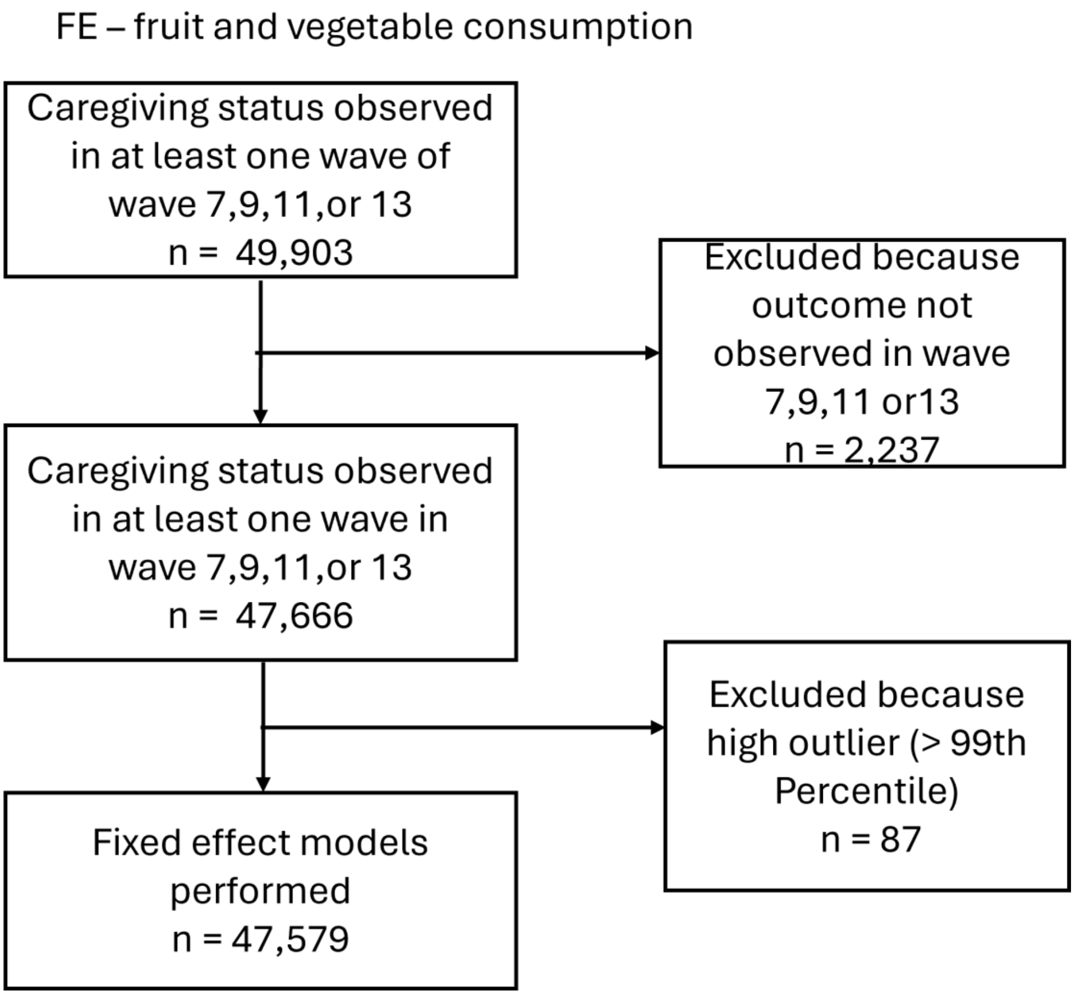


Figure A5.1 Sample size flow chart for fruit and vegetable consumption using fixed effect models.

Drinking

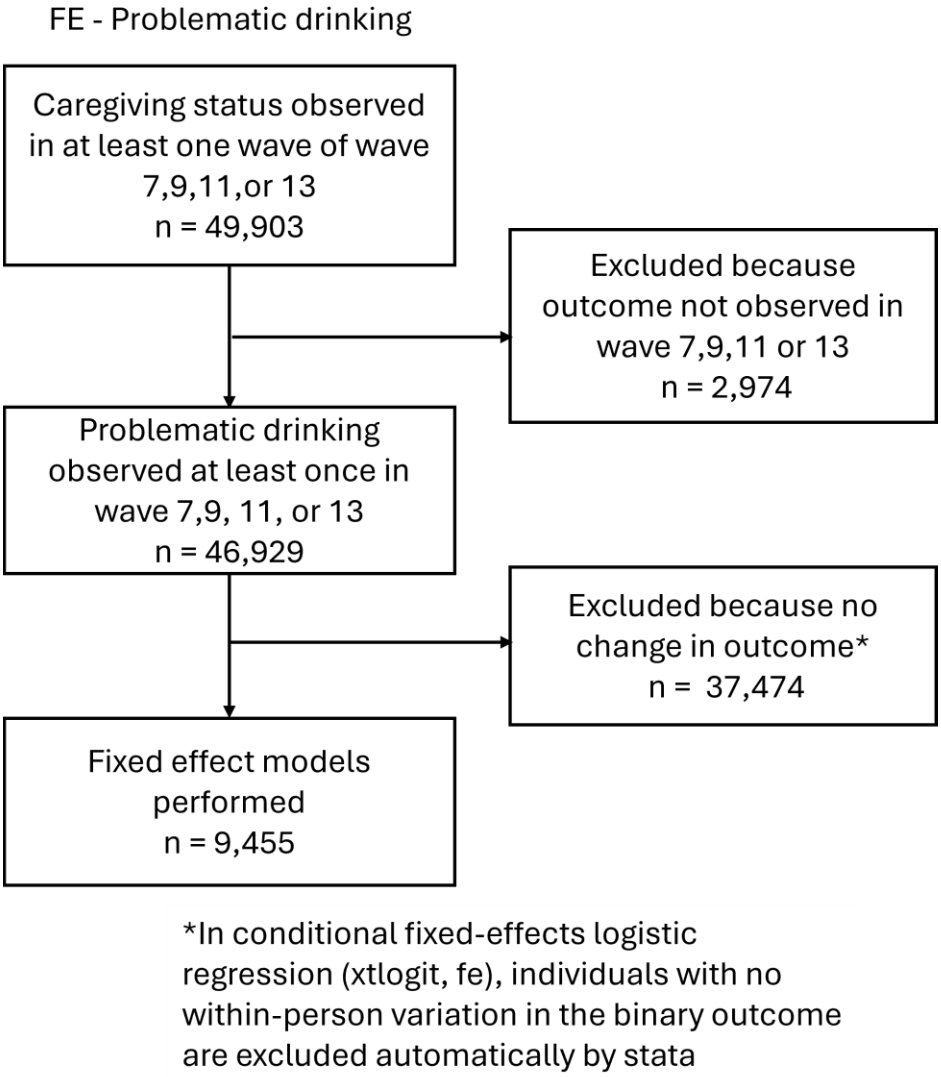


Figure A5.2 Sample size flow chart for problematic drinking using fixed effect models.

Smoking

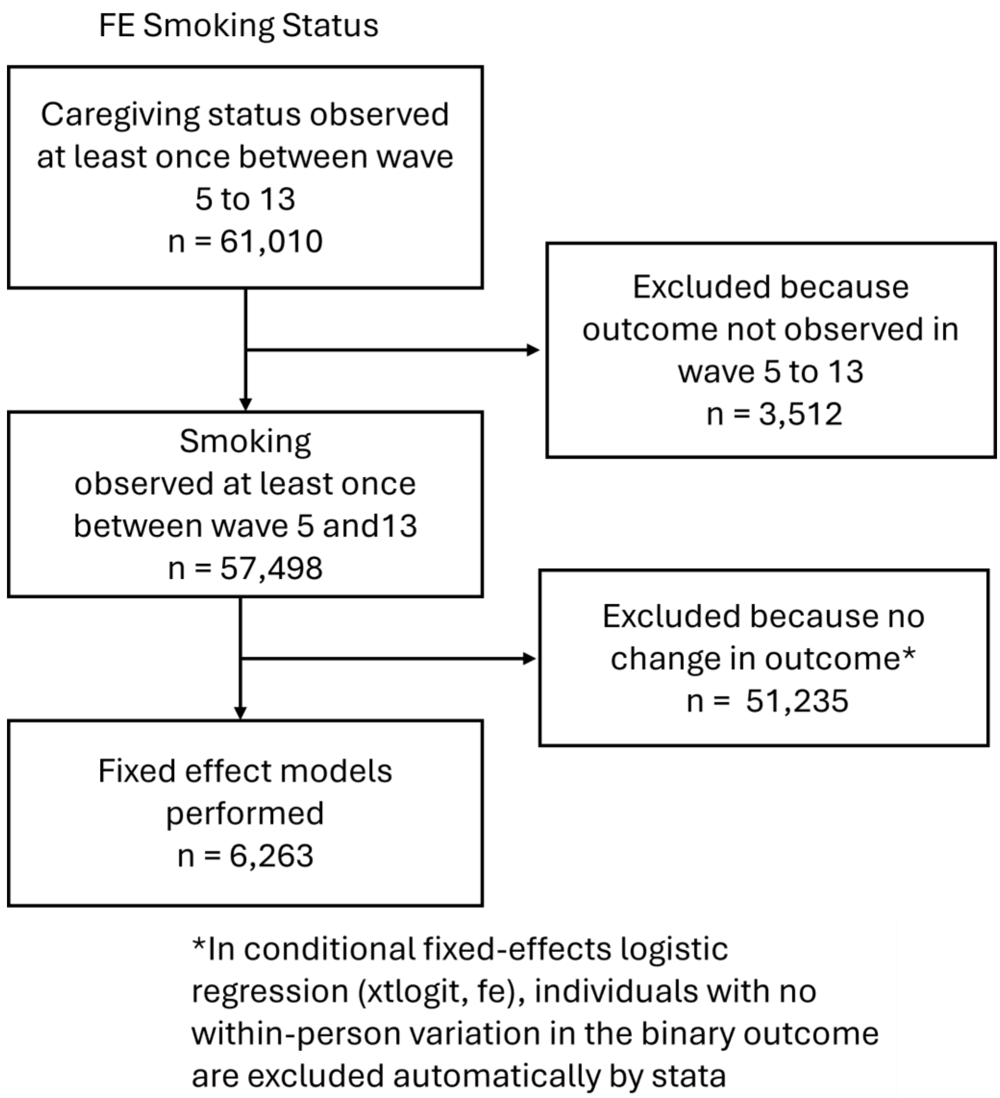


Figure A5.3 Sample size flow chart for smoking using fixed effect models.

Piecewise growth curve models

Fruit and vegetable consumption

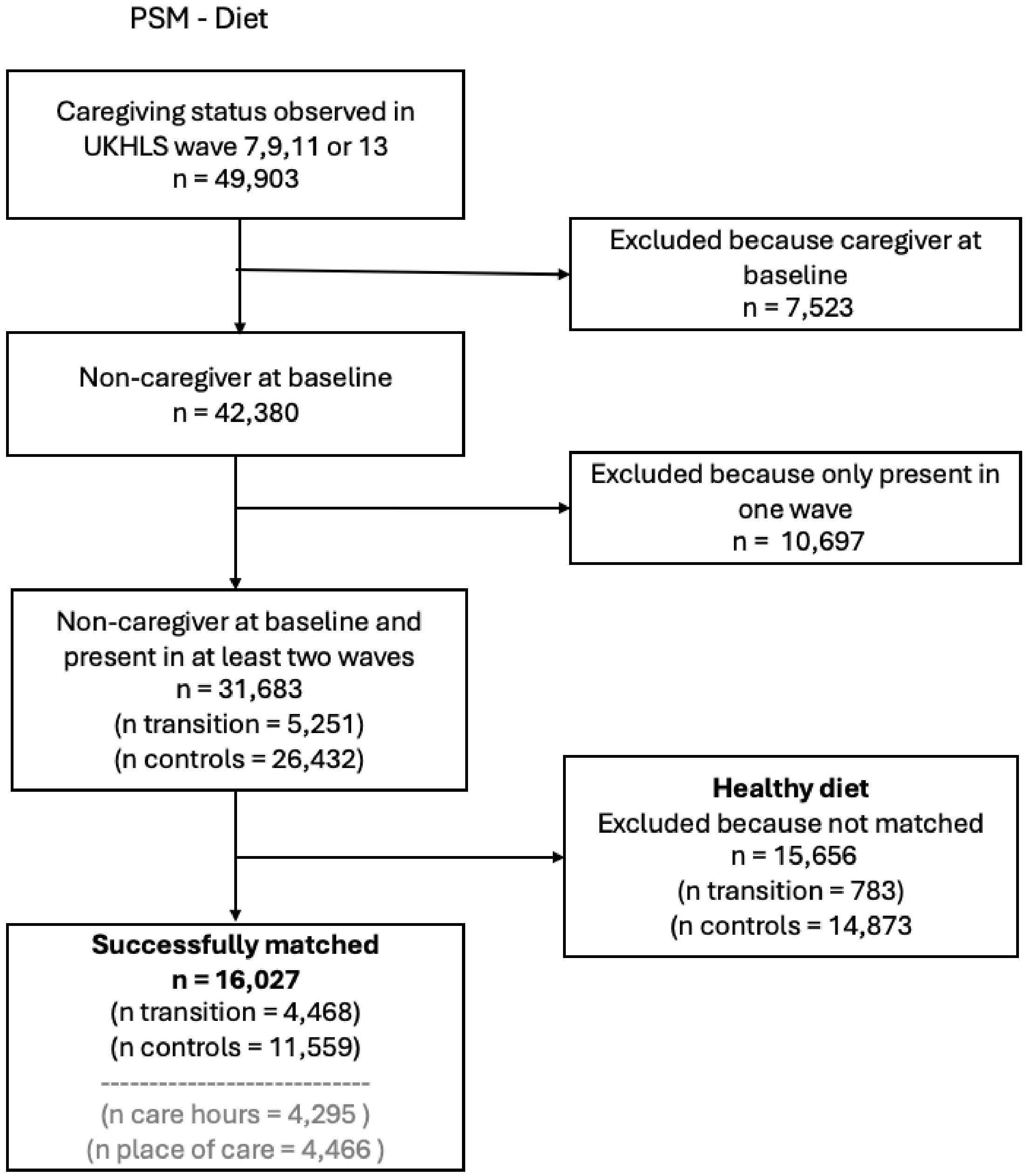


Figure A5.4 Sample size flow chart for propensity score matching for fruit and vegetables consumption.

Drinking

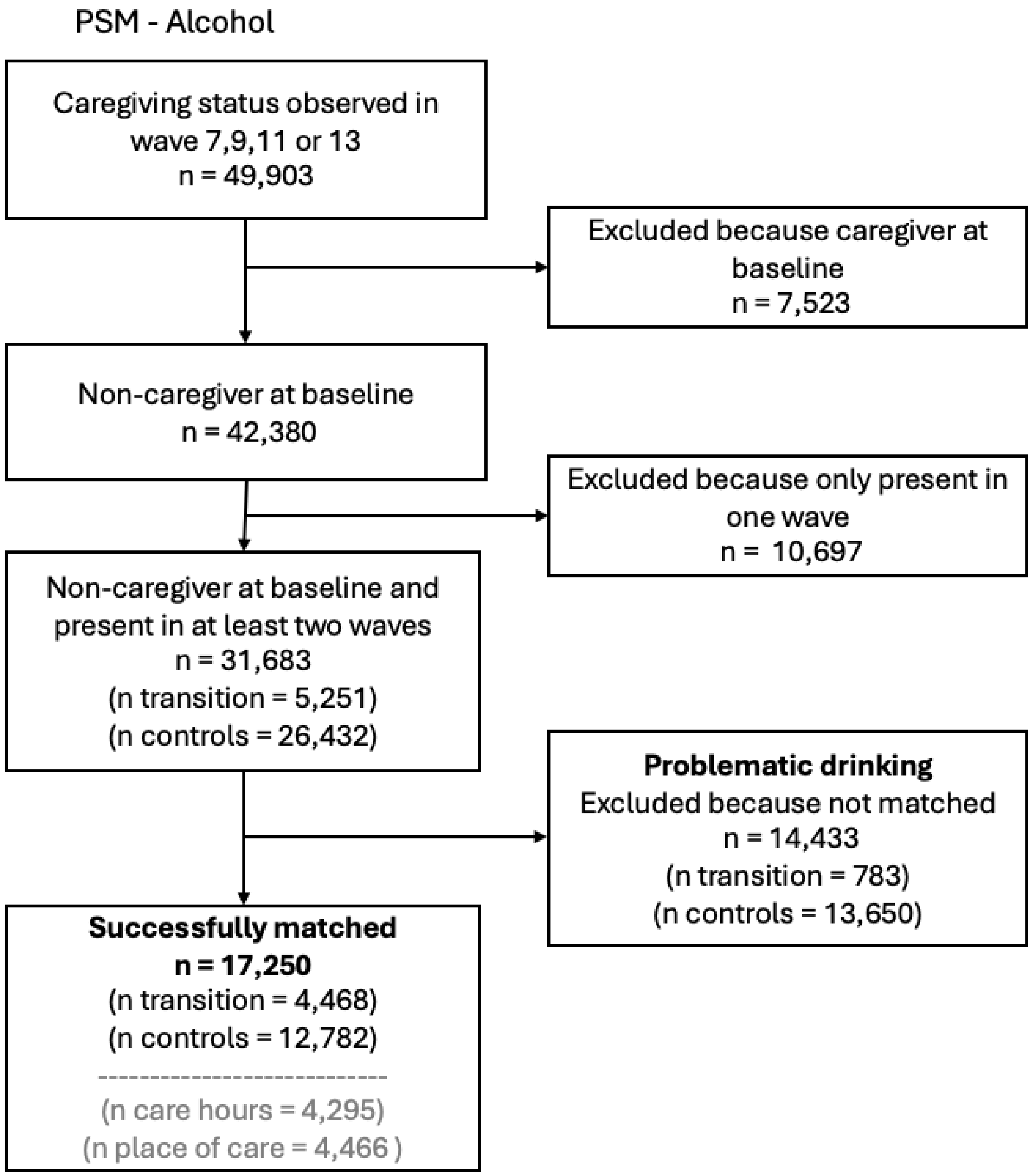


Figure A5.5 Sample size flow chart for propensity score matching and problematic drinking.

Smoking

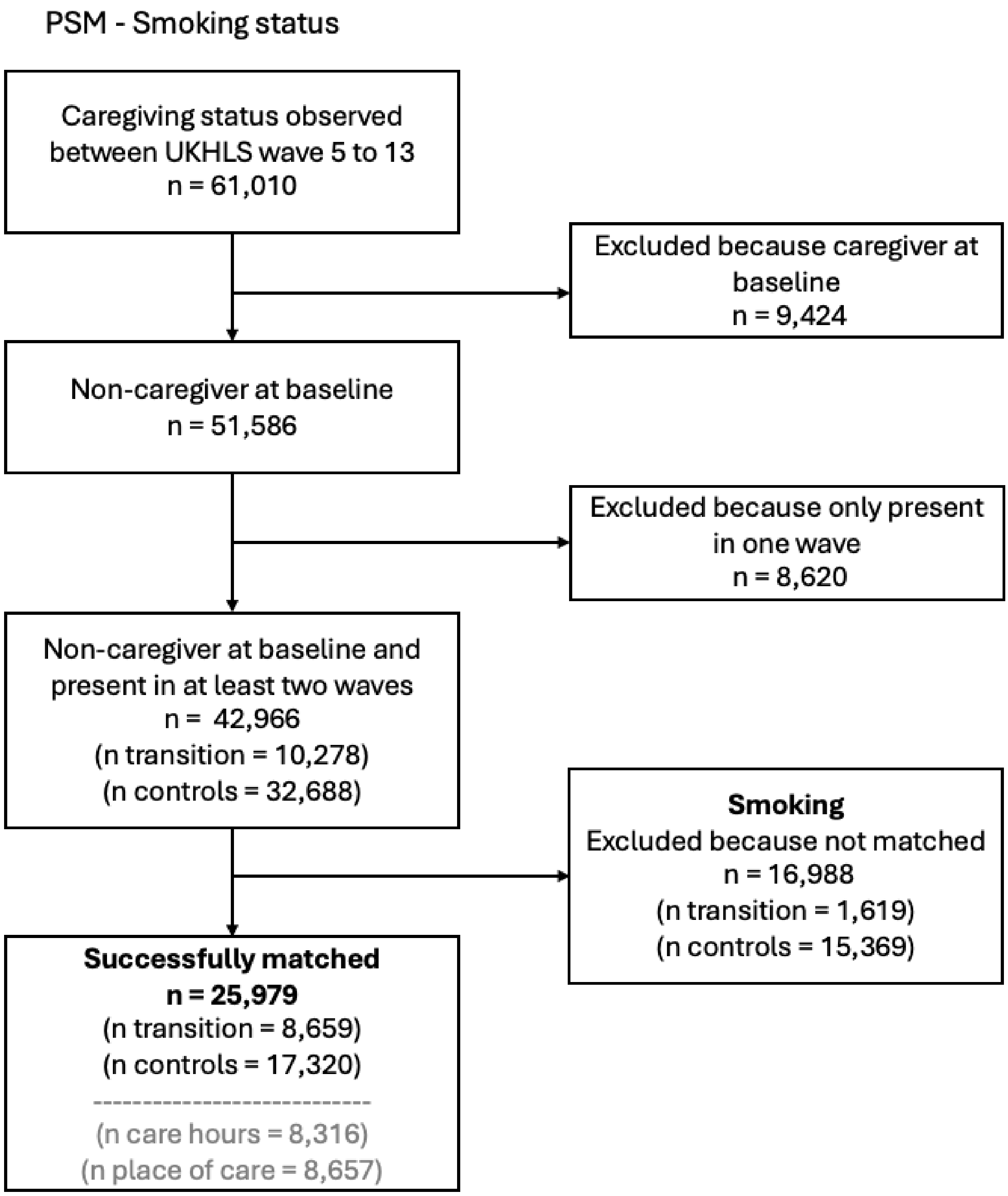


Figure A5.6 Sample size flow chart for propensity score matching and smoking.

Appendix 5.2: Matching and covariate balance

In this part of the preliminary analysis, four distinct statistical models were employed to assess the distribution of covariates and to make an informed decision as to what approach will be preferred in the analysis. To compare these models, the distribution of covariates was assessed for the outcome smoking and the exposure transitioning into caregiving. The control group were participants who were never caregivers in any of the 9 waves. Smoking and transition into care were chosen for this preliminary analysis because smoking had the highest number of waves and transition into care were most common compared to other caregiving transitions. Hence, this approach had a fairly large sample size and was therefore preferred.

In total, four comparisons were made in four models. Model 1, using only complete cases, likely suffers from selection bias, as it does not account for the potential non-randomness of caregiving roles. Model 2 introduces basic propensity score matching to mitigate this issue but does so without weighting, which may not fully account for the model's inherent variance. Model 3 adds matching weights, which helps in refining the balance achieved in Model 2, improving the model's balance in view of the distribution of covariates. Finally, Model 4 employs entropy balancing, a method known for its robustness in achieving covariate balance.

Initial unadjusted results from Model 1 (Complete cases) suggest significant differences in the distribution of most covariates between those who transition into caregiving roles and those who do not. Participants who transition into care were more likely to be older, female, white, cohabiting with partner, have more observed waves and more likely to rate their health as fair or poor. However, as we incorporate propensity score matching in Model 2 (PSM sample, unweighted), some of these differences, particularly in variables like smoking and ethnicity, become less pronounced. This change indicates that the initial differences may be partly due to sample selection biases rather than true associations. Models 3 (PSM with matching weight) and 4 (PSM with entropy balance) further adjust these distributions, aiming for a balance across all covariates. Notably, Model 4 achieves nearly identical distributions for several key variables such as age and sex, suggesting a highly effective balancing that could potentially eliminate the influence of these confounders.

Table A5.1 Covariate balance comparison of methods in the analysis of smoking and transition into caregiving. The figure compares covariate balance across three methods: complete cases, propensity score matching (PSM) without weights, PSM with weights, and PSM with entropy weights. It highlights how each method adjusts for covariate balance and demonstrates the impact of different weighting strategies on the balance between caregivers and non-caregivers.

		Model 1			**Model 2**			**Model 3**			**Model 4**		
Non-caregivers at baseline		Complete cases (n=39837)		p	PSM sample (unweighted)			PSM +matching weight			PSM + entropy balance		
		No transition	Trans into care		No trans	Trans into care		No trans	Trans		No trans	Trans	
		N= 31355	N=8482		N=17,589	N=8,485		N=17,589	N=8,485		N=17,589	N=8,485	
Smoker at baseline	No	83.3	82.9		84.0	82.9		84.0	82.2		82.9	82.9	
	Yes	16.7	17.1	0.43	16.0	17.1	0.03	16.0	17.8	<0.001	17.1	17.1	0.99
Age baseline	Mean	40.9	48.0	<0.001	45.0	48.0	<0.001	46.8	46.9	0.78	48.0	48.0	0.99
Sex	Male	47.7	41.6		44.7	41.5		43.6	43.0		41.5	41.5	
	Female	52.3	58.4	<0.001	55.3	58.5	<0.001	56.4	57.0	0.39	58.5	58.5	0.99
Ethnicity	White	80.3	84.9		82.9	85.0		84.1	83.9		85.0	85.0	
	Black	6.4	4.6		5.5	4.6		5.1	4.9		4.6	4.6	
	Indian	4.0	3.1		3.6	3.1		3.4	3.3		3.1	3.1	
	Pakistan/Bang	5.2	4.7		4.7	4.7		4.2	5.1		4.7	4.7	
	Other Asian/other	4.1	2.6	<0.001	3.3	2.6	<0.001	3.1	2.7	0.02	2.6	2.6	0.99
Cohabiting at baseline	Single	47.7	32.9		37.6	32.9		35.4	35.2		32.9	32.9	
	Cohabiting	52.3	67.1	<0.001	62.4	67.1	<0.001	64.6	64.8	0.71	67.1	67.1	0.99
Number of people living in the household at basline	1	13.7	12.5		14.5	12.5		14.8	12.5		12.5	12.5	
	2	28.0	35.8		31.9	35.8		33.8	34.7		35.8	35.8	
	3-4	41.1	38.4		39.7	38.5		38.6	38.8		38.5	38.5	
	5	17.1	13.2	<0.001	13.9	13.2	<0.001	12.8	14.0	<0.001	13.2	13.2	0.99
N waves	Mean	5.2	7.4	<0.001	6.9	7.4	<0.001	7.2	7.2	0.48	7.4	7.4	0.99
Education	No qual	11.5	10.2		10.2	10.2		10.7	10.3		10.2	10.2	
	A-Level	54.5	52.4		51.0	52.4		50.9	53.0		52.4	52.4	
	Degree	34.0	37.4	<0.001	38.8	37.4	0.08	38.5	36.7	0.001	37.4	37.4	0.99
Occupational class at baseline	Not employed	47.0	42.2		41.0	42.2		41.7	42.9		42.2	42.2	
	Management	22.9	24.9		27.1	24.8		26.5	24.5		24.8	24.8	
	Intermediate	12.1	13.9		13.6	13.9		13.7	13.6		13.9	13.9	
	Routine	18.0	19.1	<0.001	18.4	19.1	0.002	18.1	19.0	0.01	19.1	19.1	0.99

Employment status at baseline (comprehensive)	PT	18.2	21.9		21.2	21.9		21.5	20.9		21.9	21.9	
	FT	30.0	31.4		33.0	31.4		32.2	31.5		31.3	31.3	
	FT, long hours	4.8	4.6		4.9	4.6		4.8	4.7		4.5	4.5	
	Unemployed	5.2	4.9		4.4	4.9		4.4	4.9		4.9	4.9	
	Retired	16.9	21.1		19.0	21.1		20.9	20.4		21.1	21.1	
	Family care	3.8	4.3		4.7	5.3		4.8	5.1		5.3	5.3	
	FT student	17.7	6.9		9.3	6.0		7.6	8.4		6.9	6.9	
	LT sick	2.8	3.5		3.0	3.5		3.6	3.4		3.5	3.5	
	Something else	0.6	0.6	<0.001	0.5	0.6	<0.001	0.4	0.6	0.11	0.6	0.6	0.99
Income quintiles	1 (most deprived)	18.9	18.5		17.1	18.5		17.4	18.8		19.2	18.5	
	2	19.5	21.0		19.4	21.0		19.7	20.9		20.2	21.1	
	3	19.9	20.2		20.0	20.2		20.3	20.4		20.2	20.2	
	4	20.7	20.2		21.2	20.2		20.8	20.0		20.2	20.2	
	5 (least deprived)	21.0	20.0	<0.02	22.3	20.0	<0.001	21.9	19.9	<0.001	2.3	20.0	0.99
Household income	mean	1784	1735	0.12	1852	1735	0.002	1822	1722	<0.001	1769	1735	0.99
Self-rated health	Excellent – good	83.5	80.6		83.3	80.6		81.3	81.2		80.6	80.6	

Appendix 5.3: Clustering at household level

To assess the potential bias of clustering at household level, different models were generated an compared using smoking as outcome and transition into care as exposure. This was because smoking had the highest numbers of observed waves and hence this analysis had the highest sample size. The first model-1 was a model that compared those who transitioned into caregiving and participant without transition into care without any adjustment for clustering. As seen in **Figure A5.7**.

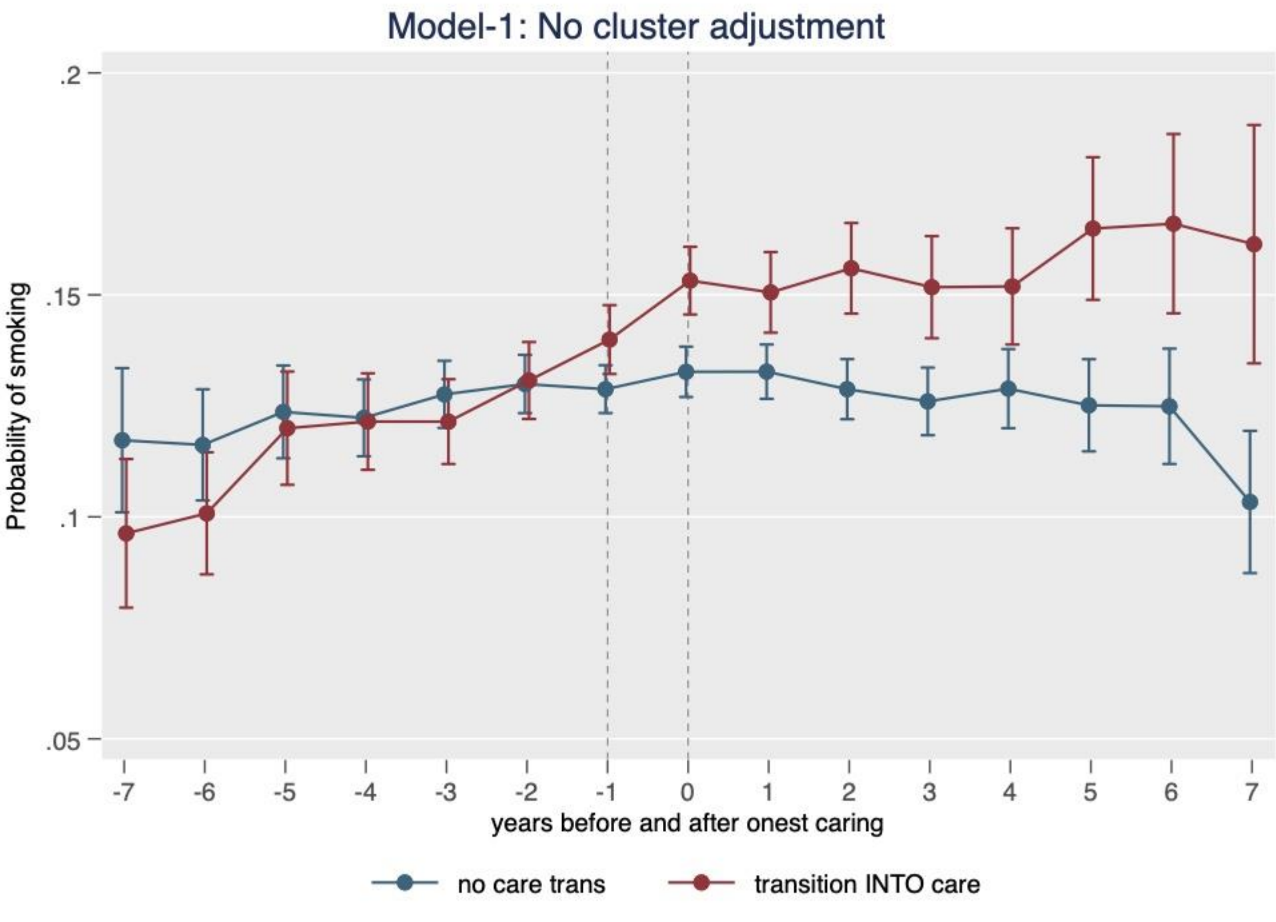


Figure A5.7 Trajectories of the probability of smoking without cluster adjustment (n=25,982 of which 8659 transitioned into caregiving and 17,323 matched non-caregiving controls).

Model-2 used the "vce cluster" option for the household identifier at the baseline observation. This method aims to adjust the variance-covariance estimation to account for clustering within households. This adjustment is considered to be critical because it is likely that people from the same household have similar smoking behaviours than randomly selected individuals from the general population. By clustering the standard errors at the household level, it is possible to correct the intra household correlation, ensuring that the statistical inference is valid and reliable.

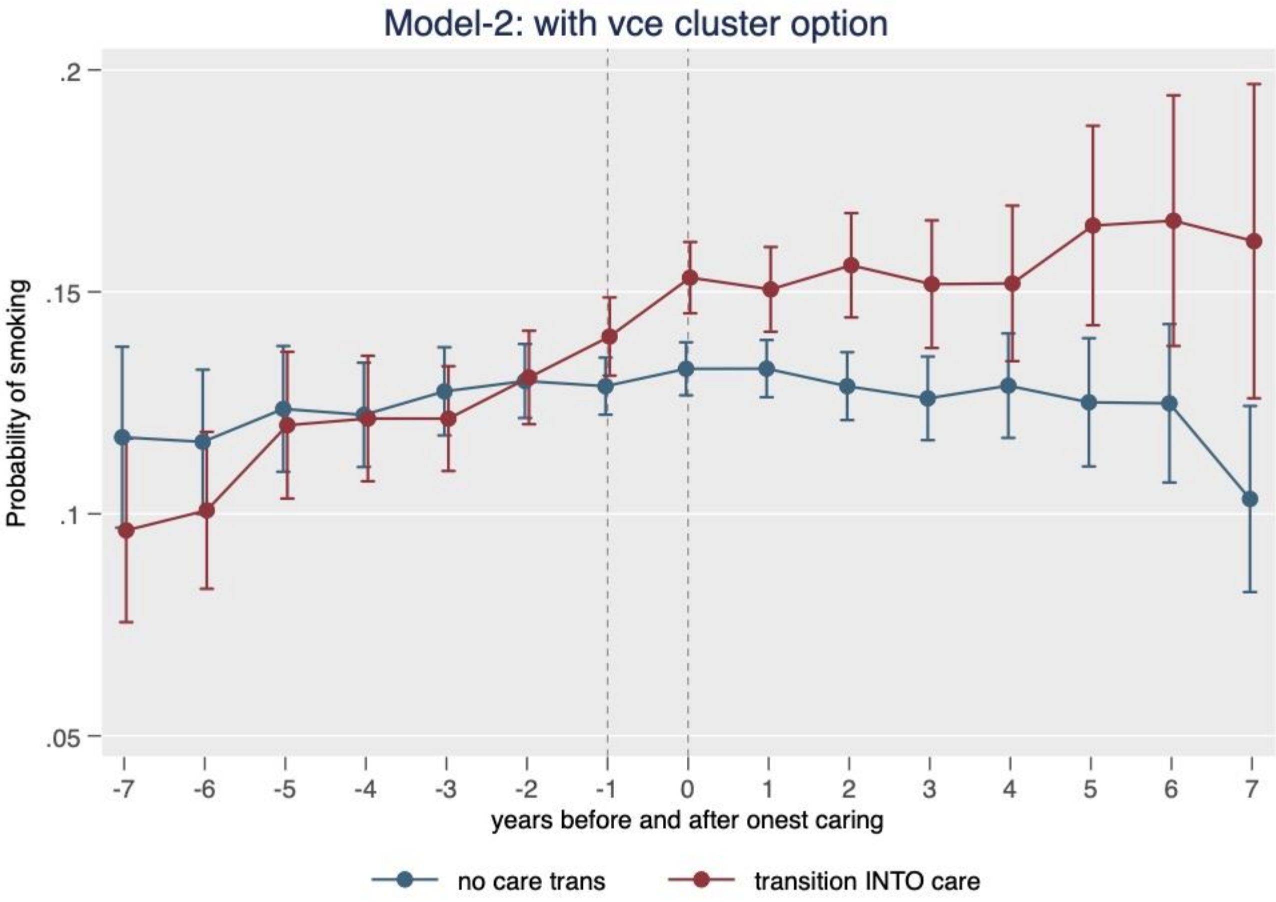


Figure A5.8 Trajectory of the probability of smoking with vce cluster option (n=25,982 of which 8659 transitioned into caregiving and 17,323 matched non-caregiving controls)

In model-3, an alternative approach was considered. To mitigate potential biases due to household clustering, a random selection procedure was implemented in stata. For this, a seed was set at „12345“ which initiated a random number generator in stata to ensure that the random selection are reproducible. Then a new variable was created that contained random numbers between 0 and 1 for each observation (participant) in the sample. The random numbers were generated uniformly which means that each value within the specified range has an equal probability of selection. Then the data was sorted by household id of the baseline observation and by previously generated random number. After sorting, the first observation per household was selected for the sample, effectively selecting one random participants per household.

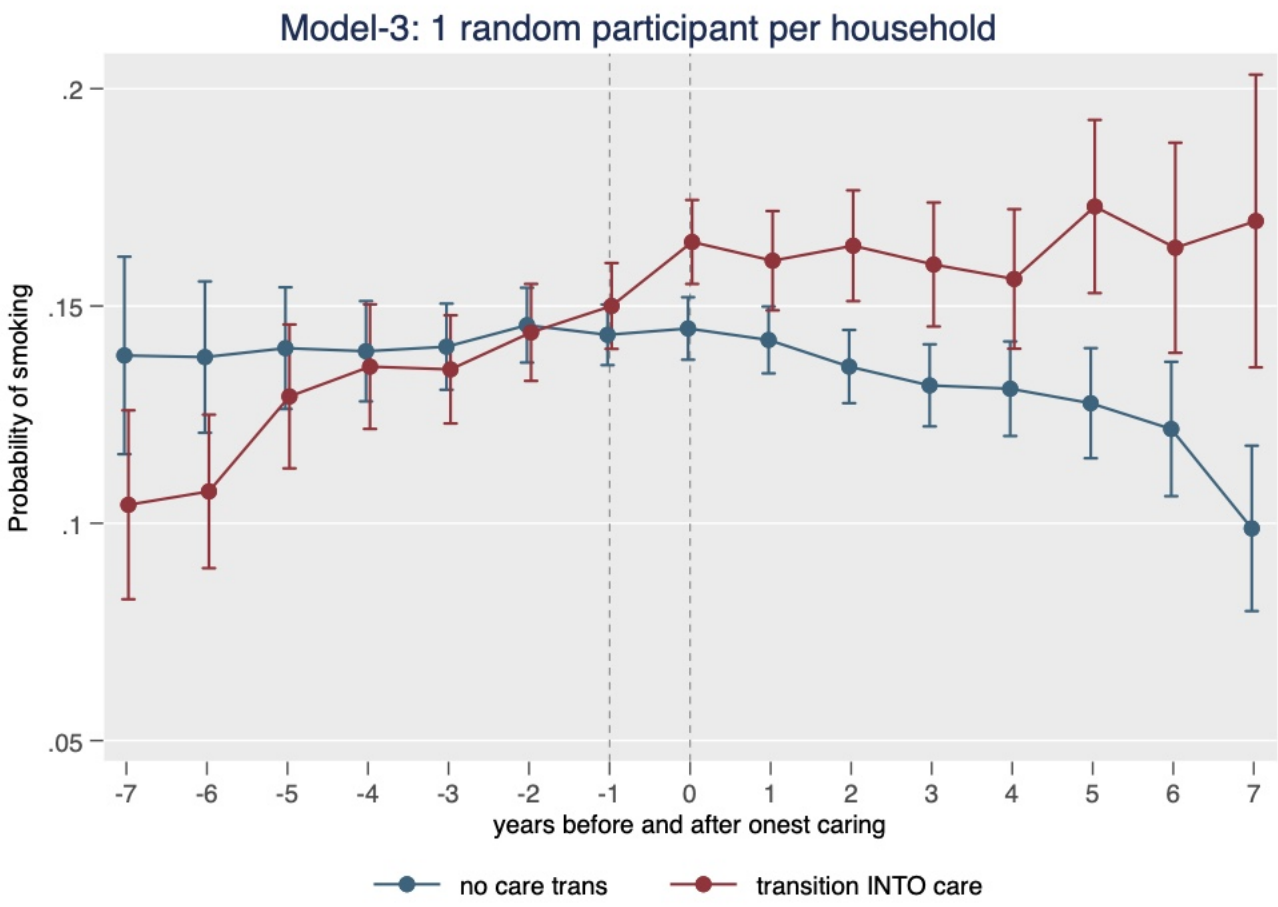


Figure A5.9 Trajectory of the probability of smoking with 1 randomly selected participant per household (n=17,566 of which 5,781 transitioned into caregiving and 11,785 matched non-caregiving controls).

Comparing all three models, it can be seen that there is a consistency in the trend and that the clustering adjustment does not change the inference between transition into caregiving and the probability of smoking. However, the choice of method to address clustering impacts the confidence intervals and the stability of the estimates over time. Model-2 offers a balance between utilising the full data set and adjusting for clustering at household level and is the preferred model. While there is no formal statistical test that may inform which of these model is superior, model-2 is preferred to maintain the sample size while being able to account for clustering within households.

Table A5.2 Sample sizes of different clustering options

	Participants			Observations		
	Transition into care	No transition	Total	Transition into care	No transition	Total
Model-1 (not accounted for clustering)	8,659 (33.3%)	17,323 (66.7%)	25,982	62,905	119,443	182,348
Model-2 (vce cluster option)	8,659 (33.3%)	17,323 (66.7%)	25,982	62,905	119,443	182,348
Model-3 (1 random participants per household)	5,781 (32.9%)	11,785 (67.1%)	17,566	41,738	78,744	120,482
	Chi-square p=0.29					

Appendix 5.4: PA graphs by age groups (caregivers only)

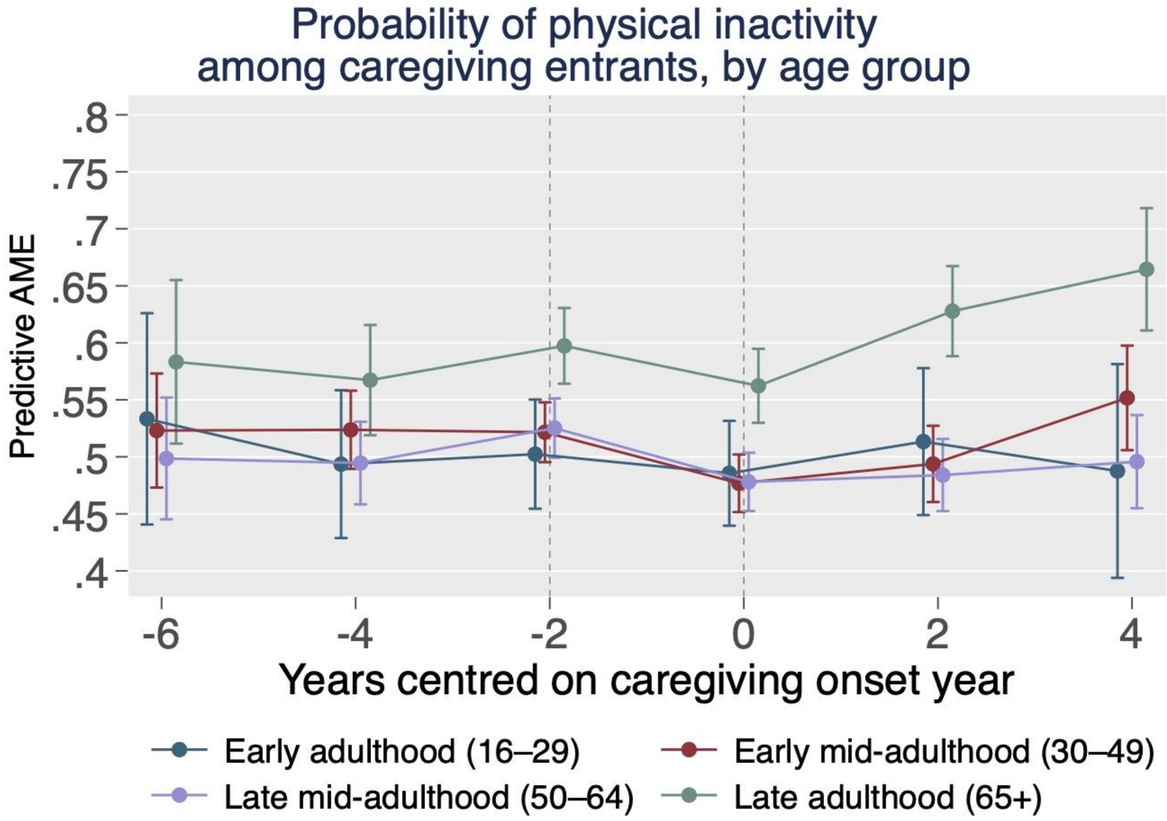


Figure A5.10 Trajectories of physical inactivity by age group; probability of physical inactivity before and after caregiving onset across UKHLS waves 7, 9, 11, and 13, stratified by age at caregiving onset, among participants who transitioned into caregiving (n=4,436; 461 early adulthood [16–29], 1,544 early mid-adulthood [30–49], 1,505 late mid-adulthood [50–64], 926 late adulthood [65+]). Time is centred around caregiving onset, with dashed lines marking transition points. All participants were non-caregivers at baseline.

Appendix 5.5: Comparison of intensity groups

Table A5.3 Comparison of low- and high intensity caregiving for the analysis of entering caregiving and smoking

		Low (<20 hours of care/week)	**High (> 20 hours of care per week)**	**p**
	N (%)	8.029 (84.5%)	1.474 (15.5%)	
age at baseline	Mean (median)	48.0 (49)	47.9 (47)	0.76
Smoker at baseline	No	83.4%	76.6%	
	Yes	16.2%	23.4%	<0.001
Sex	Male	43.5%	35.4%	
	Female	56.5%	64.6%	<0.001
Cohabiting	Single seperated widowed	32.9%	28.7%	
	Married or cohabiting with partner	67.1%	71.3%	0.002
Household group at baseline	1	12.7%	6.1%	
	2	35.3%	37.3%	
	3-4	39.0%	36.6%	
	5+	12.9%	20.0%	<0.001
Education	No qualification	10.2%	19.1/5	
	A-level/GSCE	51.8%	54.4%	
	Degree	38.0%	26.5%	<0.001
Occupational class at baseline	Not employed	40.5%	58.6%	
	Management & professional	25.8%	13.5%	
	Intermediate	15.0%	8.3%	
	routine	18.8%	19.6%	<0.001
Working status	Full-time	22.2%	18.2%	
	Part-time	22.3%	18.2%	
	Full-time long hours	4.9%	2.8%	
	Unemployed	4.7%	9.7%	
	Retired	20.7%	24.0%	
	Family caree	4.5%	12.4%	
	Student	7.1%	4.4%	
	Longterm sick	3.0%	6.8%	
	Something else	0.4%	0.8%	<0.001
Household income at baseline	mean	1.769	1.550	0.004

Income quintiles at baseline	1 (low)	17.9%	27.8%	
	2	20.0%	27.2%	
	3	20.3%	19.6%	
	4	20.4%	15.3%	
	5 (high)	21.4%	10.1%	<0.001
Ethnicity	White	84.6%	78.6%	
	Black	4.6%	5.4%	
	Indian	3.5%	4.0%	
	pakistani/bangaldesh	4.7%	9.0%	
	other	2.6%	3.1%	<0.001
Number of waves	Mean (median)	7.4 (8)	6.9 (7)	<0.001
Self-rated general health at abseline	Good to excellent	82.3%	70.8%	
	Fair or poor	17.7%	29.2%	<0.001
GHQ at baseline	Mean (median)	9.0 (9)	9.4 (10)	0.10

Appendix 5.6: Two-part model vs. poison regression techniques for numbers of cigarettes smoked

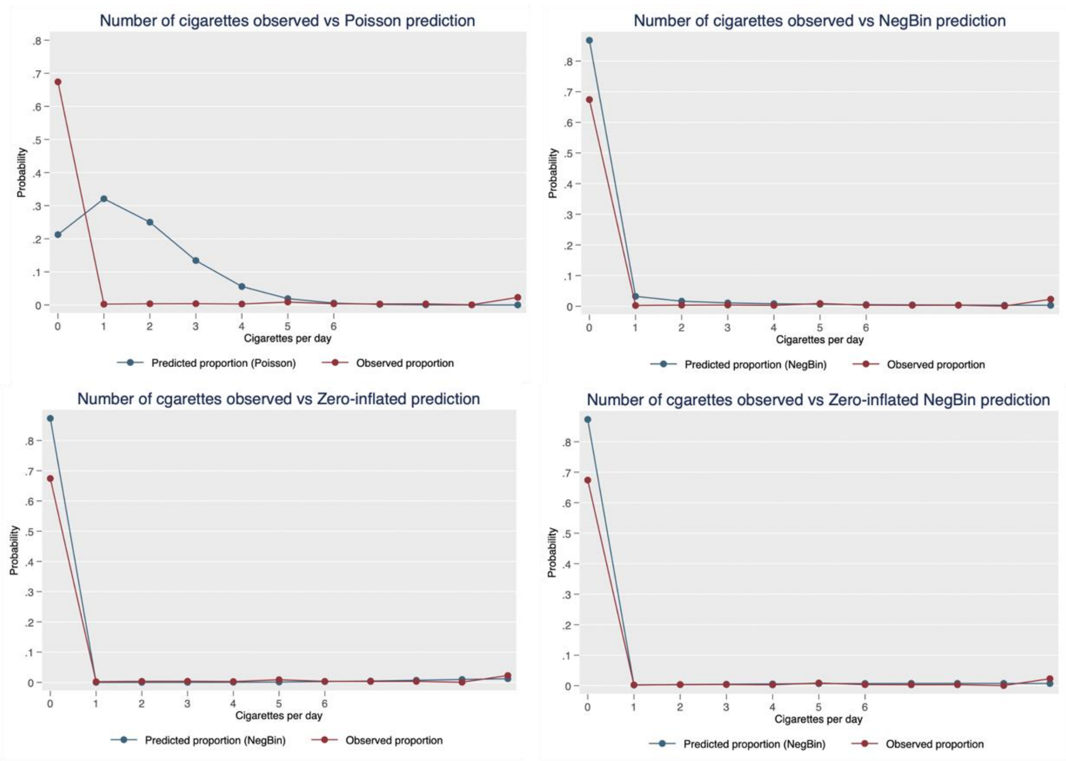


Figure A5.11 Comparison of Poison models for number of cigarettes, including standard Poisson regression, zero-inflated Poisson (ZIP), negative binomial regression, and zero-inflated negative binomial (ZINB) regression

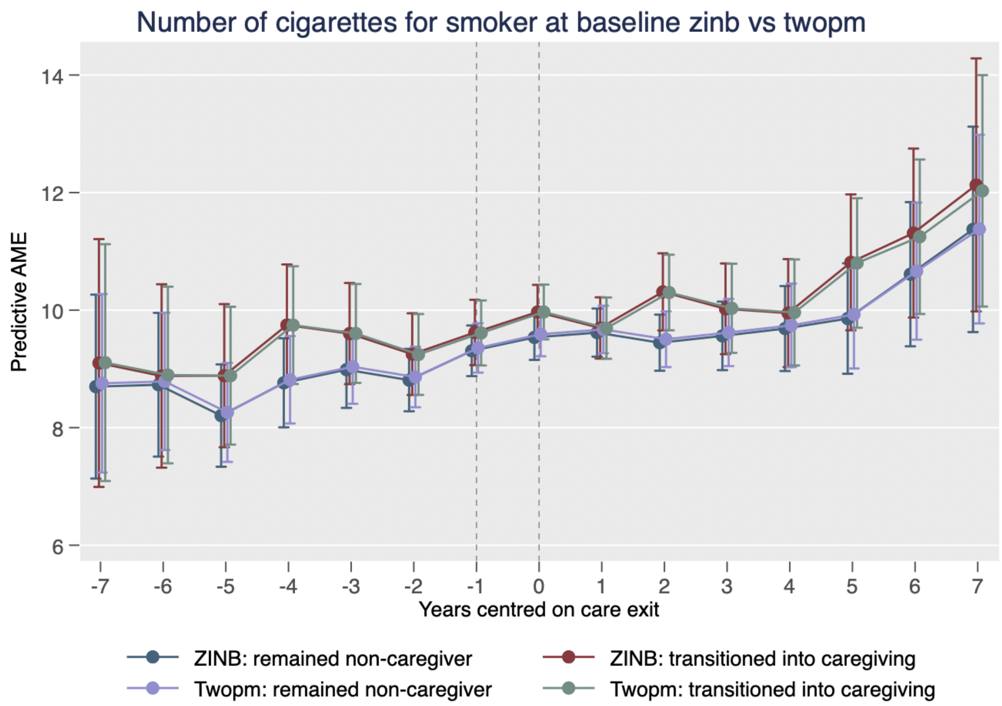


Figure A5.12 Poisson Comparison of zero-inflated negative binomial Poisson model with two-part model, showing trajectories for the number of cigarettes for individuals who transition into caregiving (n=8,659) compared to those who remain non-caregivers (n=17,323).

Appendix 5.7: P-values for piecewise regression (caregiving onset)

Table A5.4 P-values for piece wise regression (entering caregiving) by outcome, the figure the transition period and the post-transition period.

Figure	**Description**	**Physical activity (n transition)**	**Transition period ("-2 to 0")**	**Post-transition period ("0 to 4"**
Figure 5.3	Caregiving status	4,436	0.02	0.04
Figure 5.4	Caregiving intensity	4,263	0.05	0.07
Figure 5.5	Matched low & high intensity		0.12	0.52
Figure 5.6	Place of caregiving	4,434	0.01	0.34
Figure 5.7	**Transition*sex**	**4,436**	**0.83**	**0.88**
	Male only	1,800	0.05	0.06
	Female only	2,636	0.07	0.21
Figure 5.9	**Transition*age group**	**4,436**	**0.97**	**0.26**
	Early adulthood (16-29)	461	0.77	0.94
	Early mid-adulthood (30-49)	1,544	0.24	0.08
	Late mid-adulthood (50-64)	1,505	0.23	0.97
	Late adulthood (65+)	926	0.004	0.005
Figure	**Description**	**Fruit and vegetable consumption (n transition)**	**Transition period ("-2 to 0")**	**Post-transition period ("0 to 4")**
Figure 5.10	Caregiving status	4,692	0.55	0.73
Figure 5.11	Caregiving intensity	4,295	0.92	0.71
Figure 5.12	Matched low & high intensity		0.69	0.99
Figure 5.13	Place of caregiving	4,466	0.88	0.90
Figure 5.14	**Transition*sex**	**4,692**	**0.17**	**0.13**
	Male only	1,812	0.97	0.97
	Female only	2,656	0.89	0.86
Figure 5.15	**Transition*age group**	**4,692**	**0.06**	**0.73**
	Early adulthood (16-29)	467	0.28	0.75
	Early mid-adulthood (30-49)	1,550	0.07	0.22
	Late mid-adulthood (50-64)	1,515	0.08	0.35
	Late adulthood (65+)	936	0.13	0.35

Figure	Description	Problematic drinking (n transition)	Transition period ("-2 to 0")	Post-transition period ("0 to 4")
Figure 5.16	Caregiving status	4,468	0.73	0.33
Figure 5.17	Caregiving intensity	4,295	0.62	0.50
	Matched low & high intensity		0.21	0.95
Figure 5.18	Place of caregiving	4,295	0.60	0.37
Figure 5.19	**Transition*sex**	**4,468**	**0.37**	**0.27**
	Male only	1,810	0.56	0.75
	Female only	2,658	0.23	0.40
Figure 5.20	**Transition*age group**	**4,468**	**0.78**	**0.33**
	Early adulthood (16-29)	467	0.33	0.21
	Early mid-adulthood (30-49)	1,548	0.56	0.43
	Late mid-adulthood (50-64)	1,518	0.22	0.27
	Late adulthood (65+)	935	0.60	0.52
Figure	**Description**	**Smoking (n transition)**	**Transition period ("-1 to 0")**	**Post-transition period ("0 to 7")**
Figure 5.21	Caregiving status	8,659	<0.001	<0.001
Figure 5.22	Caregiving intensity	8,316	<0.001	0.08
	Matched low & high intensity		0.08	0.07
Figure 5.26	Place of caregiving	8,657	0.07	0.06
Figure 5.23	Number of cigarettes: caregiving status	8,657	<0.001	0.001
Figure 5.24	Number of cigarettes: Smoker at baseline and caregiving status	1,492	0.46	0.47
Figure 5.25	Number of cigarettes: Smoker at baseline and caregiving intensity	1,433	0.23	0.29
Figure 5.27	**Transition*sex**	**8,659**	**0.82**	**0.81**
	Male only	3,601	0.36	0.51
	Female only	5,058	0.11	0.26
Figure 5.28	**Transition*age group**	**8,659**	**0.02**	**0.05**
	Early adulthood (16-29)	1,441	0.02	0.05
	Early mid-adulthood (30-49)	3,083	<0.001	0.01
	Late mid-adulthood (50-64)	2,497	0.43	0.29
	Late adulthood (65+)	1,638	0.21	0.75

Appendix Chapter 6: Caregiving exit

Appendix 6.1: Distribution of number of cigarettes

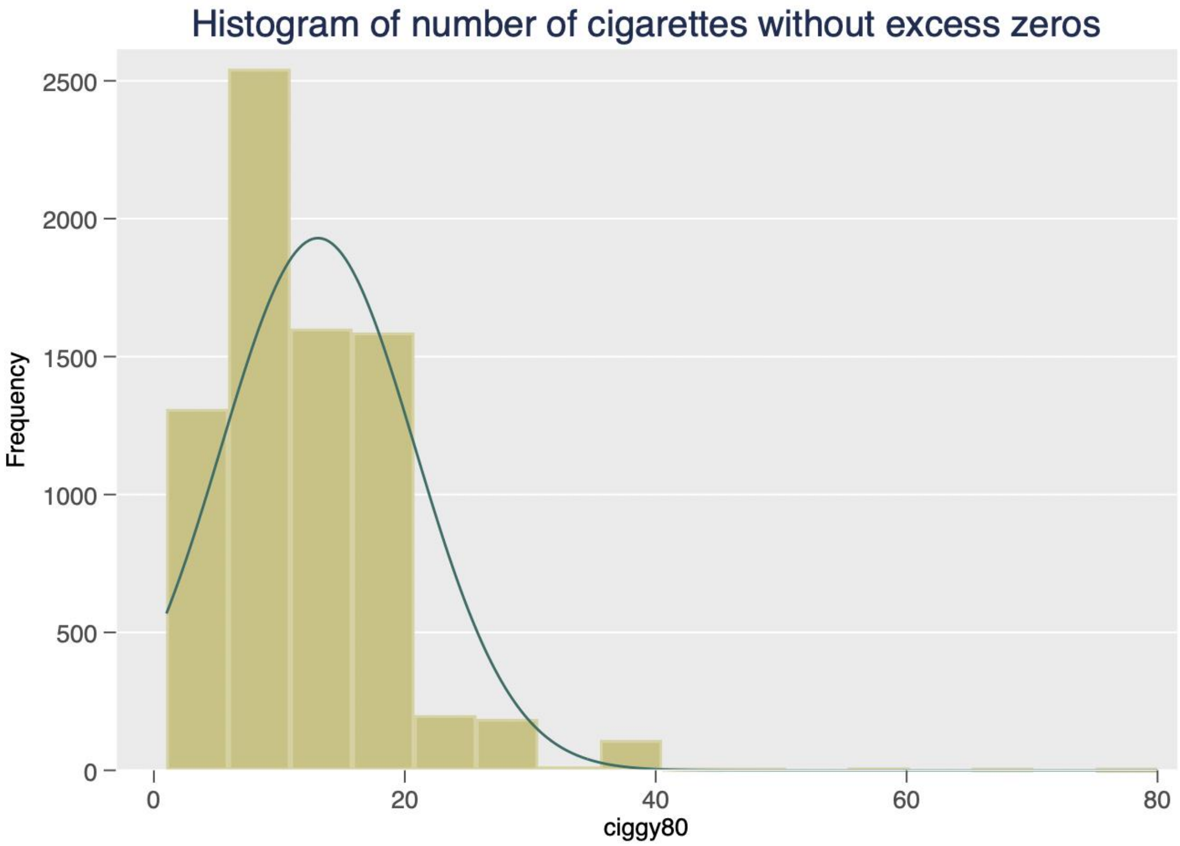


Figure A6.1 Histogram for number of cigarettes without excess zeroes for exit of caregiving; Histogram of the number of cigarettes smoked per day, excluding zeros and trimming at 80 cigarettes per day.

Appendix 6.2: Sample size flow charts for caregiving exit

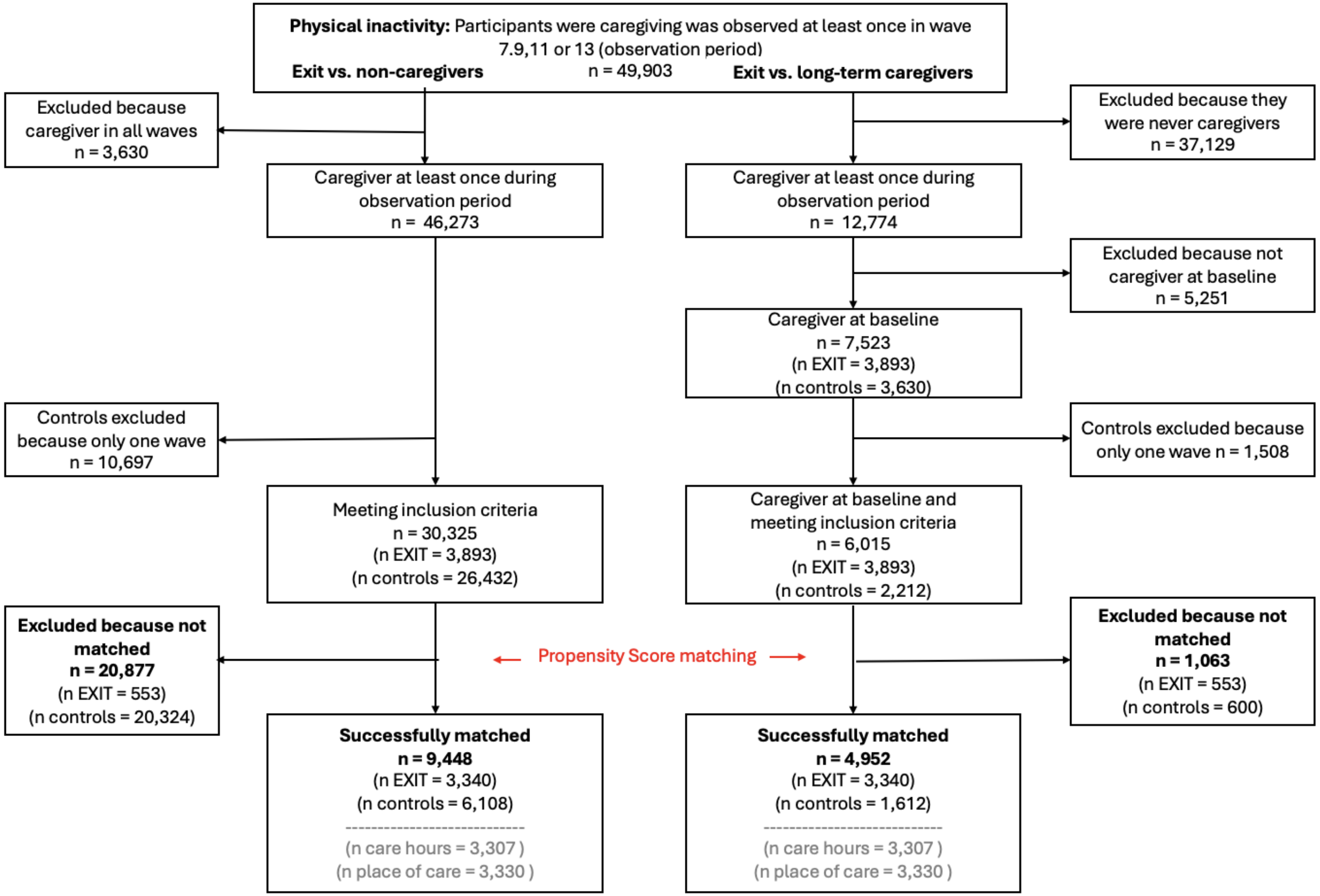


Figure A6.2 Sample size flow chart for physical inactivity and caregiving exit, comparing exit vs non-caregivers and exit vs long-term caregivers.

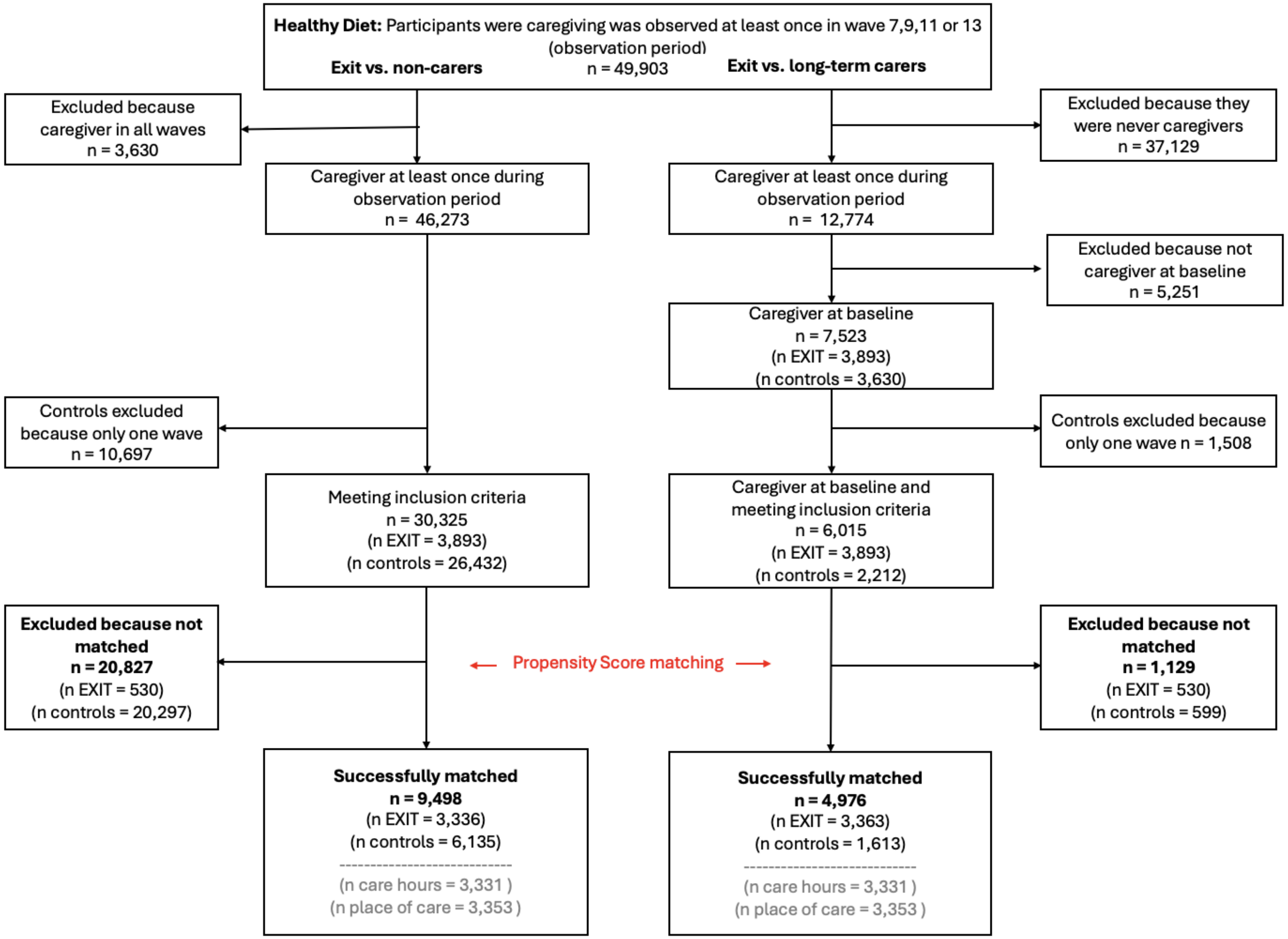


Figure A6.3 Sample size flow chart for fruit and vegetable consumption and caregiving exit, comparing exit vs non-caregivers and exit vs long-term caregivers.

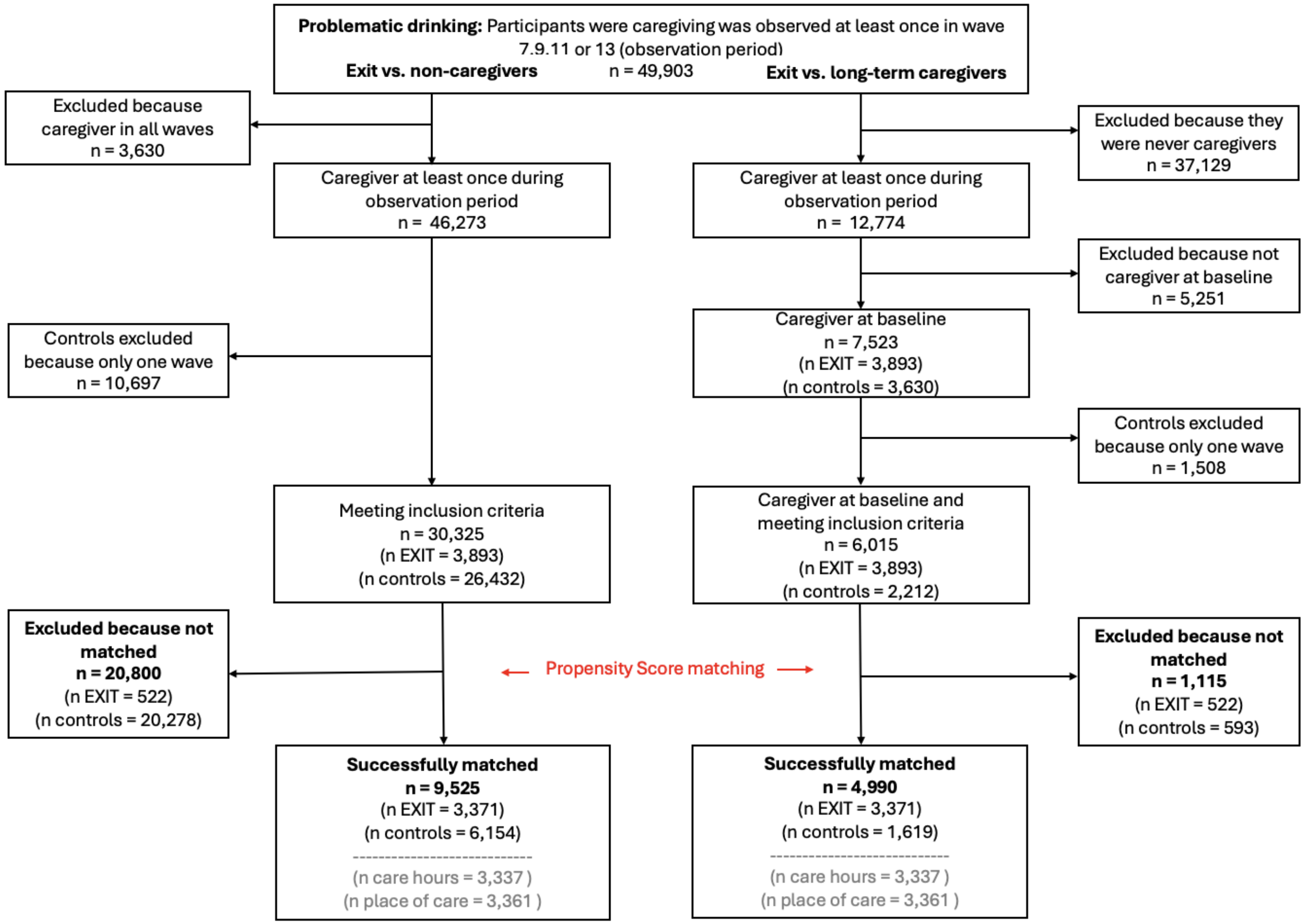


Figure A6.4 Sample size flow chart for problematic drinking and caregiving exit, comparing exit vs non-caregivers and exit vs long-term caregivers.

Appendix 6.3: P-values for piecewise regression (caregiving exit)

Table A6.1 P-values for piece wise regression (caregiving exit) by outcome, the figure the transition period and the post-transition period.

			Exit caregiving vs. continuing caregiving		**Exit caregiving vs. non-caregiving**	
Figure(s)	**Description**	**Physical activity (n exit)**	**Transition period (“-2 to 0”)**	**Post-transition period (“2 to 4”)**	**Transition period (“-2 to 0”)**	**Post-transition period (“2 to 4”)**
Figure 6.2 Figure 6.3 Figure 6.4	Caregiving status	3,340	0.002	0.001	0.06	0.31
Figure 6.5	Caregiving intensity	3,307	0.01	0.01	0.009	0.02
Figure 6.6	Place of caregiving	3,330	0.32	0.09	0.11	0.15
Figure 6.7	**Transition*sex**	**3,340**	**0.75**	**0.92**	**0.23**	**0.17**
	Male only	1,247	0.93	0.80	0.11	0.31
	Female only	2,093	0.01	0.02	0.34	0.99
Figure 6.9	**Transition*age group**	**3,340**	**0.45**	**0.82**	**0.85**	**0.85**
	Early adulthood (16-29)	287	0.42	0.84	0.49	0.51
	Early mid-adulthood (30-49)	874	0.06	0.09	0.33	0.89
	Late mid-adulthood (50-64)	1,191	0.76	0.22	0.90	0.52
	Late adulthood (65+)	988	0.16	0.11	0.21	0.14

			Exit caregiving vs. continuing caregiving		Exit caregiving vs. non-caregiving	
Figure(s)	**Description**	**Fruit and vegetable consumption (n exit)**	**Transition period (“-2 to 0”)**	**Post-transition period (“2 to 4”)**	**Transition period (“-2 to 0”)**	**Post-transition period (“2 to 4”)**
Figure 6.10 Figure 6.11 Figure 6.12	Caregiving status	3,363	0.51	0.33	0.29	0.92
Figure 6.13	Caregiving intensity	3,331	0.72	0.28	0.82	0.49
Figure 6.14	Place of caregiving	3,353	0.95	0.13	0.97	0.25
Figure 6.15 Figure 6.16	**Transition*sex**	**3,363**	**0.75**	**0.92**	**0.23**	**0.17**
	Male only	1,256	0.93	0.80	0.49	0.45
	Female only	2,107	0.01	0.02	0.07	0.14
Figure 6.17	**Transition*age group**	**3,363**	**0.58**	**0.45**	**0.82**	**0.90**
	Early adulthood (16-29)	287	0.58	0.97	0.80	0.37
	Early mid-adulthood (30-49)	879	0.64	0.77	0.90	0.92
	Late mid-adulthood (50-64)	1,197	0.04	0.08	0.72	0.53
	Late adulthood (65+)	1,000	0.56	0.37	0.43	0.59
Figure(s)	**Description**	**Problematic drinking (n)**	**Transition period (“-2 to 0”)**	**Post-transition period (“2 to 4”)**	**Transition period (“-2 to 0”)**	**Post-transition period (“2 to 4”)**
Figure 6.18 Figure 6.19 Figure 6.20	Caregiving status	3,371	0.04	0.05	0.80	0.88
Figure 6.21	Caregiving intensity	3,337	0.16	0.12	0.17	0.11
Figure 6.22	Place of caregiving	3,361	0.15	0.10	0.63	0.69
Figure 6.23 Figure 6.24	**Transition*sex**	**3,371**	**0.38**	**0.19**	**0.23**	**0.78**
	Male only	1,259	0.78	0.55	0.96	0.80
	Female only	2,112	0.41	0.65	0.92	0.51
Figure 6.25	**Transition*age group**	**3,371**	**0.42**	**0.87**	**0.23**	**0.11**
	Early adulthood (16-29)	288	0.57	0.87	0.41	0.63

			Exit caregiving vs. continuing caregiving		Exit caregiving vs. non-caregiving	
	Early mid-adulthood (30-49)	882	0.09	0.38	0.86	0.38
	Late mid-adulthood (50-64)	1,199	0.27	0.15	0.04	0.05
	Late adulthood (65+)	1,002	0.59	0.87	0.13	0.37
Figure(s)	**Description**	**Smoking (n)**	**Transition period ("-1 to 0")**	**Post-transition period ("1 to 7")**	**Transition period ("-1 to 0")**	**Post-transition period ("1 to 7")**
Figure 6.26 Figure 6.27 Figure 6.28	Caregiving status	5,385	0.72	0.88	0.08	0.04
Figure 6.30	Caregiving intensity	5,338	0.77	0.66	0.57	0.51
Figure 6.31	Place of caregiving	5,370	0.69	0.48	0.68	0.44
Figure 6.29	Number of cigarettes: Smoker at baseline and caregiving status	996	0.15	0.11	0.77	0.69
Figure 6.32 Figure 6.33	**Transition*sex**	**5,385**	**0.73**	**0.53**	**0.88**	**0.97**
	Male only	2,146	0.50	0.47	0.29	0.23
	Female only	3,239	0.02	0.06	0.95	0.80
Figure 6.34	**Transition*age group**	**5,385**	**0.23**	**0.31**	**0.27**	**0.09**
	Early adulthood (16-29)	866	0.11	0.18	0.89	0.80
	Early mid-adulthood (30-49)	1,570	0.08	0.19	0.01	0.004
	Late mid-adulthood (50-64)	1,776	0.81	0.66	0.33	0.41
	Late adulthood (65+)	1,173	0.88	0.79	0.82	0.60

Appendix Chapter 7: Caregiving intensity

Appendix 7.1: Sample size flow charts for caregiving intensity analysis

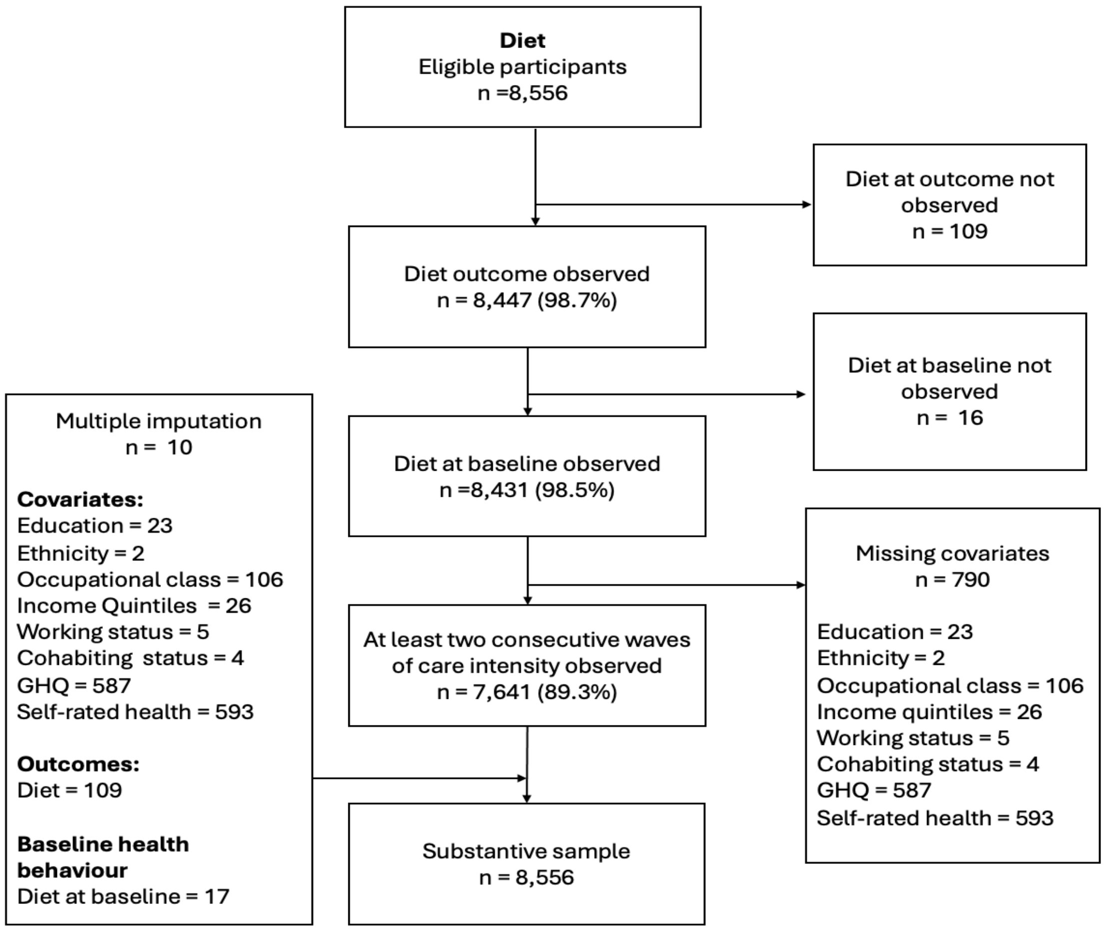


Figure A7.1 Sample size flow chart for fruit and vegetable consumption of eligible participants following LCA of caregiving intensity between wave 2 and wave 13 of UKHLS.

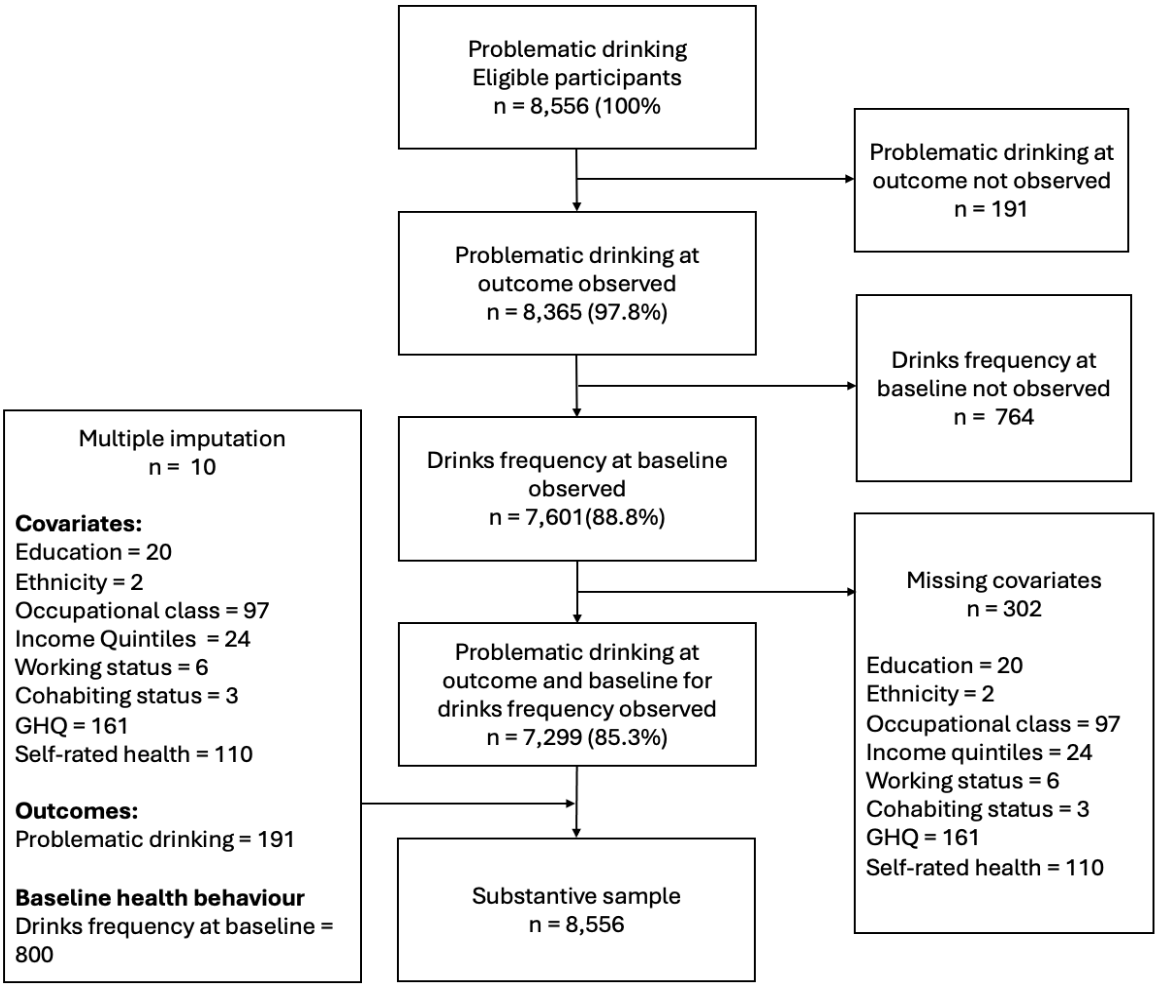


Figure A7.2 Sample size flow chart for problematic drinking of eligible participants following LCA of caregiving intensity between wave 2 and wave 13 of UKHLS.

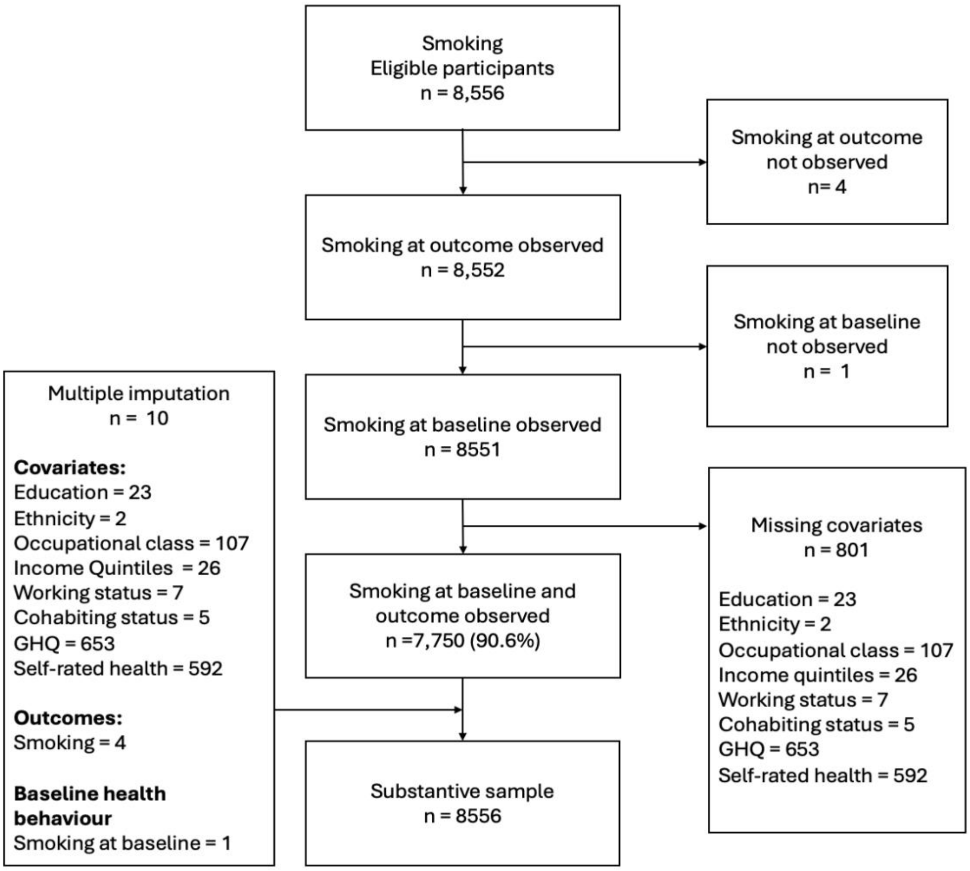


Figure A7.3 Sample size flow chart for smoking of eligible participants following LCA of caregiving intensity between wave 2 and wave 13 of UKHLS.

Appendix 7.2: State Distribution Plot with non-caring episodes

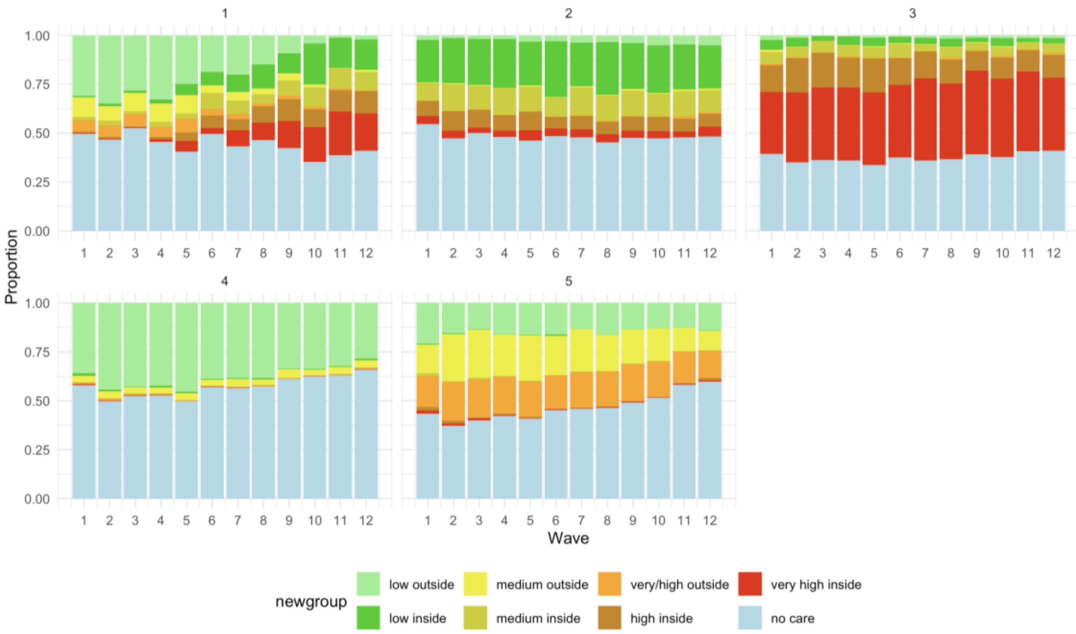


Figure A7.4 State Distribution Plot of Caregiving Intensity with non-caring episodes; 5-class solution of caregiving intensity LCA across UKHLS waves 2 to 13 among eligible participants (n=8,556) with at least two consecutive waves of caregiving intensity observed and one recorded baseline health behaviour outcome.

Appendix 7.3: Caregiving Intensity regression results

Table A7.1 Regression results for physical inactivity; logistic regression models predicting physical inactivity across latent caregiving intensity classes among UKHLS participants (n=8,556), showing pooled Odds Ratios from multiple imputation (m=10) and accounting for complex survey design and household-level clustering. Results are shown for three models: PA1 (unadjusted), PA2 (adjusted for walking at baseline), and PA3 (adjusted for selected covariates). The reference category is the 'low outside' caregiving intensity class.

		Model PA1		**Model PA2**		**Model PA3**	
	Physical inactivity	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
Latent Class	Low outside	1.00	-	1.00	-	1.00	-
	increase	1.21	(0.96, 1.53)	1.20	(0.95, 1.51)	1.11	(0.87, 1.42)
	low to medium inside	1.46	(1.26, 1.68)	1.39	(1.2, 1.61)	1.32	(1.12, 1.55)
	high inside	1.98	(1.7, 2.32)	1.84	(1.58, 2.16)	1.48	(1.24, 1.77)
	mixed outside	1.21	(1.03, 1.42)	1.18	(1.01, 1.38)	0.98	(0.83, 1.15)
Walking at baseline	0 days			1.00	-	1.00	-
	1-2 days			0.67	(0.58, 0.76)	0.82	(0.71, 0.94)
	3-4 days			0.59	(0.49, 0.7)	0.72	(0.6, 0.86)
	5-6 days			0.57	(0.47, 0.68)	0.69	(0.57, 0.85)
	Every day			0.48	(0.41, 0.56)	0.57	(0.48, 0.68)
Age group at baseline	Early adulthood (16-29)					1.00	-
	Early mid-adulthood (30-49)					0.94	(0.74, 1.2)
	Late mid-adulthood (50-64)					1.1	(0.86, 1.4)
	Late adulthood (65+)					1.43	(1.08, 1.88)
Sex	Men					1.00	-
	women					1.57	(1.4, 1.76)
Education	No Qualification					1.00	-
	A-Level, GCSE, other qualification					0.82	(0.68, 0.98)
	Degree or other higher qualification					0.68	(0.56, 0.83)
Ethnicity	White					1.00	-
	black					1.15	(0.77, 1.73)
	indian					1.25	(0.81, 1.92)

	Physical inactivity	Model PA1 Odds Ratio	Model PA1 95% CI	Model PA2 Odds Ratio	Model PA2 95% CI	Model PA3 Odds Ratio	Model PA3 95% CI
	pakistani/ bangladeshi					1.20	(0.81, 1.79)
	other asian/other					0.87	(0.53, 1.41)
Occupational Class	Not employed					1.00	-
	Managment & professional					1.11	(0.77, 1.6)
	intermediate					0.99	(0.68, 1.44)
	eroutine					0.99	(0.69, 1.42)
Income quintiles	1 (low)					1.00	-
	2					0.92	(0.77, 1.1)
	3					0.99	(0.83, 1.2)
	4					0.90	(0.74, 1.09)
	5 (high)					0.81	(0.67, 0.99)
Working status	Not employed					1.00	-
	full-time employed					0.96	(0.67, 1.39)
	part-time employed					0.86	(0.6, 1.23)
Number of children in household	0					1.00	-
	1					0.97	(0.8, 1.18)
	2					0.90	(0.73, 1.12)
	3 or more					1.03	(0.74, 1.45)
Cohabiting at baseline	Single, divorced, widowded					1.00	-
	married or cohabiting					0.93	(0.78, 1.1)
	1					1.00	-
	2					0.94	(0.75, 1.19)
	3-4					0.92	(0.71, 1.2)
	5 or more					0.86	(0.61, 1.2)
	GHQ At baseline					1.01	(1, 1.02)
Self-rated general health	Good or excellent					1.00	-
	fair or poor					1.15	(0.96, 1.38)
	sf12_base					0.98	(0.97, 0.98)
Wave outcome observed	UKHLS 7						
	UKHLS 9					0.83	(0.7, 0.98)
	UKHLS 11					0.84	(0.72, 0.99)

	Model PA1		Model PA2		Model PA3	
Physical inactivity	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
UKHLS 13					0.91	(0.8, 1.04)

Table A7.2 Regression results for fruit and vegetable consumption; linear regression models predicting average daily fruit and vegetable intake across latent caregiving intensity classes among UKHLS participants (n=8,556), showing pooled coefficient estimates from multiple imputation (m=10) and accounting for complex survey design and household-level clustering. Results are shown for three models: DIET1 (unadjusted), DIET2 (adjusted for fruit and vegetable intake at baseline), and DIET3 (adjusted for selected covariates). The reference category is the 'low outside' caregiving intensity class.

		Model DIET1		**Model DIET2**		**Model DIET3**	
	Diet	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**
Latent Class	Low outside	Ref.	-	Ref.	-	Ref.	-
	increase	-0.2	(-0.5, 0.0)	-0.2	(-0.4, 0.1)	-0.1	(-0.4, 0.1)
	low to medium inside	-0.6	(-0.7, -0.5)	-0.4	(-0.6, -0.3)	-0.3	(-0.4, -0.1)
	high inside	-0.7	(-0.9, -0.5)	-0.5	(-0.6, -0.3)	-0.3	(-0.4, -0.1)
	mixed outside	-0.1	(-0.3, 0.0)	-0.1	(-0.2, 0.1)	0.0	(-0.1, 0.2)
Portions fruit / vegetable at baseline	0			Ref.	-	Ref.	-
	1-3			2.0	(1.7, 2.3)	1.7	(1.4, 2)
	4			3.1	(2.8, 3.5)	2.7	(2.3, 3)
	5 or more			4.1	(3.7, 4.4)	3.5	(3.2, 3.9)
Age group at baseline	Early adulthood (16-29)					Ref.	-
	Early mid-adulthood (30-49)					0.0	(-0.2, 0.2)
	Late mid-adulthood (50-64)					0.3	(0.1, 0.5)
	Late adulthood (65+)					0.3	(0.0, 0.5)
Sex	Men					Ref.	-
	women					0.2	(0.1, 0.3)
Education	No Qualification					Ref.	-
	A-Level, GCSE, other qualification					0.2	(0.1, 0.4)
	Degree or other higher qualification					0.6	(0.4, 0.8)
Ethnicity	White					Ref.	-
	black					0.1	(-0.3, 0.4)
	indian					0.1	(-0.3, 0.6)
	pakistani/ bangladeshi					-0.2	(-0.6, 0.2)
	other asian/other					0.1	(-0.4, 0.5)

		Model DIET1		Model DIET2		Model DIET3	
	Diet	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**
Occupational Class	Not employed					Ref.	-
	Management & professional					0.1	(-0.2, 0.4)
	intermediate					0.1	(-0.3, 0.4)
	routine					0.1	(-0.3, 0.4)
Income quintiles	1 (low)					Ref.	-
	2					0.2	(0, 0.3)
	3					0.3	(0.1, 0.4)
	4					0.4	(0.3, 0.6)
	5 (high)					0.6	(0.4, 0.8)
Working status	Not employed					Ref.	-
	full-time employed					-0.1	(-0.4, 0.2)
	part-time employed					0.1	(-0.3, 0.4)
Number of children in household	0					Ref.	-
	1					0.1	(0, 0.3)
	2					0.0	(-0.2, 0.2)
	3 or more					-0.2	(-0.5, 0.1)
Cohabiting at baseline	Single, divorced, widowded					Ref.	-
	married or cohabiting					0.2	(0, 0.3)
Number of people living in the household	1					Ref.	-
	2					0.0	(-0.2, 0.2)
	3-4					-0.1	(-0.3, 0.2)
	5 or more					0.2	(-0.1, 0.5)
	GHQ At baseline					0.0	(0, 0)
Self-rated general health	Good or excellent					Ref.	-
	fair or poor					-0.2	(-0.3, -0.1)
Wave outcome observed	UKHLS 7					Ref.	-
	UKHLS 9					0.0	(-0.1, 0.1)
	UKHLS 11					0.2	(0.1, 0.4)
	UKHLS 13					0.1	(0, 0.2)

Table A7.3 Regression results for Problematic Drinking; logistic regression models predicting problematic drinking across latent caregiving intensity classes among UKHLS participants (n=8,556), showing pooled odds ratio estimates from multiple imputation (m=10) and accounting for complex survey design and household-level clustering. Results are shown for three models: ALC1 (unadjusted), ALC2 (adjusted for drinks frequency at baseline), and ALC3 (adjusted for selected covariates). The reference category is the 'low outside' caregiving intensity class.

		Model ALC1		**Model ALC2**		**Model ALC3**	
	Problematic drinking	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
Latent Class	Low outside	1.00	-	1.00	-	1.00	-
	increase	0.6	(0.48, 0.75)	0.69	(0.53, 0.91)	0.77	(0.57, 1.04)
	low to medium inside	0.55	(0.47, 0.63)	0.63	(0.53, 0.75)	0.71	(0.59, 0.85)
	high inside	0.49	(0.42, 0.57)	0.66	(0.54, 0.8)	0.75	(0.61, 0.93)
	mixed outside	0.69	(0.59, 0.81)	0.84	(0.7, 1.01)	0.86	(0.71, 1.04)
Walking at baseline	Non-drinker			1.00	-	1.00	-
	Monthly/weekly			3.59	(2.68, 4.81)	2.91	(2.12, 4.01)
	1-4 days/week			20.5	(15.38, 27.32)	21.2	(15.37, 29.24)
	5+ days a week			64.65	(46.12, 90.61)	89.37	(60.94, 131.07)
Age group at baseline	Early adulthood (16-29)					1.00	-
	Early mid-adulthood (30-49)					0.56	(0.42, 0.76)
	Late mid-adulthood (50-64)					0.42	(0.31, 0.58)
	Late adulthood (65+)					0.21	(0.15, 0.3.0)
Sex	Men					1.00	-
	women					1.69	(1.48, 1.94)
Education	No Qualification					1.00	-
	A-Level, GCSE, other qualification					0.99	(0.79, 1.23)
	Degree or other higher qualification					0.83	(0.66, 1.06)
Ethnicity	White					1.00	-
	black					0.76	(0.48, 1.2)
	indian					0.5	(0.27, 0.93)
	pakistani/ bangladeshi					0.27	(0.1, 0.75)

		Model ALC1		Model ALC2		Model ALC3	
	Problematic drinking	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
	other asian/other					0.56	(0.27, 1.13)
Occupational Class	Not employed					1.00	-
	Managment & professional					1.1	(0.72, 1.69)
	intermediate					0.92	(0.6, 1.42)
	eroutine					0.87	(0.57, 1.34)
Income quintiles	1 (low)					1.00	-
	2					1.14	(0.91, 1.42)
	3					1.12	(0.9, 1.41)
	4					1.41	(1.12, 1.77)
	5 (high)					1.26	(1, 1.6)
Working status	Not employed					1.00	-
	full-time employed					1.13	(0.73, 1.73)
	part-time employed					1.11	(0.73, 1.69)
Number of children in household	0					1.00	-
	1					1.26	(1, 1.57)
	2					1.18	(0.91, 1.52)
	3 or more					0.99	(0.63, 1.55)
Cohabiting at baseline	Single, divorced, widowded					1.00	-
	married or cohabiting					1.2	(0.97, 1.49)
	1					1.00	-
	2					0.94	(0.71, 1.24)
	3-4					0.9	(0.66, 1.22)
	5 or more					0.93	(0.61, 1.4)
	GHQ At baseline					1	(0.99, 1.02)
Self-rated general health	Good or excellent					1.00	-
	fair or poor					0.79	(0.65, 0.94)
Wave outcome observed	UKHLS 7					1.00	-
	UKHLS 9					1.17	(0.96, 1.43)
	UKHLS 11					0.81	(0.67, 0.98)
	UKHLS 13					0.77	(0.66, 0.9)

Table A7.4 Regression results for Smoking; logistic regression models predicting smoking status across latent caregiving intensity classes among UKHLS participants (n=8,556), showing pooled odds ratio estimates from multiple imputation (m=10) and accounting for survey weights and household-level clustering. Results are shown for three models: SMOK1 (unadjusted), SMOK2 (adjusted for smoking status at baseline), and SMOK3 (adjusted for selected covariates). The reference category is the 'low outside' caregiving intensity class.

		Model SMOK1		**Model SMOK2**		**Model SMOK3**	
		Odds Ratio	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
Latent Class	Low outside	1.00	-	1.00	-	1.00	-
	increase	1.21	(0.86, 1.71)	0.80	(0.5, 1.26)	0.9	(0.54, 1.51)
	low to medium inside	1.61	(1.31, 1.97)	1.70	(1.25, 2.29)	1.75	(1.26, 2.42)
	high inside	2.23	(1.82, 2.72)	1.50	(1.13, 2)	1.58	(1.14, 2.19)
	mixed outside	1.78	(1.43, 2.21)	1.28	(0.95, 1.74)	1.19	(0.86, 1.65)
Smoking at baseline	Non-smoker			1.00	-	1.00	-
	Ex-smoker			5.26	(3.25, 8.51)	6.42	(4.01, 10.26)
	Current smoker			235.54	(149.68, 370.66)	247.75	(158.75, 386.66)
Age group at baseline	Early adulthood (16-29)					1.00	-
	Early mid-adulthood (30-49)					0.84	(0.54, 1.3)
	Late mid-adulthood (50-64)					0.51	(0.32, 0.79)
	Late adulthood (65+)					0.30	(0.18, 0.51)
Sex	Men					1.00	-
	women					1.22	(0.96, 1.54)
Education	No Qualification					1.00	-
	A-Level, GCSE, other qualification					0.8	(0.59, 1.08)
	Degree or other higher qualification					0.66	(0.47, 0.95)
Ethnicity	White					1.00	-
	black					0.8	(0.33, 1.99)
	indian					0.57	(0.21, 1.54)
	pakistani/ bangladeshi					1.09	(0.42, 2.78)

		Model SMOK1		Model SMOK2		Model SMOK3	
		Odds Ratio	95% CI	Odds Ratio	95% CI	Odds Ratio	95% CI
	other asian/other					2.18	(0.7, 6.86)
Occupational Class	Not employed					1.00	-
	Managment & professional					1.39	(0.63, 3.04)
	intermediate					1.23	(0.55, 2.74)
	eroutine					1.83	(0.85, 3.94)
Income quintiles	1 (low)					1.00	-
	2					0.98	(0.71, 1.35)
	3					0.77	(0.55, 1.07)
	4					1.09	(0.76, 1.55)
	5 (high)					0.68	(0.44, 1.06)
Working status	Not employed					1.00	-
	full-time employed					0.68	(0.32, 1.47)
	part-time employed					0.82	(0.38, 1.79)
Number of children in household	0					1.00	-
	1					0.96	(0.64, 1.43)
	2					0.59	(0.38, 0.89)
	3 or more					0.38	(0.19, 0.79)
Cohabiting at baseline	Single, divorced, widowded					1.00	-
	married or cohabiting					0.78	(0.57, 1.07)
	1					1.00	-
	2					0.7	(0.46, 1.05)
	3-4					0.76	(0.47, 1.21)
	5 or more					1.49	(0.74, 2.98)
	GHQ At baseline					0.99	(0.97, 1.01)
Self-rated general health	Good or excellent					1.00	-
	fair or poor					1.62	(1.25, 2.11)
Wave outcome observed	UKHLS 7					1.00	-
	UKHLS 9					0.94	(0.68, 1.29)
	UKHLS 11					0.77	(0.56, 1.05)
	UKHLS 13					0.42	(0.32, 0.56)

Appendix 7.4: Complete case Analysis

Table A7.5 Descriptive statistics for caregiving intensity classes (n=8,556), based on complete cases. Estimates account for complex survey design and clustering at the household level.

		Unweighted n = 8,556	Weighted proportions					
Complete Cases	**level**	**n(%)**	**low outside**	**increase**	**low to medium inside**	**high inside**	**mixed outside**	**p**
			3,961	388	1,394	1,175	889	
Health behaviour outcome								
Fruit and vegetable consumption	Mean(sd)	3.70 (2.17)	3.95 (2.13)	3.72 (2.32)	3.34 (2.04)	3.25 (2.18)	3.81 (2.29)	<0.001
	Missing	109 (1.3%)						
Physical activity	Active	3724 (43.5%)	50.2%	45.4%	41.0%	33.6%	45.8	<0.001
	Inactive	4647 (54.3%)	49.8%	54.6%	59.0%	66.4%	54.2	
	Missing	185 (2.2%)						
Problematic drinking	No	4513 (52.7%)	46.4%	59.3%	61.0%	63.6%	55.7	<0.001
	Yes	3852 (45.0%)	53.6%	40.7%	39.0%	36.4%	44.3	
	Missing	191 (2.2%)						
Smoking	Non-smoker	7347 (85.9%)	89.5%	87.5%	84.1%	79.3%	82.8	<0.001
	Smoker	1205 (14.1%)	10.5%	12.5%	15.9%	20.7%	17.2	

		Unweighted n = 8,556	Weighted proportions					
Complete Cases	**level**	**n(%)**	**low outside**	**increase**	**low to medium inside**	**high inside**	**mixed outside**	**p**
	Missing	4 (0.0%)						
Health behaviour at baseline								
Walking at baseline	none	2335 (27.3%)	20.5%	25.0%	31.9%	36.6%	26.2	<0.001
	1-2 days	2969 (34.7%)	37.9%	34.1%	31.9%	31.0%	34.9	
	3-4 days	1115 (13.0%)	14.8%	13.8%	11.2%	9.6%	12.0	
	5-6 days	813 (9.5%)	10.4%	9.3%	8.8%	9.2%	11.3	
	Every day	1316 (15.4%)	16.4%	17.8%	16.1%	13.6%	15.6	
	Missing	8 (0.1%)						
Daily fruit and vegetable consumption at baseline	0 portions	66 (0.8%)	0.5%	1.4%	1.4%	1.5%	1.0	<0.001
	1-3 portions	4672 (54.6%)	50.8%	52.3%	58.1%	60.7%	54.4	
	4 portions	1616 (18.9%)	20.3%	19.5%	18.0%	16.6%	17.4	
	5+ portions	2185 (25.5%)	28.5%	26.8%	22.5%	21.2%	27.2	
	Missing	17 (0.2%)						
Smoking status at baseline	never smoked	3808 (44.5%)	44.7%	40.3%	44.1%	36.2%	40.6	<0.001
	ex-smoker	3177 (37.1%)	40.7%	39.5%	37.6%	37.5%	36.4	
	current smoker	1570 (18.3%)	14.5%	20.2%	18.3%	26.3%	22.9	

		Unweighted n = 8,556	Weighted proportions					
Complete Cases	**level**	**n(%)**	**low outside**	**increase**	**low to medium inside**	**high inside**	**mixed outside**	**p**
	Missing	1 (0.0%)						
Drinks frequency at baseline	no drinks	1050 (12.3%)	8.2%	13.2%	15.5%	18.3%	14.8	<0.001
	monthly or weekly	2598 (30.4%)	30.3%	36.4%	36.4%	39.2%	34.8%	
	1-4 per week	3045 (35.6%)	46.0%	37.4%	33.5%	30.8%	38.1%	
	5+ per week	1063 (12.4%)	15.5%	13.1%	14.6%	11.6%	12.2%	
	Missing	800 (9.4%)						
Covariates								
Age group at baseline	Early adulthood (16-29)	636 (7.4%)	6.4%	5.2%	16.0%	7.8%	4.9%	<0.001
	Early mid-adulthood (30-49)	2892 (33.8%)	31.2%	33.4%	28.3%	35.1%	32.4%	
	Late mid-adulthood (50-64)	3244 (37.9%)	43.9%	37.7%	28.3%	25.4%	47.9%	
	Late adulthood (65+)	1784 (20.9%)	18.5%	23.7%	27.4%	31.7%	14.8%	
Sex	men	3208 (37.5%)	43.0%	38.9%	51.0%	36.8%	29.1%	<0.001
	women	5348 (62.5%)	57.0%	61.1%	49.0%	63.2%	70.9%	
	Missing	0						
Education	No qualification	1130 (13.2%)	8.3%	13.0%	17.0%	24.3%	12.6%	<0.001

	Unweighted n = 8,556		Weighted proportions					
Complete Cases	**level**	**n(%)**	**low outside**	**increase**	**low to medium inside**	**high inside**	**mixed outside**	**p**
	A-Level, GCSE, other qualification	4407 (51.5%)	51.6%	55.5%	52.6%	52.9%	55.7%	
	Degree or other higher qualification	2996 (35.0%)	40.1%	31.4%	30.4%	22.8%	31.7%	
	Missing	23 (0.3%)						
Ethnicity	white	7749 (90.6%)	96.4%	95.9%	92.1%	94.4%	94.9%	<0.001
	black	218 (2.5%)	1.0%	0.5%	1.8%	1.8%	1.7%	
	indian	174 (2.0%)	1.0%	1.1%	2.1%	1.2%	0.8%	
	pakistani/bangladeshi	277 (3.2%)	0.6%	1.5%	2.9%	1.5%	1.4%	
	other asian/other	136 (1.6%)	1.0%	1.0%	1.1%	1.1%	1.2%	
	Missing	2 (0.0%)			%			
Occupational Class at baseline	not employed	3906 (45.7%)	35.8%	49.2%	51.3%	71.5%	45.9%	<0.001
	Managment & professional	1950 (22.8%)	30.3%	22.5%	18.5%	8.0%	20.4%	
	intermediate	1111 (13.0%)	15.3%	11.3%	11.4%	6.0%	14.3%	
	routine	1481 (17.3%)	18.6%	17.0%	18.8%	14.5%	19.4%	
	Missing	108 (1.3%)						

		Unweighted n = 8,556	**Weighted proportions**					
Complete Cases	**level**	**n(%)**	**low outside**	**increase**	**low to medium inside**	**high inside**	**mixed outside**	**p**
Income quintiles at baseline	1 (low)	1497 (17.5%)	12.9%	19.7%	17.9%	24.2%	21.1%	<0.001
	2	1741 (20.3%)	16.2%	18.8%	26.3%	26.8%	20.5%	
	3	1716 (20.1%)	19.1%	17.8%	21.7%	24.3%	19.3%	
	4	1777 (20.8%)	22.9%	21.3%	20.1%	16.4%	18.9%	
	5 (high)	1799 (21.0%)	28.9%	22.5%	14.0%	8.4%	20.1%	
	Missing	26 (0.3%)						
Employment status at baseline	not in paid employment	3701 (43.3%)	33.3%	44.0%	48.1%	68.3%	43.1%	<0.001
	full-time employed	3342 (39.1%)	47.4%	36.6%	37.6%	19.1%	37.3%	
	part-time employed	1506 (17.6%)	19.2%	19.4%	14.3%	12.5%	19.6%	
	Missing	7 (0.1%)						
Number of children living in the household at baseline	0	6330 (74.0%)	77.7%	74.1%	78.8%	68.2%	78.3%	<0.001
	1	940 (11.0%)	10.6%	9.2%	9.1%	10.4%	11.8%	
	2	872 (10.2%)	9.2%	10.2%	7.5%	11.0%	7.2%	
	3+	414 (4.8%)	2.5%	6.5%	4.5%	10.4%	2.7%	
	Missing	0						

		Unweighted n = 8,556	Weighted proportions					
Complete Cases	**level**	**n(%)**	**low outside**	**increase**	**low to medium inside**	**high inside**	**mixed outside**	**p**
Cohabiting status at baseline	single, seperated, widowed	2238 (26.2%)	27.5%	18.0%	26.4%	21.4%	39.1%	<0.001
	married or cohabiting	6313 (73.8%)	72.5%	82.0%	73.6%	78.6%	60.9%	
	Missing	5 (0.1%)						
Self-rated general health at baseline	excellent, very good or good	6312 (73.8%)	85.7%	75.4%	74.3%	65.4%	76.2%	<0.001
	fair or poor	1651 (19.3%)	14.3%	24.6%	25.7%	34.6%	23.8%	
	Missing	593 (6.9%)						
Household size at baseline	1	1019 (11.9%)	17.8%	4.4%	0.3%	0.6%	27.1%	<0.001
	2	3497 (40.9%)	38.7%	49.9%	44.2%	46.7%	35.2%	
	3-4	3089 (36.1%)	36.7%	31.5%	41.0%	37.6%	31.6%	
	5+	951 (11.1%)	6.8%	14.2%	14.6%	15.1%	6.0%	
	Missing	0						
Age at baseline	Mean(sd)	52.24 (14.63)	52.67 (13.53)	53.45 (14.51)	51.32 (18.46)	53.66 (17.00)	52.59 (12.39)	0.070
	Missing	0						
	Mean(sd)	11.68 (5.69)	10.86 (5.08)	11.63 (5.65)	11.85 (5.71)	13.56 (6.70)	12.40 (6.26)	<0.001

		Unweighted n = 8,556	Weighted proportions					
Complete Cases	**level**	**n(%)**	**low outside**	**increase**	**low to medium inside**	**high inside**	**mixed outside**	**p**
GHQ at baseline	Missing	655 (7.7%)						
SF12 at baseline	Mean(sd)	49.36 (10.70)	51.02 (9.50)	48.31 (11.54)	47.67 (11.43)	46.39 (12.26)	48.82 (10.71)	<0.001
	Missing	907 (10.6%)						

Table A7.6 Complete Case Analysis: regression results for physical inactivity; logistic regression models predicting physical inactivity across latent caregiving intensity classes among UKHLS participants (n=7,311) using complete case analysis. The table presents odds ratios from three models: PA1CC (unadjusted), PA2CC (adjusted for walking at baseline), and PA3CC (adjusted for selected covariates). The reference category is the 'low outside' caregiving intensity class. The analysis accounts for complex survey design and clustering at the household level.

		Model PA1CC		**Model PA2CC***		**Model PA3CC****	
	Physical inactivity	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
Latent Class	Low outside	1.00	-	1.00	-	1.00	-
	increase	1.22	(0.96, 1.56)	1.20	(0.94, 1.53)	1.09	(0.85, 1.41)
	low to medium inside	1.47	(1.27, 1.71)	1.41	(1.21, 1.64)	1.34	(1.13, 1.58)
	high inside	1.99	(1.69, 2.35)	1.87	(1.59, 2.20)	1.52	(1.27, 1.82)
	mixed outside	1.20	(1.02, 1.41)	1.17	(0.99, 1.38)	0.98	(0.83, 1.16)

*adjusted for health behaviour at baseline; ** adjusted for adjusted health behaviour at baseline for age group, sex, education, ethnicity, occupational class, income quintiles, employment status, number of children in the household, cohabiting status, self-rated general health, household size, GHQ, and SF12 at baseline

Table A7.7 Complete Case Analysis: regression results for fruit and vegetable consumption; logistic regression models predicting physical inactivity across latent caregiving intensity classes among UKHLS participants (n=7,641) using complete case analysis. The table presents odds ratios from three models: DIET1CC (unadjusted), DIET2CC (adjusted for baseline diet), and DIET3CC (adjusted for selected covariates). The reference category is the 'low outside' caregiving intensity class. The analysis accounts for complex survey design and clustering at the household level.

		Model DIET1		**Model DIET2***		**Model DIET3*****	
	Fruit and vegetable consumption	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**
Latent Class	Low outside	Ref.	-	Ref.	-	Ref.	-
	increase	-0.3	(-0.6, 0.0)	-0.2	(-0.5, 0.0)	-0.2	(-0.4, 0.1)
	low to medium inside	-0.6	(-0.7, -0.4)	-0.4	(-0.6, -0.3)	-0.3	(-0.4, -0.1)
	high inside	-0.7	(-0.8, -0.5)	-0.4	(-0.6, -0.3)	-0.3	(-0.4, -0.1)
	mixed outside	-0.1	(-0.2, 0.1)	0.0	(-0.2, 0.2)	0.1	(-0.1, 0.2)

*adjusted for health behaviour at baseline; *** adjusted for adjusted health behaviour at baseline for age group, sex, education, ethnicity, occupational class, income quintiles, employment status, number of children in the household, cohabiting status, self-rated general health, household size and GHQ at baseline.

Table A7.8 Complete Case Analysis: regression results for problematic drinking; logistic regression models predicting physical inactivity across latent caregiving intensity classes among UKHLS participants (n=7,299) using complete case analysis. The table presents odds ratios from three models: ALC1CC (unadjusted), ALC2CC (adjusted for drinks frequency at baseline), and ALC3CC (adjusted for selected covariates). The reference category is the 'low outside' caregiving intensity class. The analysis accounts for complex survey design and clustering at the household level.

		Model ALC1CC		**Model ALC2CC***		**Model ALC3CC*****	
	Problematic drinking	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
Latent Class	Low outside	1.00	-	1.00	-	1.00	-
	increase	0.60	(0.487 0.76)	0.70	(0.52, 0.93)	0.80	(0.58, 1.09)
	low to medium inside	0.58	(0.50, 0.68)	0.68	(0.56, 0.81)	0.75	(0.61, 0.91)
	high inside	0.52	(0.45, 0.62)	0.70	(0.57, 0.86)	0.77	(0.61, 0.96)
	mixed outside	0.71	(0.60, 0.83)	0.84	(0.69, 1.02)	0.85	(0.70, 1.04)

*adjusted for health behaviour at baseline; *** adjusted for adjusted health behaviour at baseline for age group, sex, education, ethnicity, occupational class, income quintiles, employment status, number of children in the household, cohabiting status, self-rated general health, household size and GHQ at baseline.

Table A7.9 Complete Case Analysis: regression results for smoking; logistic regression models predicting physical inactivity across latent caregiving intensity classes among UKHLS participants (n=7,750) using complete case analysis. The table presents odds ratios from three models: SMOK1CC (unadjusted), SMOK2CC (adjusted for smoking status at baseline), and SMOK3CC (adjusted for selected covariates). The reference category is the 'low outside' caregiving intensity class. The analysis accounts for complex survey design and clustering at the household level.

		Model SMOK1CC		**Model SMOK2CC***		**Model SMOK3CC*****	
	Smoking	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
Latent Class	Low outside	1.00	-	1.00	-	1.00	-
	increase	1.31	(0.92, 1.87)	0.95	(0.58, 1.53)	1.16	(0.68, 1.98)
	low to medium inside	1.73	(1.40, 2.13)	1.85	(1.36, 2.52)	1.91	(1.37, 2.67)
	high inside	2.23	(1.81, 2.76)	1.51	(1.12, 2.05)	1.63	(1.15, 2.32)
	mixed outside	1.73	(1.40, 2.13)	1.27	(0.92, 1.75)	1.20	(0.85, 1.70)

*adjusted for health behaviour at baseline; *** adjusted for adjusted health behaviour at baseline for age group, sex, education, ethnicity, occupational class, income quintiles, employment status, number of children in the household, cohabiting status, self-rated general health, household size and GHQ at baseline

Appendix 7.5: Walking vs sports

This appendix compares the variable walking at baseline with sports engagement at baseline.

Table A7.10 Comparison of walking frequency at baseline vs. sports frequency at baseline among 8,557 UKHLS participants eligible for inclusion in the analysis.

Walking frequency	N	%	Sport frequency	N	%
None	2,335	27.3%	No sport	86	1.0%
1-2 days a week	2,669	34.7%	Less than monthly	1,419	16.6%
3-4 days a week	1,115	13.0%	Monthly	1,091	12.8%
5-6 days a week	813	9.5%	1-3 times a week	1,614	18.9%
everyday	1,316	15.4%	3 or mor times a week	1,095	12.8%
Missing	8	0.1%	Missing	3,251	38.0%

Over one third of participants do not have a valid measure for this variable while walking at baseline has only a few missing cases.

Appendix 7.6: Prediction of baseline health behaviours

Walking at baseline predicted physical inactivity at the end of the study. The portions of fruits and vegetables per week at baseline predicted daily portions of fruits and vegetables at the outcome wave. The number of drinks at baseline predicted problematic drinking at the outcome wave. Smoking status at baseline predicted smoking status at the outcome wave.

Table A7.11 Prediction of outcomes by baseline health behaviours of UKHLS participants who were eligible for analysis (n=8,556).

Physical activity **Walking frequency at baseline**	**OR**	**95% CI**	**p**
None	1.00	-	-
1-2 days	0.59	0.53-0.66	
3-4 days	0.52	0.45-0.60	
5-6 days	0.51	0.44-0.60	
Every day	0.43	0.37-0.49	<0.001
Fruit and vegetable consumption **Daily Fruit and vegetable portions**	**Coefficient**	**95% CI**	**p**
0 portions	Ref.	-	-
1-3 portions	2.0	1.5-2.5	
4 portions	3.1	2.6-3.6	
5 or more portions	4.1	3.6-4.6	<0.001
Problematic drinking **Drinks frequency at baseline**	**OR**	**95% CI**	**p**
None	1.00	-	-
Monthly or weekly	4.40	3.38-5.69	
1-4 per week	25.84	20.01-33.37	
5 or more per week	91.84	67.76-124.47	<0.001
Smoking **Smoking status at baseline**	**OR**	**95% CI**	**p**
Non-smoker	1.00	-	-
Ex-smoker	5.70	2.38-8.44	
Current smoker	234.58	162.27-339.12	<0.001

Appendix 7.7: Regression with longitudinal weights

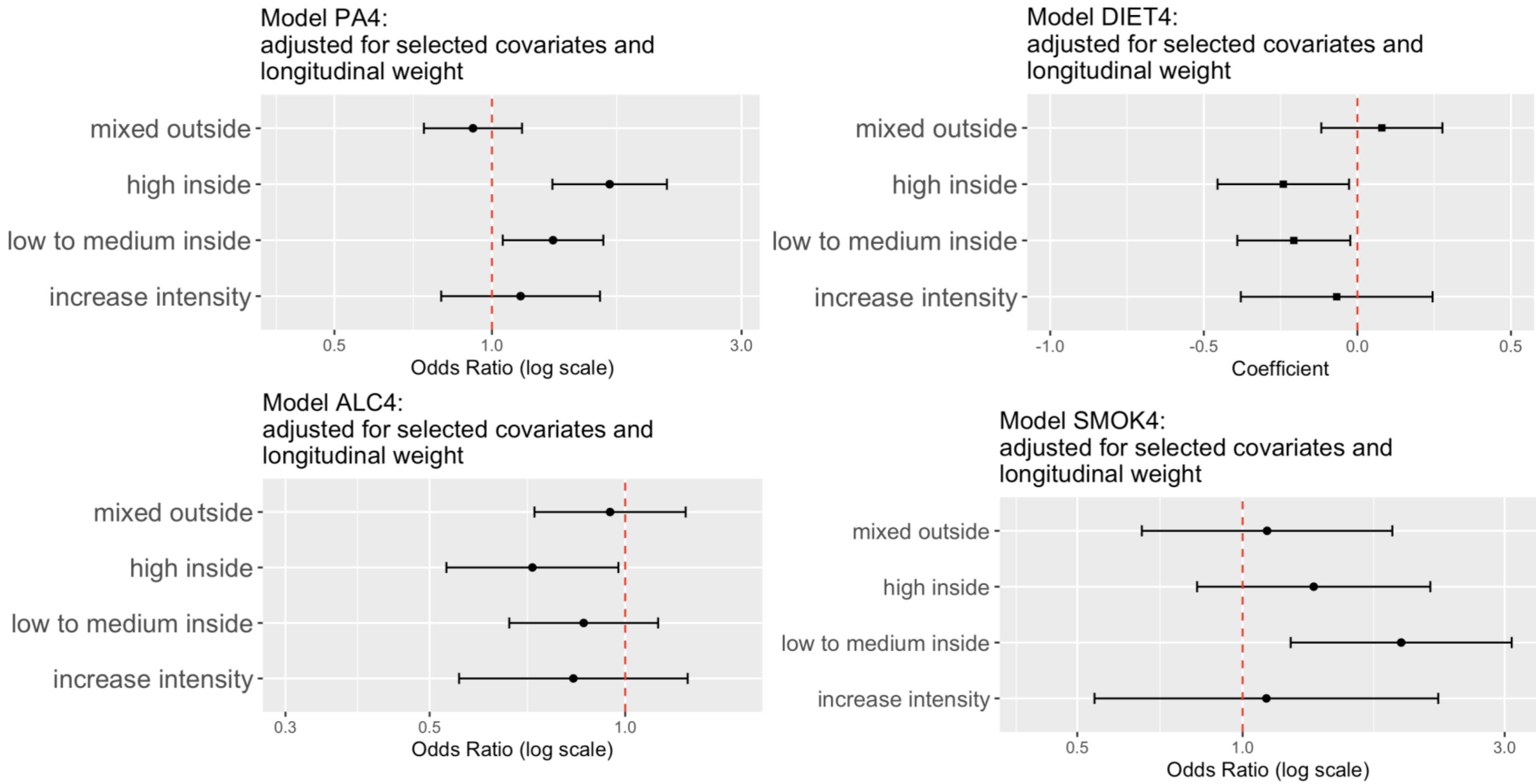


Figure A7.5 Sensitivity analysis with longitudinal weights for physical inactivity, diet, problematic drinking, and smoking among UKHLS participants (n=8,556). The table presents the, incorporating longitudinal weights and pooled results on imputed data sets (m=10) and accounts for complex survey design and clustering at household level.

Appendix 7.8: Analysis of missingness

Table A7.12 Analysis of missingness for the analysis of caregiving intensity classes

		Complete cases n= 6,803 (79.5%)	Missing cases n= 1,749 (20.5%)	p
Outcome				
Caregiving intensity Class	Low outside	3,538 (83.5%)	697 (16.5%)	
	Mixed outside	833 (77.3%)	245 (22.7%)	
	Low to medium inside	1,145 (76.7%)	346 (23.2%)	<0.001
	High inside	941 (71.4%)	377 (28.6%)	
	increase	346 (79.2%)	88 (20.2%)	
Physical inactivity	Active	3,126 (83.9%)	598 (16.1%)	
	Inactive	3,677 (79.1%)	970 (20.9%)	<0.001
Diet (daily fruit and vegetable portions)	Mean(SD)	3.8 (2.2)	3.4 (2.2)	<0.001
Smoking status	Non-smoker	5,902 (80.3%)	1,445 (19.7%)	
	Current Smoker	901 (74.7%)	304 (25.2%)	<0.001
Problematic drinking	No	3,539 (78.4%)	974 (21.6%)	
	Yes	3,264 (84.7%)	588 (15.3%)	<0.001
Health behaviour at baseline				
Walking frequency at baseline	None	1,753 (75.1%)	582 (24.9%)	
	1-2 days	2,392 (80.6%)	577 (19.4%)	
	3-4 days	931 (83.5%)	184 (16.5%)	
	5-6 days	671 (82.5%)	142 (17.5%)	
	Every day	1,056 (80.2%)	260 (19.8%)	<0.001
Daily Fruit and vegetable frequency	0 portions	51 (77.3%)	15 (22.7%)	
	1-3 portions	3,642 (78.0%)	1,030 (22.0%)	
	4 portions	1,316 (81.4%)	300 (18.6%)	
	5+ portions	1,794 (79.7%)	391 (17.9%)	<0.001
Drinks frequency at baseline	No drinks	839 (79.9%)	211 (20.1%)	
	Monthly or weekly	2,279 (87.7%)	319 (12.3%)	
	1-4 per week	2,728 (89.6%)	317 (10.4%)	
	5+ per week	957 (90.0%)	106 (10.0%)	<0.001
Smoking status at baseline	Never smoked	3,000 (78.8%)	808 (21.2%)	
	Ex-smoker	2,627 (82.7%)	550 (17.3%)	
	Current Smoker	1,176 (74.9%)	1,752 (20.5%)	<0.001
Covariates				
Sex	Male	2,529 (78.3%)	679 (21.2%)	
	Female	4,274 (79.9%)	1,074 (20.1%)	0.23
Age group at abseline	16-29	480 (75.5%)	156 (24.5%)	
	30-49	2,295 (79.4%)	597 (20.6%)	
	50-64	2,651 (81.7%)	593 (18.3%)	
	65+	1,377 (77.2%)	407 (22.8%)	<0.001
Cohabiting status	Single/not-cohabiting	1,753 (78.3%)	485 (21.7%)	
	Married/cohabiting	5,050 (80.0%)	1,263 (20.0%)	0.09
Education	No qualification	762 (67.4%)	368 (32.6%)	
	A-Level/GCSE/Other	3,544 (80.4%)	863 (19.6%)	
	Degree/Higher qualification	2,497 (83.3%)	499 (16.7%)	<0.001
Occupational class	Management/Professional	1,679 (86.1%)	271 (13.9%)	
	Intermediate	934 (84.1%)	177 (15.9%)	
	Routine	1,187 (80.2%)	294 (19.9%)	
	Not employed	3,003 (76.9%)	903 (23.1%)	<0.001
Being in paid employment	Full-time employed	2,279 (81.7%)	613 (18.3%)	
	Part-time employed	1,247 (82.8%)	259 (17.2%)	
	Not in paid employment	2,827 (76.4%)	874 (23.6%)	
Wealth quintiles	1 (low)	1,082 (72.3%)	415 (27.7%)	
	2	1,343 (77.1%)	398 (22.9%)	
	3	1,289 (80.9%)	327 (19.1%)	
	4	1,464 (82.4%)	313 (17.6%)	

	5 (high)	1,525 (84.8%)	274 (15.2%)	<0.001
Household size	1	820 (80.5%)	199 (19.5%)	
	2	2,827 (80.8%)	670 (19.2%)	
	3-4	2,464 (79.8%)	625 (20.2%)	
	5+	692 (72.8%)	259 (27.2%)	<0.001
Number of children living in the household	0	5,060 (79.9%)	1,270 (20.1%)	
	1	763 (81.2%)	177 (18.8%)	
	2	682 (78.2%)	190 (21.8%)	
	3+	298 (72.0%)	116 (28.0%)	0.001
General health	Good to excellent	5,455 (86.4%)	857 (13.6%)	
	Fair or poor	1,348 (81.7%)	303 (18.4%)	<0.001
GHQ	(Mean score)	11.6 (0.07)	12.1 (0.18)	0.002
SF12-PCS	Mean score	49.5 (0.13)	48.0 (0.39)	<0.001
Age	Mean age	52.3 (0.17)	52.1 (0.38)	0.66

Appendix 7.9: Exclusion of participants with non-consecutive wave participation

Table A7.13 Fit indices of LCA models including participants without two consecutive waves of caregiving intensity observed (n=10,200)

Model	log-likelihood	resid. df	BIC	aBIC	cAIC	likelihood-ratio	Entropy
Model 1	-78436.62	10128	157537.8	157309.0	157609.8	8760.333	-
Model 2	-62653.29	10055	126644.9	126184.2	126789.9	5690.644	0.933
Model 3	-60096.33	9982	122204.8	121512.1	122422.8	5255.981	0.847
Model 4	-57808.92	9909	118303.8	117379.1	118594.8	4648.193	0.824
Model 5	-57190.35	9836	117740.5	116583.7	118104.5	4532.706	0.783
Model 6	-56691.58	9763	117416.7	116028.0	117853.7	4445.011	0.719
Model 7	-56188.45	9690	117084.3	115463.6	117594.3	4290.017	0.711
Model 8	-55775.39	9617	116932.0	115079.3	117515.0	4219.763	0.734

Table A7.14 Matrix of Average posterior probabilities of 5 class solution in LCA including participants without two consecutive waves of caregiving intensity observed (n=10,200)

	[1]	[2]	[3]	[4]	[5]
[1]	0.77	0.08	0.04	0.08	0.03
[2]	0.05	0.87	0.06	0.01	0.00
[3]	0.02	0.07	0.90	0.00	0.00
[4]	0.04	0.01	0.00	0.91	0.04
[5]	0.05	0.00	0.00	0.10	0.85

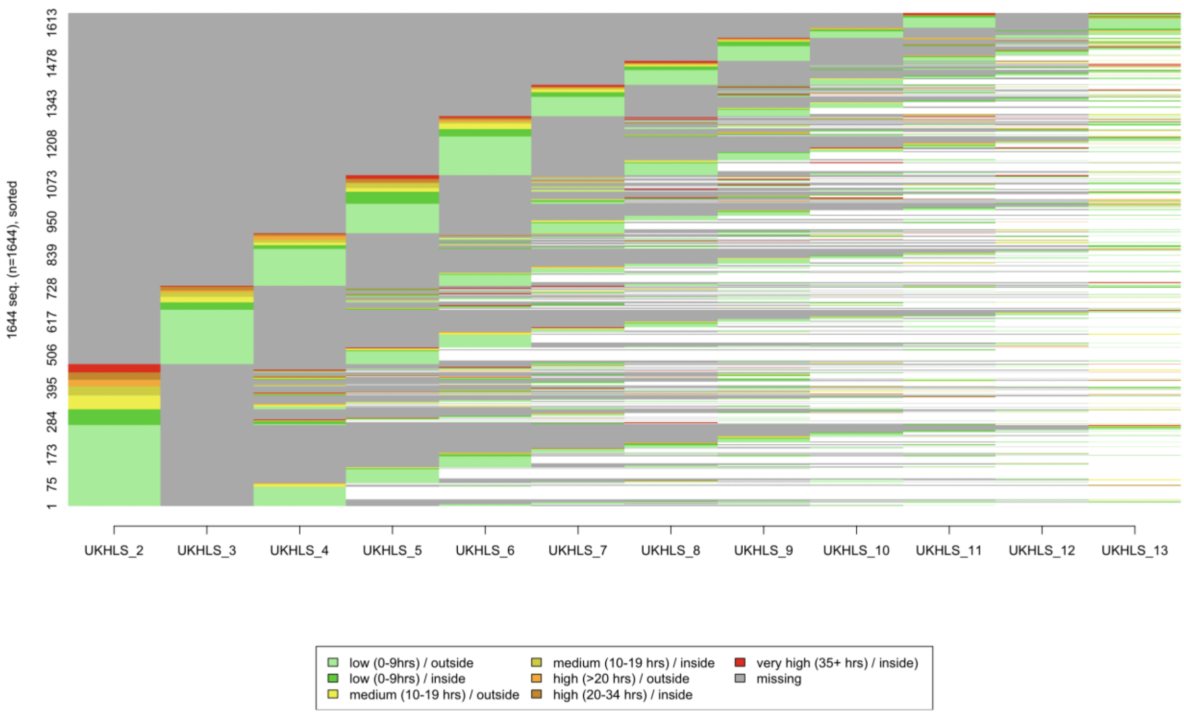


Figure A7.6 Sub-group Sequence index plot by caregiving intensity of those excluded due to no having two consecutive waves of caregiving intensity observed (n=1,644)

Appendix Chapter 8: Multiple transitions

Appendix 8.1: Sample size flow charts for analysis of multiple caregiving transitions

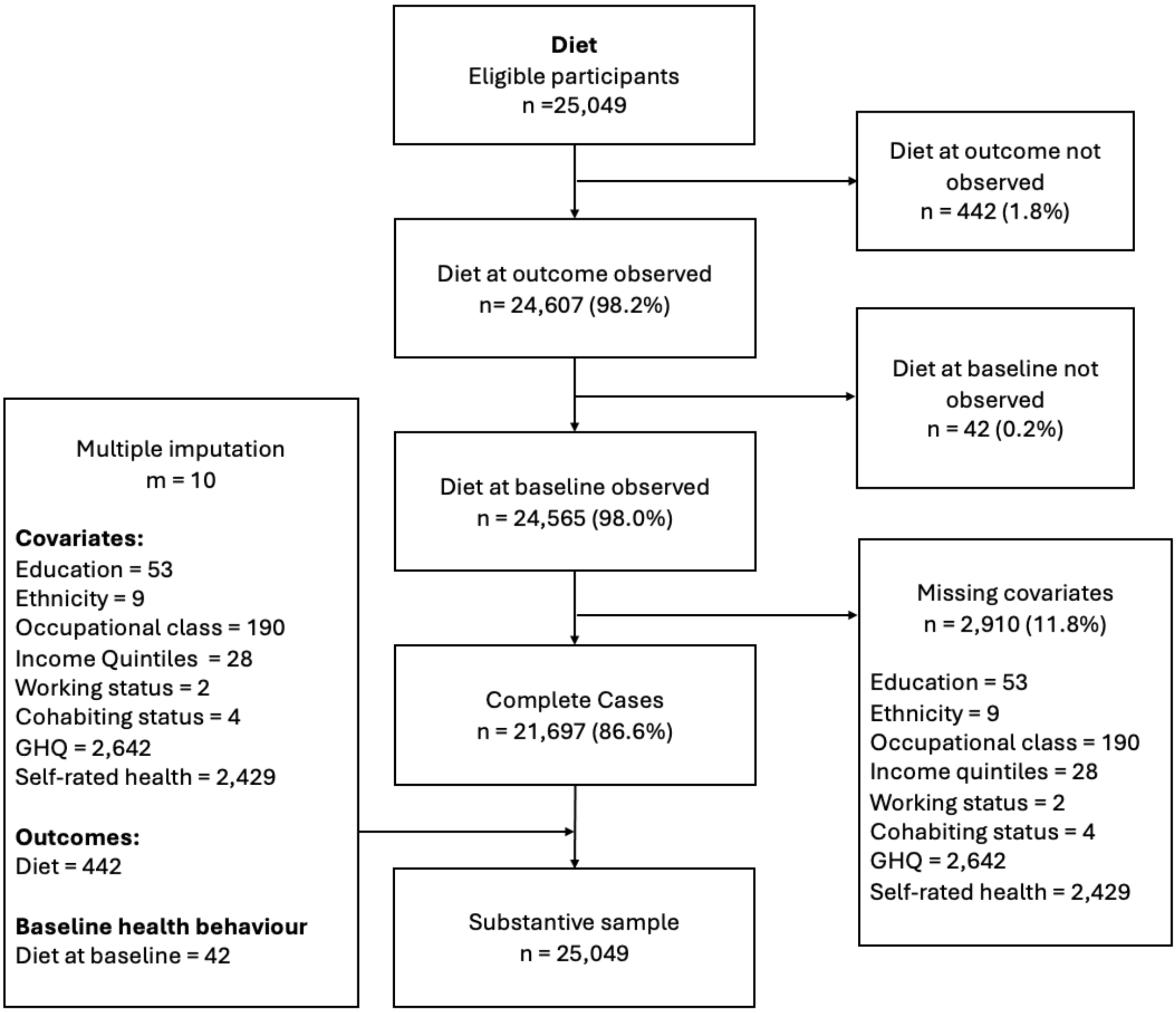


Figure A8.1 Sample size flow chart for fruit and vegetable consumption of eligible participants following application of inclusion criteria

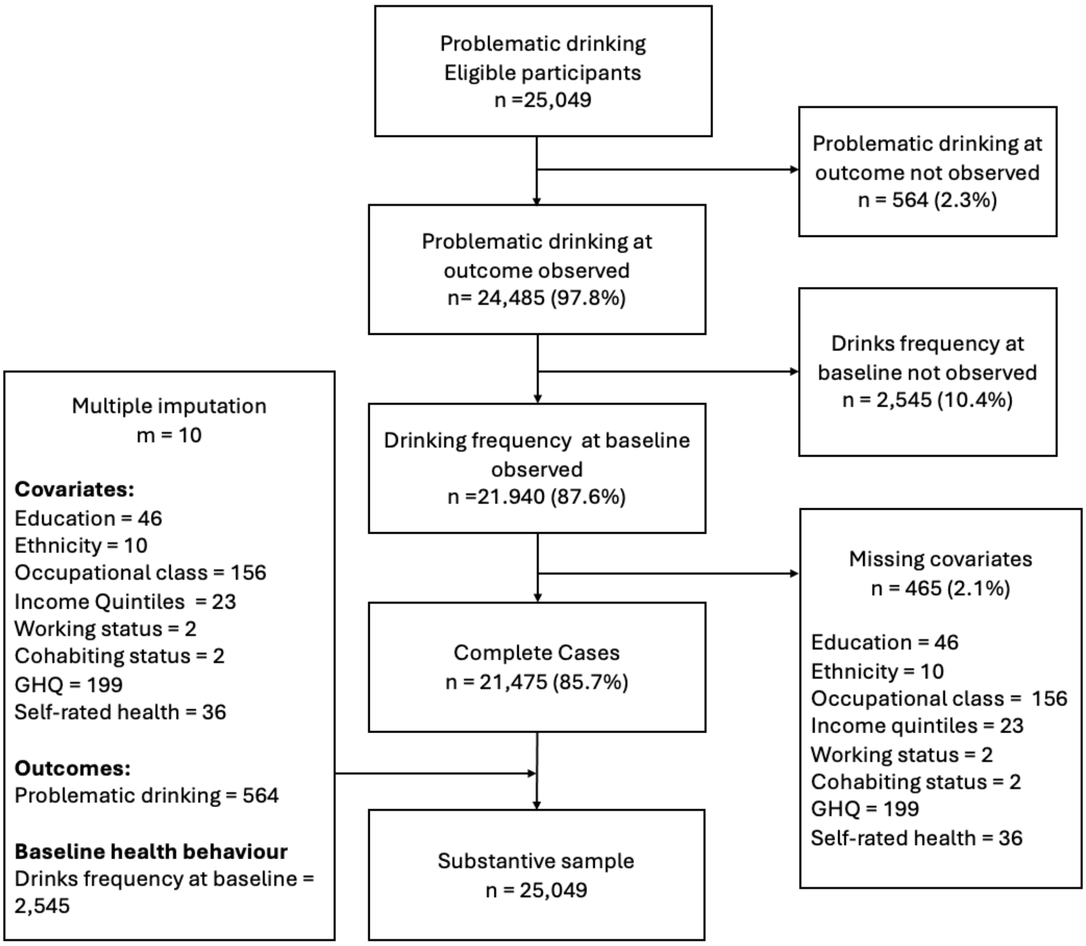


Figure A8.2 Sample size flow chart for problematic drinking of eligible participants following application of inclusion criteria

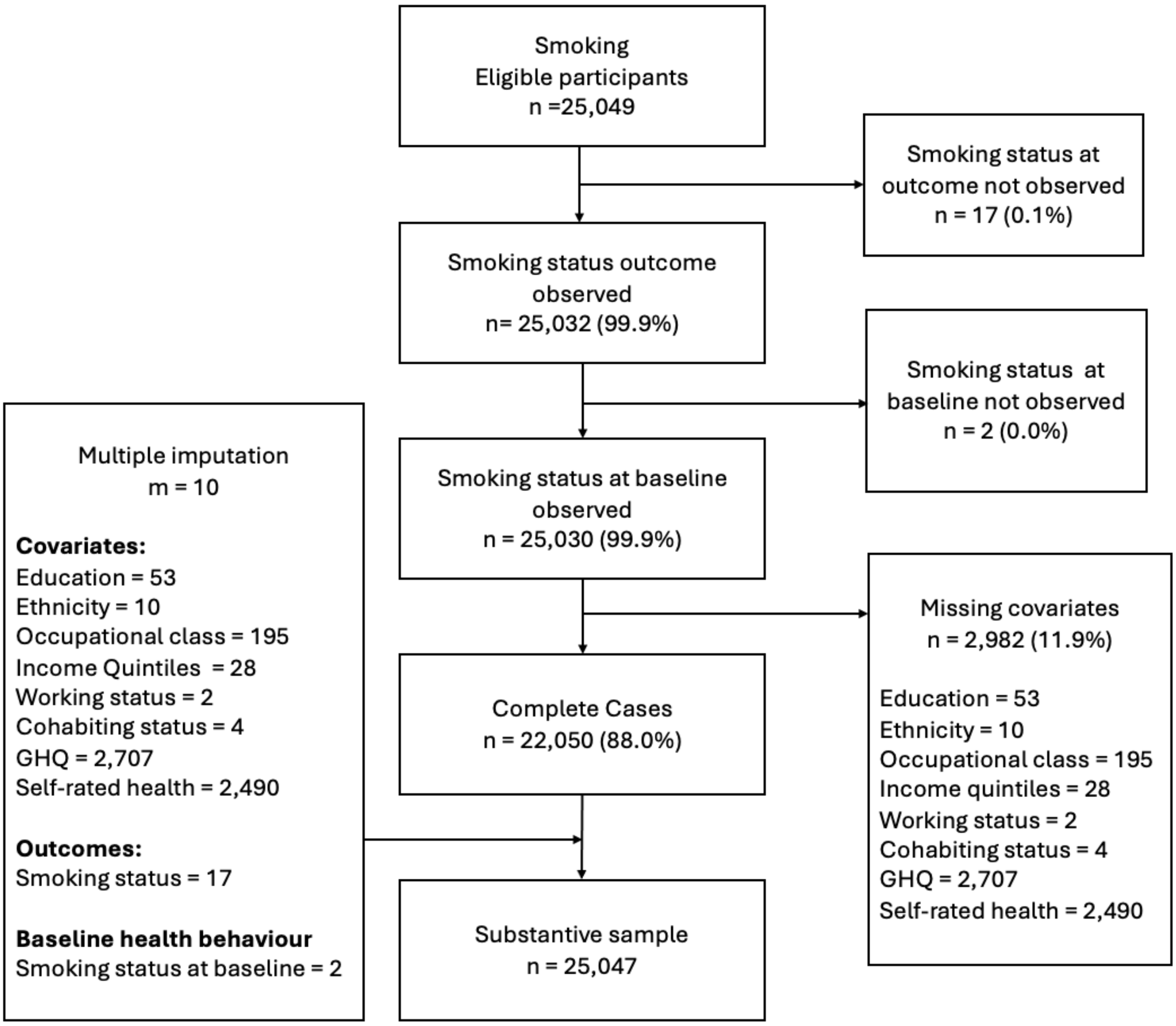


Figure A8.3 Sample size flow chart for smoking of eligible participants following application of inclusion criteria.

Appendix 8.2: Sequence analysis

Sequence analysis (SA) Methods

Process

An alternative approach to LCA is Sequence Analysis (SA) in which categorical time-series variables can be studied as states or events over time in view of their patterns, transitions, and similarities.[497] While many scholars have argued that LCA is a superior approach compared to SA[330–332], the advantage of sequence analysis (SA) lies in its ability to perform sequence imputation on gaps within a sequence. This approach was developed by Halpin[498] in 2016 and advanced with the release of a new R package by Emery in March 2024[335]. It must be noted that sequence imputation is a fairly new approach that is still in the process of being refined. Besides, it remains an open problem how to perform cluster analyses on imputed data sets[335] but the proposed approach by Halpin[334] was performed in which cluster analysis is performed on the stacked imputed dataset. Nevertheless, Sequence imputation is superior to 'regular' multiple imputation for categorical time-series data because it preserves the temporal and sequential structure of the data. In multiple imputation, each time point is treated independently whereas sequence imputation considers the dependency between consecutive time points.[334,498]

Unfortunately, it is only possible to perform sequence imputation on the sequence variable of interesting which is caregiving status for this analysis, but it is not possible to impute missing data of covariate simultaneously within the same package. However, it is possible to run a sperate multiple imputation using Multiple Imputation by Chained equation (MICE) to impute missing covariates with the mice package in R. Following the imputations that occurred, the mice data set and the sequence imputed data set can be merged and pooled regression be performed. The macro flowchart below explains the process.

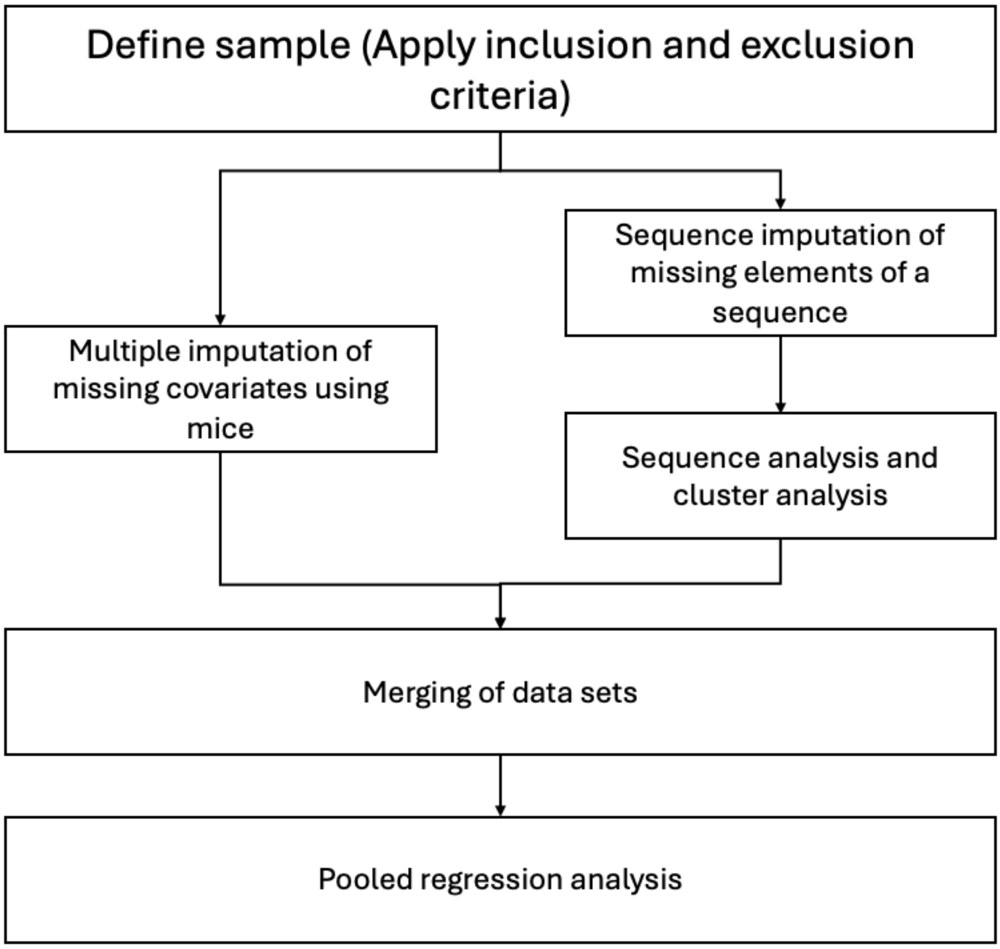


Figure A8.4 Flowchart of approach for sequence imputation & analysis

The following steps will be needed to perform SA and subsequent regression on the cluster variable:

a) Define sample

After inclusion and exclusion criteria are applied, the patterns of missingness will be assessed for this sample.

b) MICE

Multiple imputation by chained equation will be performed using the mice package in R. For this, five imputations will be conducted because missingness of covariates is 17.4% and there are over 20,000 participants over 12 time points in the data set. It was considered that imputing five data set would strike a balance between enhancing accuracy and making the analysis computational feasible. It was decided to perform an imputation with five data sets because literature suggest that at least five imputation are required to handle uncertainty associated with missing data.[339] Also, imputing sequences is computationally intensive, and five imputations is still feasible while providing variation in the estimates. It is also the standard approach that was proposed by Halpin.[334] Therefore, it was considered that five imputations provide a reasonable balance between accuracy and practicality. All covariates that serve for the final regression model were used for the imputation model because all were associated with missingness.

c) Sequence imputation

Sequence imputation will be performed with the seqimpute package from R. For this, five imputations will be conducted because the number of imputations had to align with the number of imputation from step b (mice). Because the data set was large and due to a high number of distinct sequences, the data was aggregated using the R package WeighedCluster. Then sequence analysis is performed on the aggregated datasets with weights.

d) Dissimilarity measures

To measure dissimilarity between sequences, a wide range of approaches is available as summarised in the table below. To answer the research question, two approaches were considered most suitable, namely Number of matching sub-sequences (NMS) and optimal matching (OM). NMS was considered suitable because multiple transitions might create complex sequences were individuals transitions between caregiving states. Counting the number of matching sub-sequences allows to identify similarity in the complexity of patterns. Likewise, OM seems like a suitable approach that is flexible and allows to measure dissimilarity and temporal alignment of sequences.[499,500] Since caregiving status only had two states (non-caregiving or caregiving), more complex dissimilarity measures such as time-ward-edit edit distance (TWED) would probably only add complexity while not adding much analytical value.

Table A8.1 Dissimilarity measures of sequence analysis[337,499,500]

WHAT IS IT?	WHAT DOES IT?	STRENGTH	WEAKNESS
Optimal matching	Measures the minimal cost of transforming one sequence into another through operations such as insertion, deletion, and substitution.	Flexible and allows handling of sequences of different lengths; can consider both duration and ordering of events.	Choosing appropriate costs for operations can be subjective and influence results significantly.
Number of matching subsequences	Counts common subsequences shared between two sequences, regardless of their positions.	Provides a measure based on shared patterns rather than editing costs.	Less sensitive to the order and timing of elements in sequences compared to other measures.
Time-warp Edit Distance	A distance measure that considers temporal gaps between matching elements, allowing for flexible alignment while maintaining sequence structure.	Suitable for comparing sequences with elements that have significant timing differences; integrates penalties for time differences.	More computationally complex and may require fine-tuning of its penalty parameters for time gaps.
Hamming	Measures the number of positions at which two sequences of equal length differ.	Simple and computationally efficient.	Only applicable to sequences of equal length and does not consider insertions or deletions.
Dynammic Hamming	An extension of the standard Hamming distance that can align sequences of different lengths dynamically.	Maintains simplicity while allowing flexibility in handling sequences of different lengths.	Loses some interpretability compared to the standard Hamming distance and may be less sensitive to complex alignment issues.
Holister	A distance metric that considers shared elements and their positional alignment within sequences, often	Suitable for comparing sequences with different durations of states and aligning these durations.	Can be complex to implement and interpret due to its integration of both shared elements and their durations.

	used when duration within states matters.		
OMstran	A variant of optimal matching that incorporates transition information between states when calculating substitution costs.	Captures not only the differences in states but also how transitions between states affect similarity.	More complex to set up due to the need for specifying detailed transition costs, potentially subjective.

e) Number of clusters

The ideal number of clusters was determined by the following indicators Point Biserial Correlation (PBC), Hubert's Gamma (HG), Hubert's Somers D (HGSD), Hubert's C (HC), Average Silhouette Width (ASW), Calinski-Harabasz Index (CH), Pseudo R2 (R2). Each cluster solution is assigned a value for any of these indicators and higher values indicate better fit with the exception for Hubert's C (HC) for which lower values indicate better fit. The fit indicators are summaries below in **Table A8.2** Fit indicators for cluster analysis which is available in the publication from Studer.[501] For the analysis, a graph will be produced with the WeightedCluster package to assess all of these quality measures simultaneously.

Table A8.2 Fit indicators for cluster analysis, based on Studer (2013) A practical guide to creating typologies of trajectories in the social sciences with R. 10.12682/lives.2296-1658.2013.24.

Name	Abrv.	Range	Min/Max	Interpretation
Point Biserial Correlation	PBC	[-1;1]	Max	Capacity of the clustering to reproduce the original distance matrix.
Hubert's Gamma	HG	[-1;1]	Max	Capacity of the clustering to reproduce the original distance matrix (Order of magnitude).
Hubert's Somers D	HGSD	[-1;1]	Max	Same as above, taking into account ties in the distance matrix.
Hubert's C	HC	[0;1]	**Min**	Gap between the current quality of clustering and the best possible quality for this distance matrix and number of groups.
Average Silhouette Width	ASW	[-1;1]	Max	Coherence of the assignments. A high coherence indicates high between groups distances and high intra group homogeneity.
Calinski-Harabasz index	CH	[0;+∞[	Max	Pseudo F computed from the distances.
Calinski-Harabasz index	CHsq	[0;+∞[	Max	Idem, using the *squared* distances.
Pseudo R^2	R2	[0;1]	Max	Share of the discrepancy explained by the clustering.
Pseudo R^2	R2sq	[0;1]	Max	Idem, using the *squared* distances.

f) Cluster linkage

Several linkages of clustering dissimilarity matrix are available including ward's linkage and average linkage. Average linkage calculates the distance between two clusters as the average of the distance between all pairs of points from the two clusters and it a suitable method if outliers are to be expected.[502] In contrast, ward linkage minimises the variance within clusters by merging the pair that results in the smallest increase in total within-cluster variance, making it effective for producing clusters that are roughly equally sized and cohesive.[503,504] Whether ward linkage or average linkage will be used for a particular cluster solution will depend on the fit indicators and whether the emerging clusters are conceptually plausible.

g) Merge data sets

Both imputation data sets will be merged by unique identifier for each participant (pidp) and cross-tabulation and assessment of duplicates will be performed to ensure this occurs correctly.

h) Regression and pooled results

Regression analysis will be performed on each imputed data set and each iteration will also be adjusted for clustering at household level and complex survey design using the svyglm package in R.

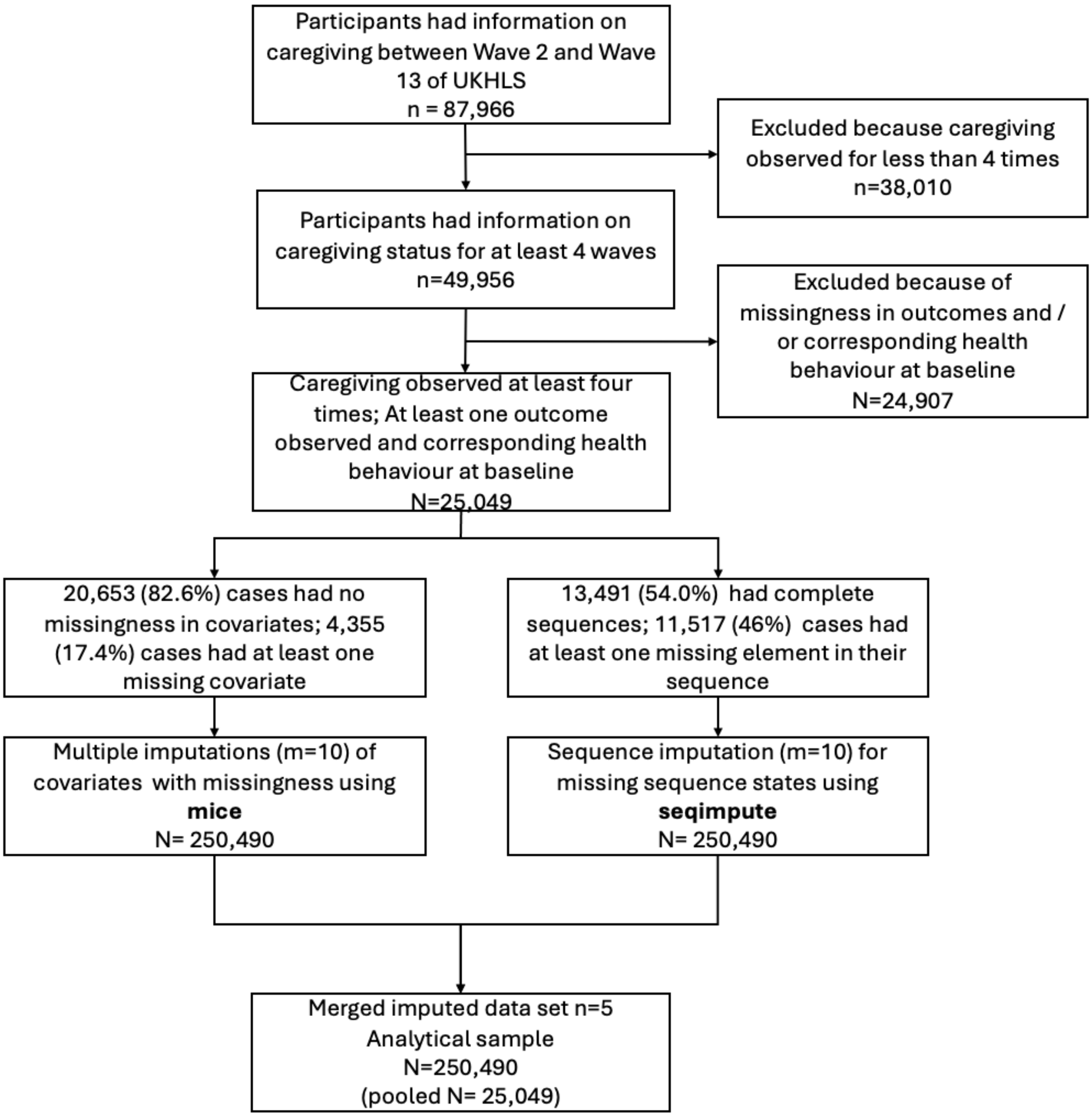


Figure A8.5 Macro flow chart for sequence imputation and analysis with 10 imputations based on 25,049 eligible UKHLS participants from waves 2 to 13.

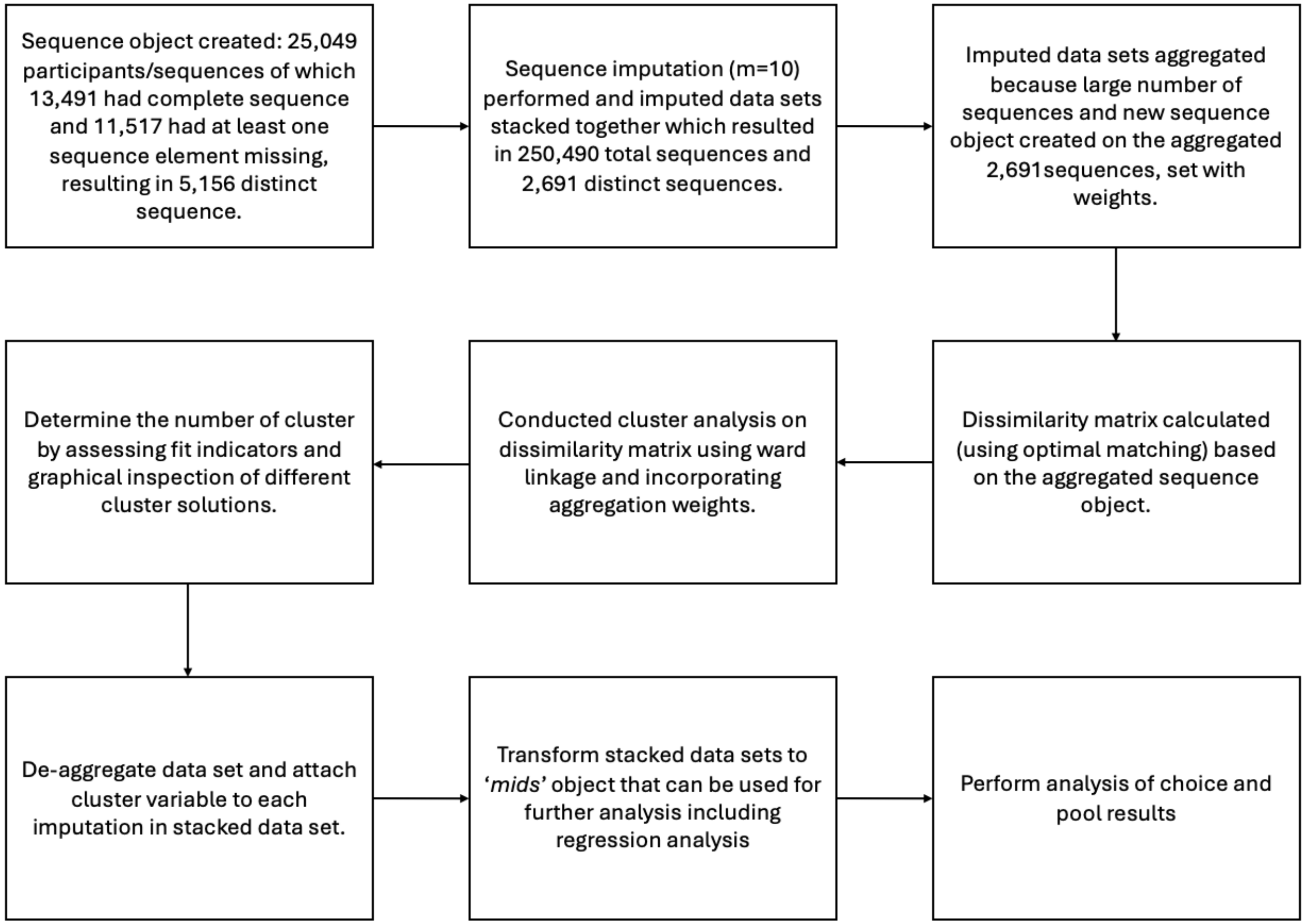


Figure A8.6 Macro flow chart for sequence imputation and analysis with 10 imputations based on 25,049 eligible UKHLS participants from waves 2 to 13.

Sequence analysis

Patterns of missingness

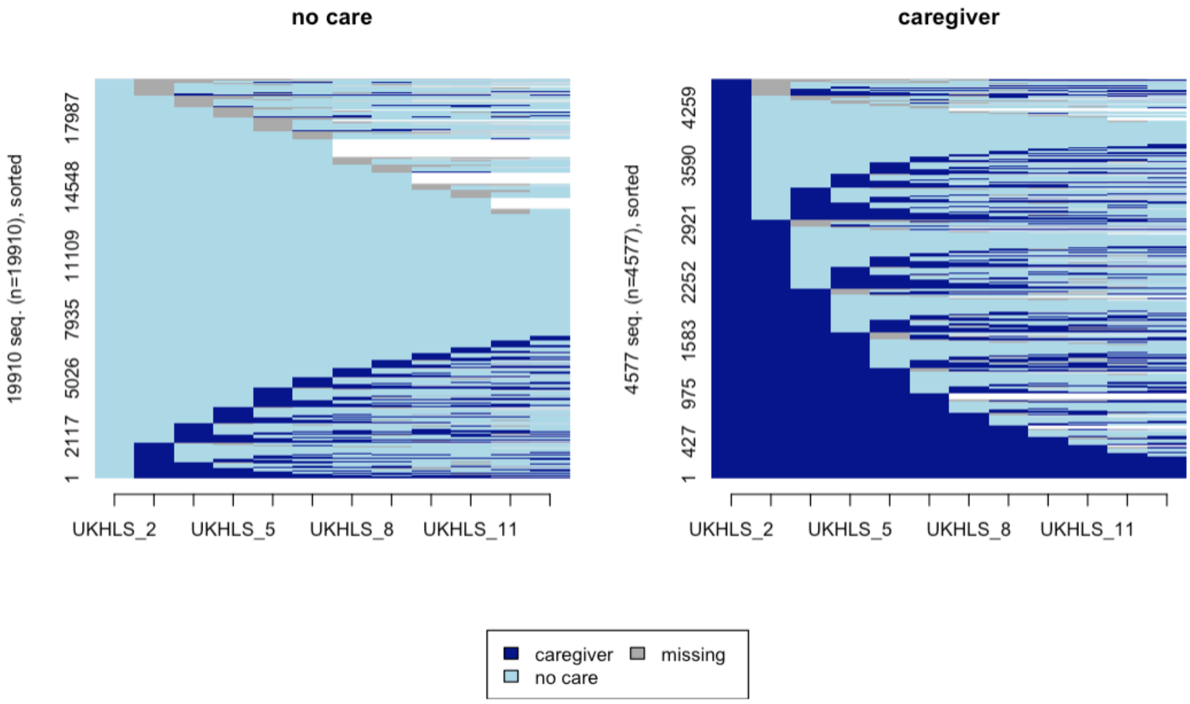


Figure A8.7 Sequence index plot of caregiving status by caregiving at baseline (n=25,049) among UKHLS participants, showing caregiving trajectories from waves 2 to 13.

Next, missingness was assessed using implication statistic available in the seqimoute package in R. The graph displays the implication statistic for two groups 'missing' and 'observed'. The implication statistic measures the degree to which a particular state is indicative of a sequence being in the missing or observed group. The dotted line represents the confidence interval of 0.95, indicating whether the implication statistic is significantly different from zero. The graph suggests that missingness is associated with non-caregiving rather than caregiving.

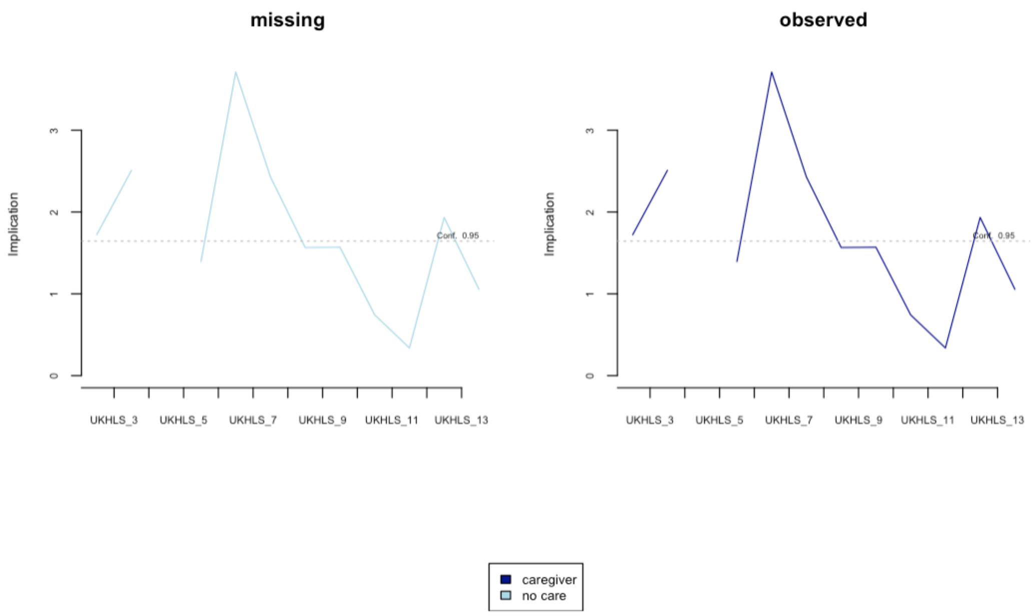


Figure A8.8 Implications statistics for caregiving status UKHLS wave 2-13 (n=25,049)

Next, a sequence missingness plot was generated as seen in **Figure A8.9**. It visualised the 10 most frequent sequence missing plots across the 12 waves of observation. Observed states in blue are observed and missing states are in red. The plot indicates that the majority of sequences are observed across all waves but that missing data is present sporadically at certain waves. The patterns of missingness suggests that missing data is relatively scattered and infrequent. Missingness at the beginning and end point of the study is not a major problem which makes sequence imputation a suitable approach.

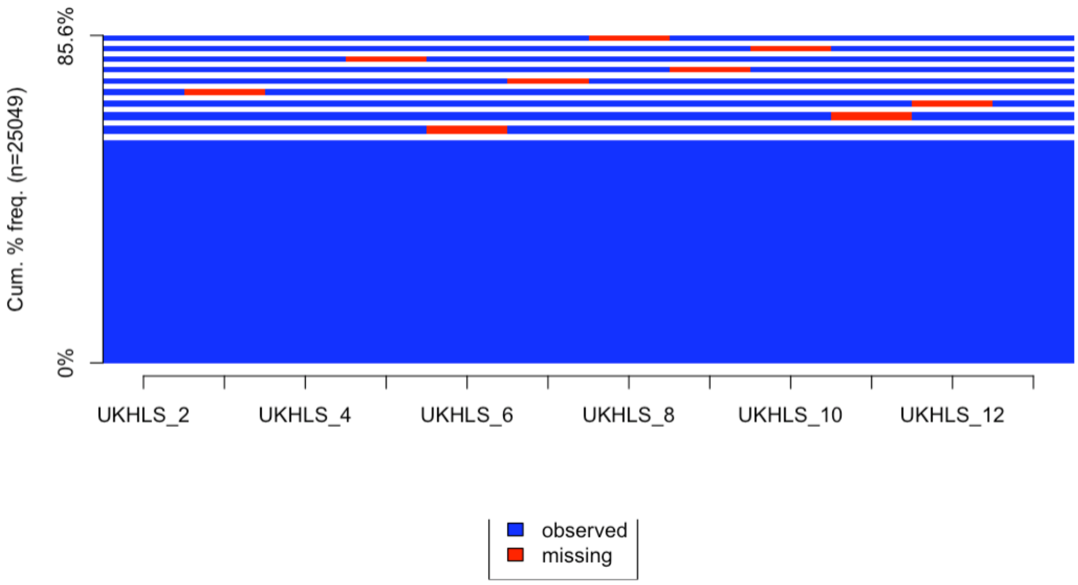


Figure A8.9 Patterns of missingness of caregiving status variable; 10 most common patterns), n=25,049

Next, sequence imputation was performed and five imputations were conducted. Data sets were stacked together, aggregated and dissimilarity measurement was performed.

Sequence imputation

Sequence imputation of ten data sets was performed on 25,049 which resulted in a total of 250,490 sequences. Sequence analysis was performed on the aggregated 2,691 distinct sequences. A comparison was made between two approaches which were conceptually suitable: Number of Matching Sub-sequences (NMS) and Optimal Matching. Some clusters from the NMS approach were similar to the observed variable and a cluster emerged from this analysis that contained participants who had more than one transition. However, some clusters were very small and did not align well with the conceptual framework. In contrast, the clusters from OM resembled the classes from LCA and, therefore, the solution from OM was explored in further detail for this analysis.

Figure A8.10 below depicts the indicator statistic for the different cluster solutions. The graph suggests that with the number of classes, the indicator statistic. This improvement is rather gradual which makes it difficult which cluster solution is superior.

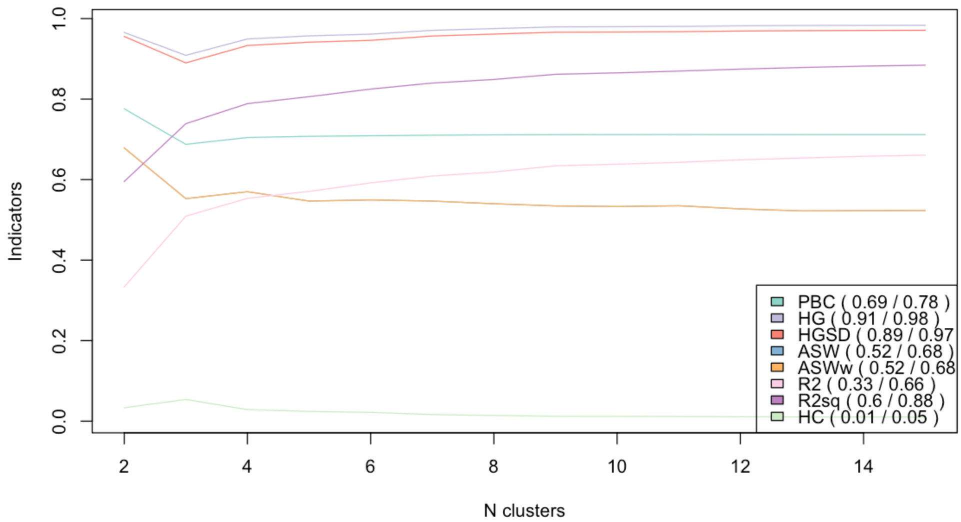


Figure A8.10 Fit indicators from optimal matching of sequence analysis following sequence imputation (m=10) for UKHLS participants (n=25,049), showing model fit statistics for the sequence clusters.

To aid decision-making on the number of clusters, a cluster-tree was generated. A cluster-tree is a hierarchical representation that illustrates how observations are grouped into clusters at different levels of similarity or dissimilarity. It can be produced when hierarchical clustering is used and is presented as a dendrogram which is a tree like diagram showing the relationship among clusters. **Figure A8.11** shows the cluster tree for the optimal matching using ward linkage on the sequence imputed data sets. It shows that eight clusters are quite dissimilar from one another and when splitting the second cluster on the left, no new cluster patterns emerge. Hence, the eight-cluster solution was explored further.

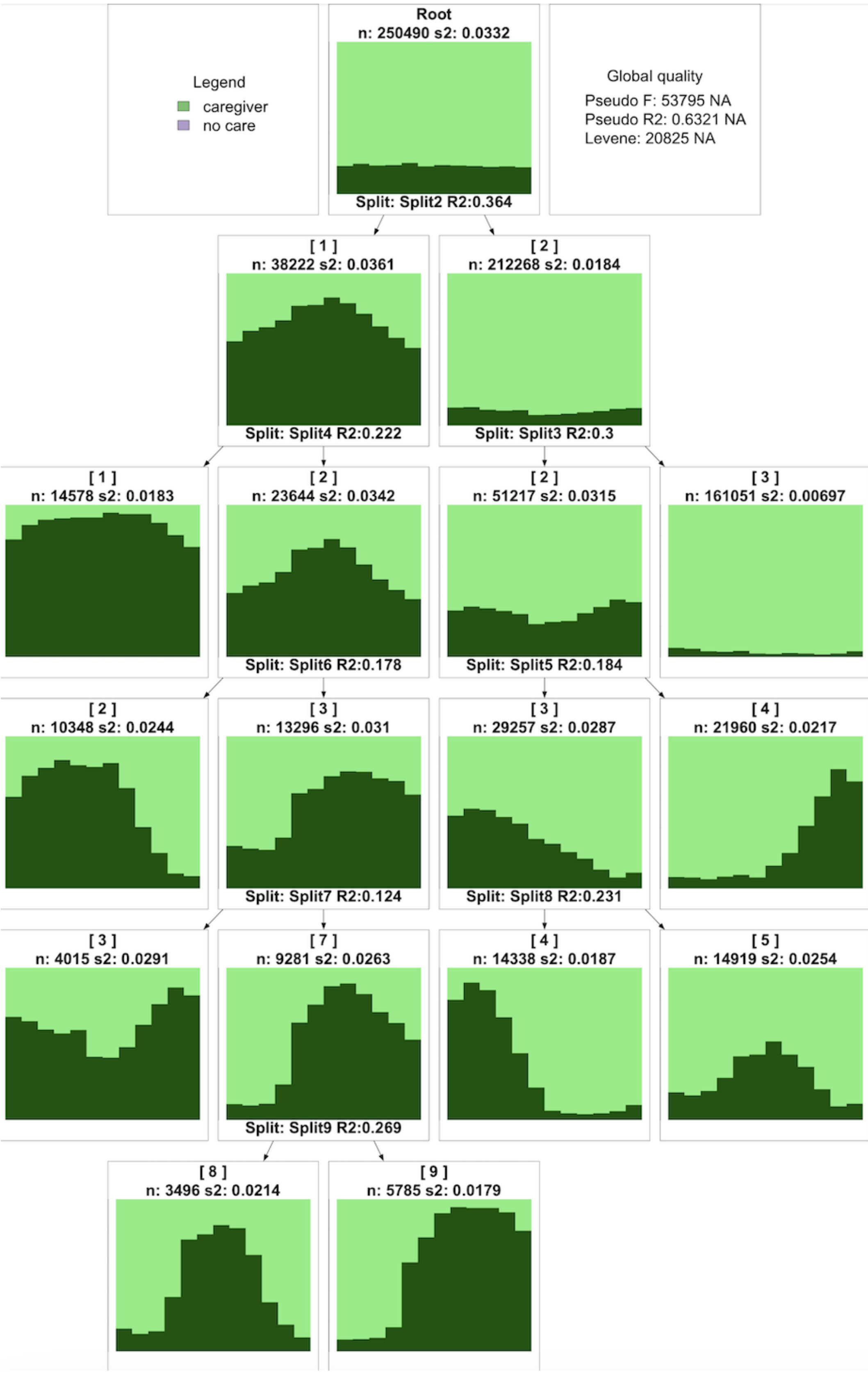


Figure A8.11 Cluster tree from optimal matching (n=25,049)

Next, a state distribution plot was generated on the eight-cluster solution. Interestingly, these eight clusters largely overlap with the eight-class solution from LCA:

- **Cluster 1: Long-term** caregivers where caregiving is the dominant state throughout all time points.
- **Cluster 2: Former-long** caregivers with long periods of caregiving prior to exit
- **Cluster 3: Recurrent** caregiver with caregiving at start of study, longer break and transition back into caregiving.
- **Cluster 4: Former-short** caregivers with a longer period of non-caregiving after caregiving exit.
- **Cluster 5: Temporary** caregivers, characterised by transition into caregiving and exit.
- **Cluster 6: Emerging-short** caregivers with transition into care and a prior longer episode of non-caregiving followed by a short period of caregiving.
- **Cluster 7: Non-caregivers** with non-caregiving being the dominant state in all waves
- **Cluster 8: Emerging-long** caregivers with transitioning into caregiving followed by a longer period of caregiving.

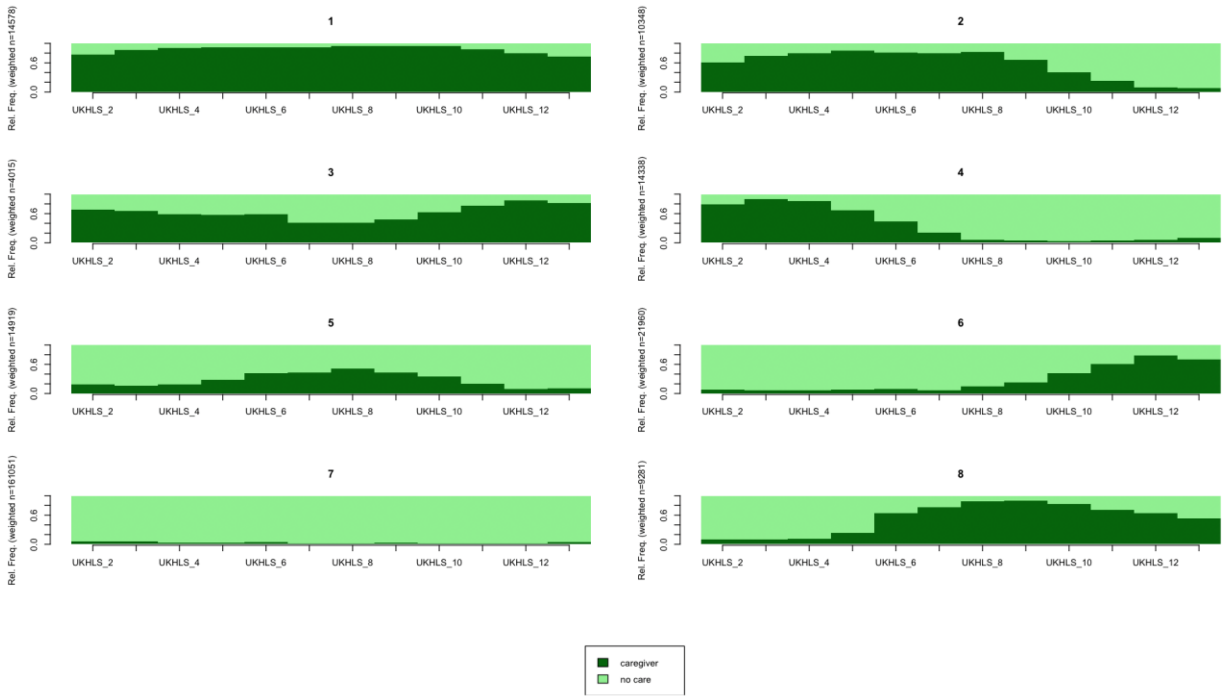


Figure A8.12 State Distribution Plot of 8 cluster solution from cluster analysis (n=25,049) based on sequence imputed data (m=10) from wave 2 to 13 of UKHLS.

Next, sequence index plots below were inspected and assessed whether the preliminary assigned cluster labels align with the trend from the sequence index plots. The overall trend and stability of trajectory determined the clusters rather than the absolute number of the transitions which was also found in the LCA. Also, the characteristics of the clusters in the sequence index plot seem to correspond with the initial labelling of the clusters from the state distribution plot.

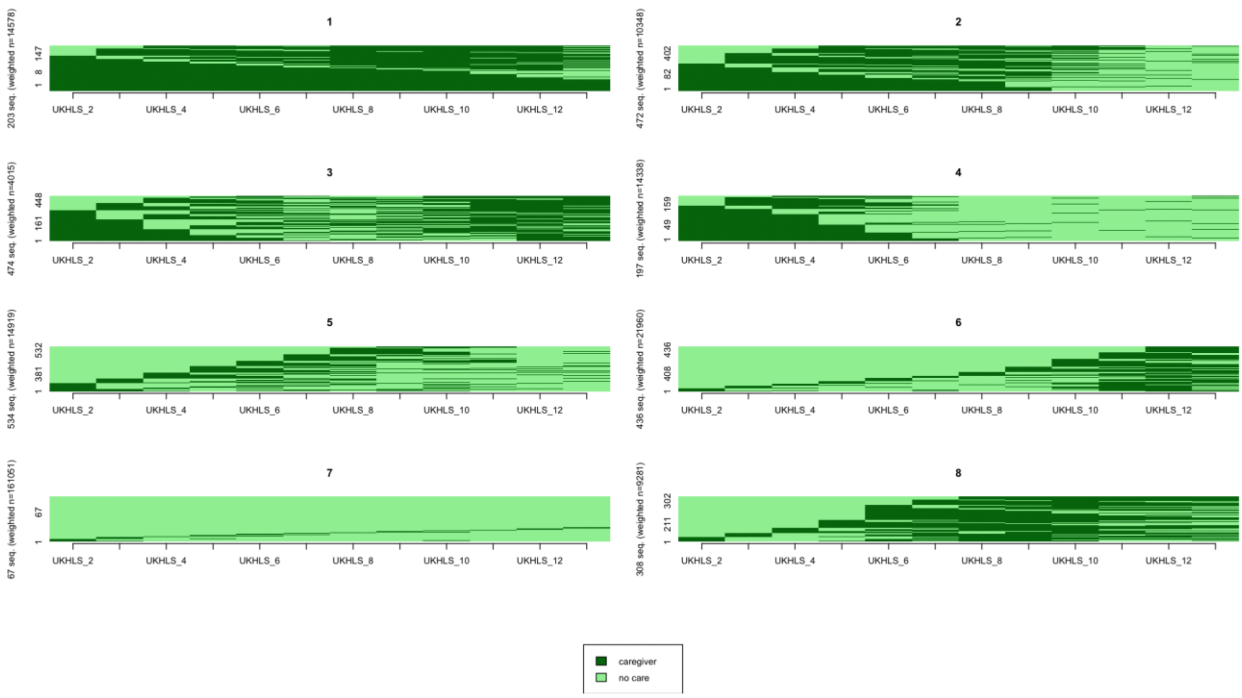


Figure A8.13 Sequence index plot of 8 cluster solution from cluster analysis (n=25,049) based on sequence imputed data (m=10) from wave 2 to 13 of UKHLS.

To assess transitioning better, a sequence modal state plot was also generated for the eight-cluster solution. It can be seen that the cluster solutions align with the previously defined cluster labels except for cluster three, which seem to start with a non-caregiving, followed by a short period of caregiving and exit to caregiving. However, is the state distribution plot and sequence index plot above, it is evident that caregiving takes up a large proportion at that time point despite not being the modal state for this cluster at the first time point. It can be concluded that the initial labelling of the cluster represent a reasonable description of the clusters and that the clusters depict similar transition patterns as the classes in LCA.

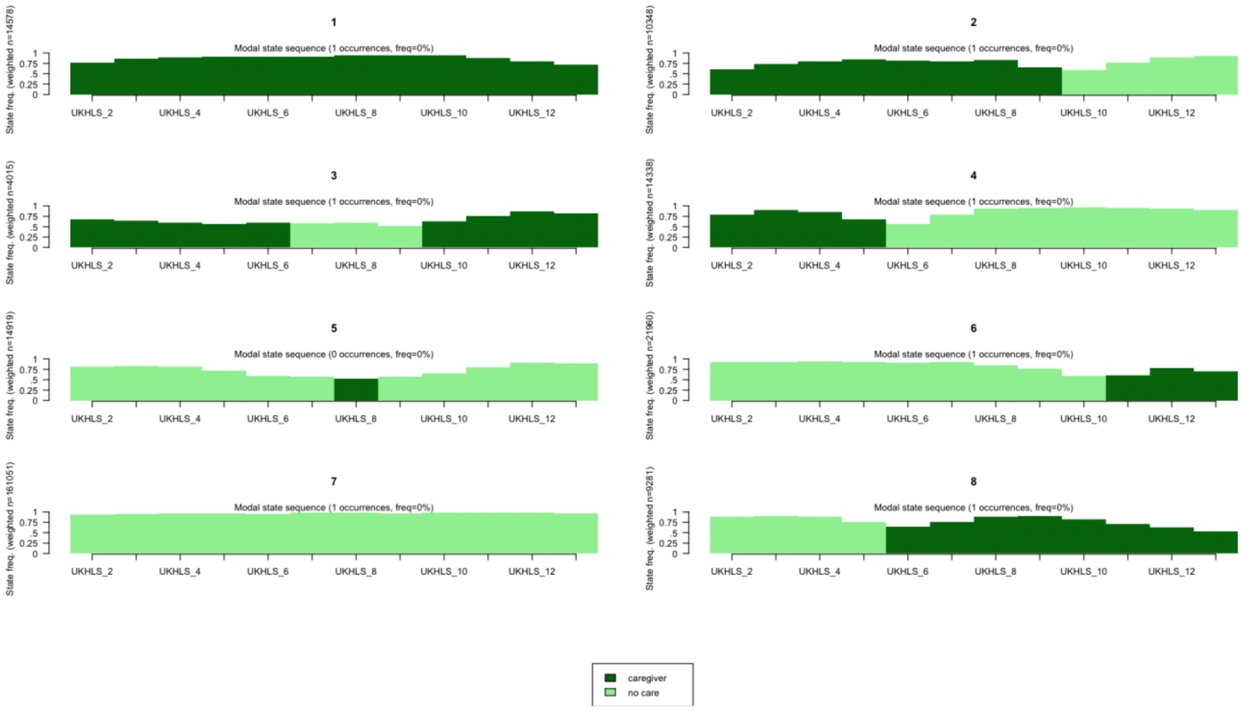


Figure A8.14 Sequence modal state plot of 8 cluster solution from cluster analysis (n=25,049) based on sequence imputed data (m=10) from wave 2 to 13 of UKHLS.

Because of the overlap between the classes from LCA and SA, a table was produced to compare the size of each class and cluster. **Table A8.3** shows the proportions of the different clusters and compared the proportions of SA with the proportions of LCA. The relative size of clusters is similar compared to SA. Non-caregivers remain the largest group (65.7%) and recurrent caregivers the smallest group (1.4%). The only exception is ‘former-short’ caregiving and ‘temporary’ caregiving. In SA, more people are classified as former caregivers with short caregiving duration while in LCA more participants were classified. This is not particularly problematic since both of these groups could be conceptualised as similar. In view of recurrent caregiving, which is the main group of interest for this analysis, it can be seen that in SA fewer participants were classified as recurrent caregiver compared to LCA (1.4% vs 2.4% respectively).

Table A8.3 Comparison of classes from LCA and clusters from SA

Cluster	Count	Proportion all n=125,040	Proportion amongst caregivers N=42,861	Proportion ALL from LCA (Change from SA)	Proportion amongst caregivers (Change from SA)
1 – Long-term	8,642	6.9%	20.2%	5.9% **(-1.0%)**	15.8% **(-4.4%)**
2 – Former-long	3.892	3.1%	9.1%	4.0% **(+0.9%)**	10.8% **(+0.9%)**
3 – Former-short	15,071	12.1%	35.2%	7.6% **(-4.5%)**	20.4% **(-14.8%)**
4 - Recurrent	1,784	1.4%	4.2%	2.4% **(+1.0%)**	6.4% **(+2.2%)**
5 – Temporary	2,602	2.1%	6.1%	7.3% **(+5.3%)**	19.6% **(+13.5)**
6 – Emerging-short	6,389	5.1%	14.9%	5.8% **(+0.7%)**	15.6% **(+0.7%)**
7 – Emerging-long	4,481	3.6%	5.5%	4.2% **(+0.6%)**	11.3% **(+5.8%)**
8 – No care	82,179	65.7%	-	62.9% **(-2.8%)**	-
Total	125,040	-	-	-	-

Sequence Analysis: Regression of clusters

Based on the fully adjusted pooled estimated from the SA clusters, recurrent caregiving was associated with lower odds of physical inactivity which was statistically significant. Also, recurrent caregivers had higher odd of smoking and lower odds of problematic drinking but this was statistically not significant. In these models, healthy eating was not significantly associated with recurrent caregiving.

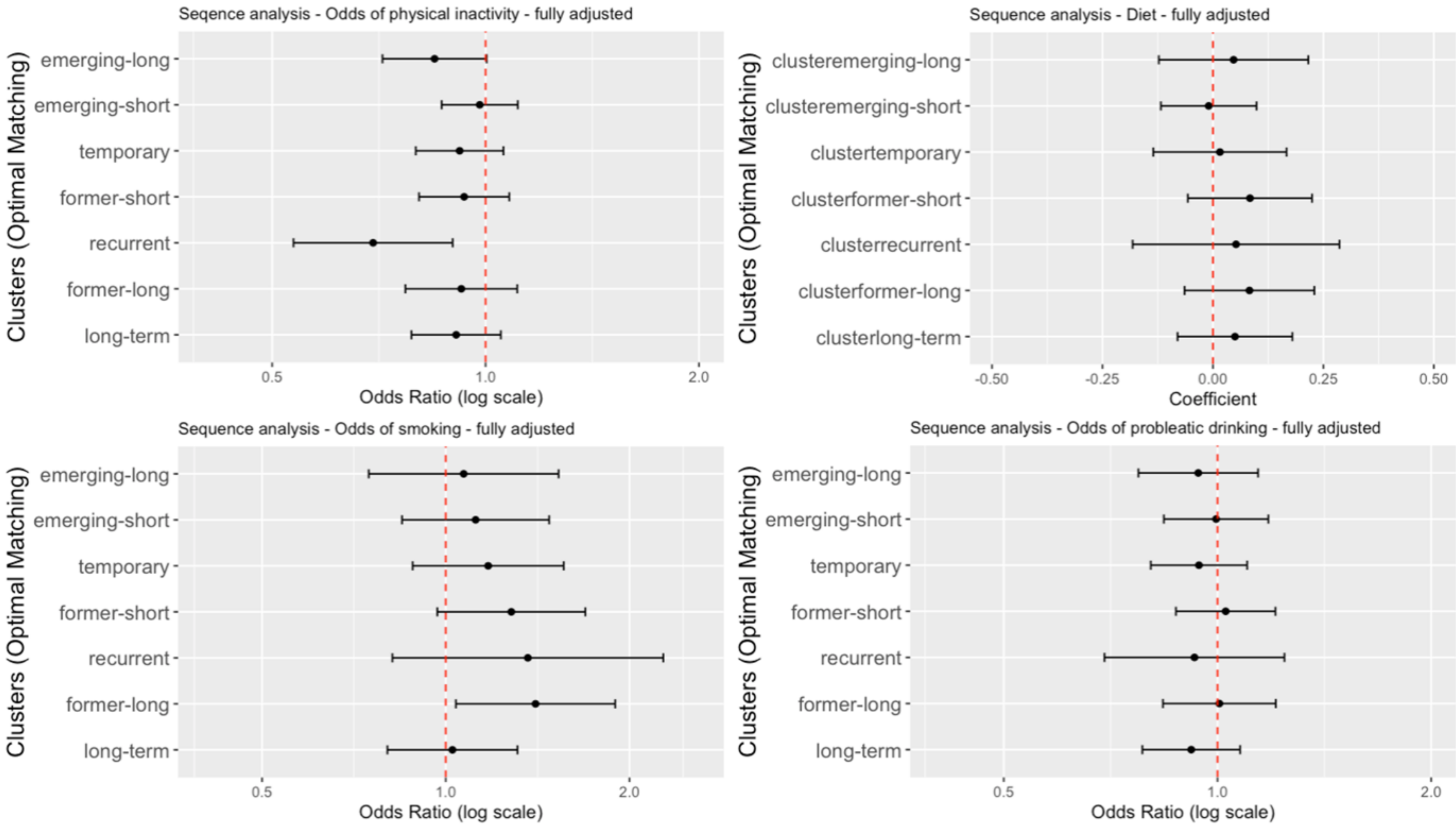


Figure A8.15 Regression results of clusters from sequence analysis (n=25,049, m=10), accounting for complex survey design, clustering, and adjusting for selected covariates.

Appendix 8.3: LCA on sequence imputed data set

LCA was performed on the imputed data sets (m=10) that were stacked together.

Fit indices are slightly improved from the LCA with complete cases but not by a large margin. For example, for eight-class solution, the entropy was 0.74 while in the imputed LCA, entropy was 0.80.

Table A8.4 Fit indices for LCA on sequence imputed dataset (n=250,490) from UKHLS waves 2 to 13.

Model	log-likelihood	resid. df	BIC	aBIC	cAIC	likelihood-ratio	Entropy
Model 01	-725494.2	4083	1451129	1451091	1451141	449907.44	-
Model 02	-577597.7	4070	1155489	1155409	1155514	154114.42	0.88
Model 03	-556039.2	4057	1112524	1112404	1112562	110997.44	0.85
Model 04	-532693.9	4044	1065986	1065824	1066037	64306.92	0.837
Model 05	-526559.5	4031	1053870	1053667	1053934	52038.11	0.831
Model 06	-521662.1	4018	1044228	1043983	1044305	42243.39	0.817
Model 07	-517944.8	4005	1036946	1036660	1037036	34808.70	0.798
Model 08	-516167.8	3992	1033545	1033217	1033648	31254.76	0.802
Model 09	-514374.4	3979	1030110	1029742	1030226	27667.91	0.798
Model 10	-512751.6	3966	1027017	1026607	1027146	24422.30	0.792

The elbow plot of the imputed LCA follows the same pattern as the elbow plot for the complete case LCA.

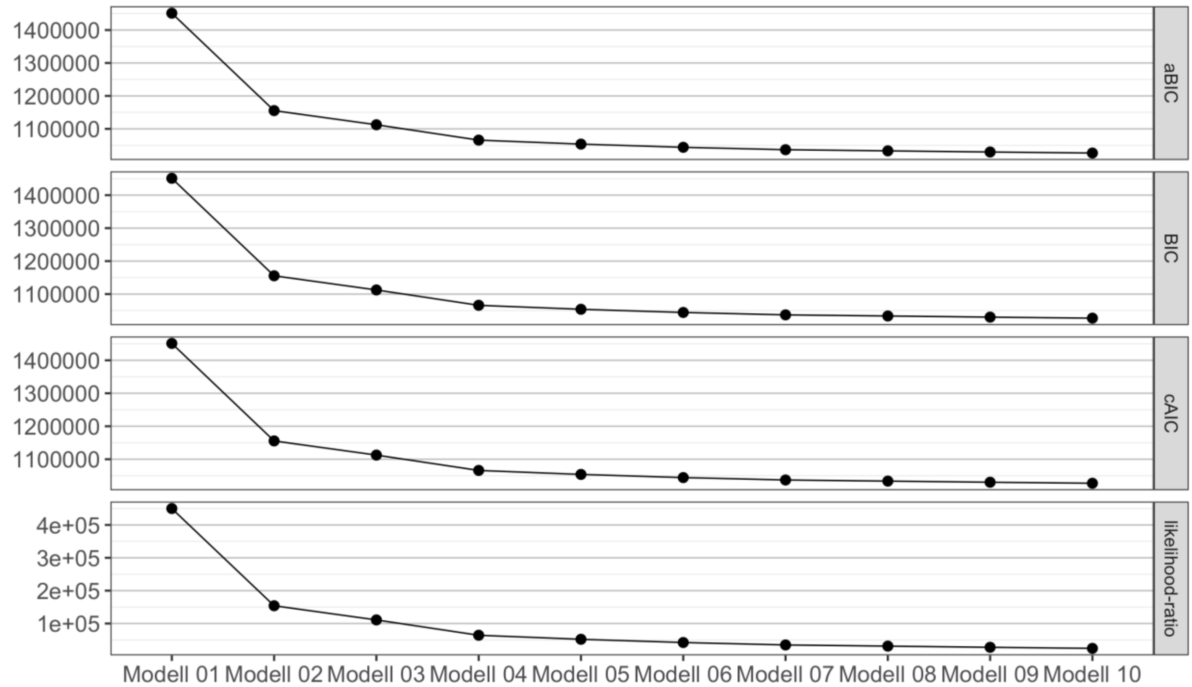


Figure A8.16 Elbow plot of fit indices of LCA on sequence imputed data (n=250,490)

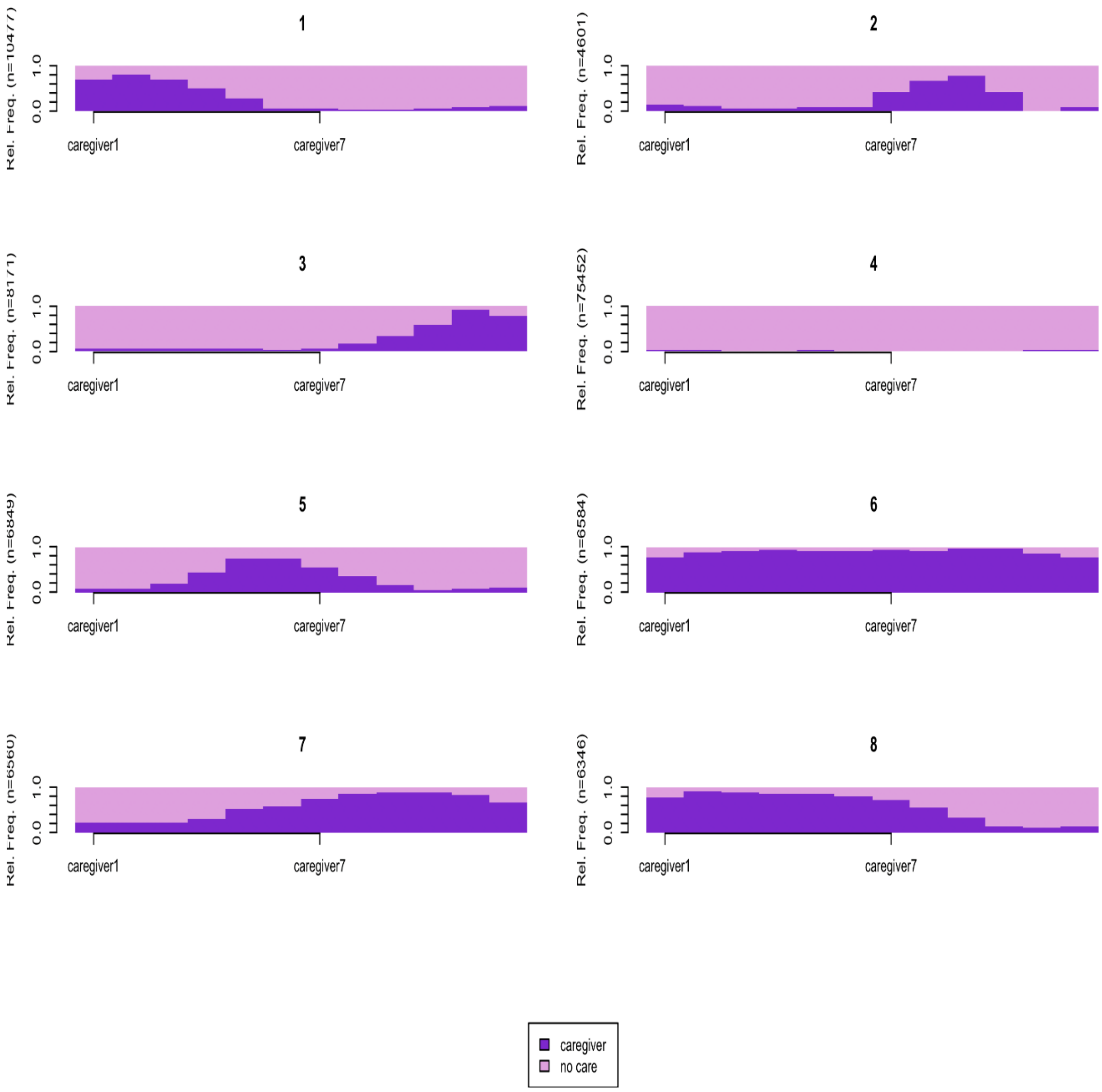


Figure A8.17 State Distribution Plot of 8 class solution of LCA on sequence imputed datasets (n=250,490)

The State Distribution Plot of the eight-class solution does not reveal the group 'recurrent caregiver', rather an additional 'temporary caregiver' class emerges in this solution.

In the nine-class solution, the class 'recurrent caregivers' emerges. In total, 3,013 out of 125,245 sequences were grouped in this class which is equivalent to a proportion of 2.4% which is the same proportion of people who were classified as recurrent caregivers in the complete case LCA.

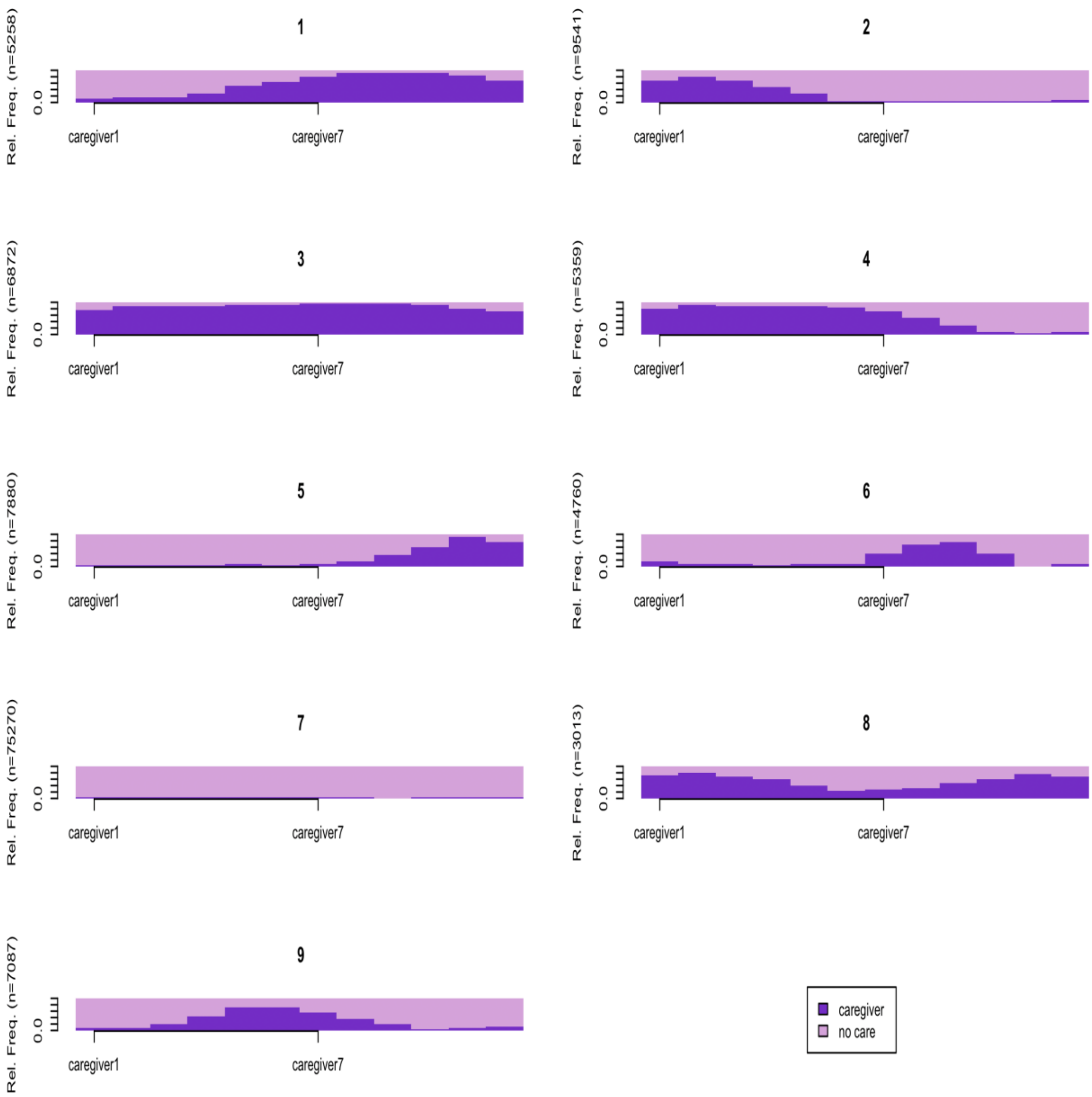


Figure A8.18 State Distribution Plot of 8 class solution of LCA on sequence imputed datasets (n=250,490)

Table A8.5 Average posterior probabilities 9-class solution (LCA on sequence imputation)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
[1]	**0.84**	0.00	0.04	0.00	0.03	0.03	0.00	0.04	0.02
[2]	0.00	**0.86**	0.00	0.03	0.00	0.01	0.05	0.02	0.03
[3]	0.05	0.00	**0.88**	0.04	0.00	0.00	0.00	0.03	0.00
[4]	0.00	0.05	0.02	**0.86**	0.00	0.00	0.00	0.04	0.04
[5]	0.05	0.00	0.00	0.00	**0.86**	0.03	0.04	0.02	0.01
[6]	0.03	0.01	0.00	0.00	0.04	**0.73**	0.07	0.02	0.10
[7]	0.00	0.02	0.00	0.00	0.04	0.02	**0.95**	0.00	0.01
[8]	0.05	0.04	0.03	0.04	0.05	0.01	0.00	**0.74**	0.02
[9]	0.02	0.04	0.00	0.04	0.01	0.05	0.05	0.01	**0.75**

Combining Sequence imputation with LCA

Given the possibility to impute missing elements of a sequence or latent class variables, raises the question whether LCA could be performed on a sequence imputed dataset. It was attempted to perform LCA on the 125,040 imputed sequences. In this analysis, the class of recurrent caregivers only emerged in the nine-class solution but not in the eight-class solution as this was the case with the LCA on complete cases. Further, the entropy only improved marginally and was 0.80 in the LCA with the imputed data. In the nine-class solution, three out of the nine diagonal average posterior probabilities were still below the benchmark of 0.80 and one off-diagonal was with 0.10 further away from zero than the solution with the complete case LCA. Hence it seems as the sequence imputation does not solve the problem of a borderline classification indicators for the LCA. In view of proportion, 3,013 out of 125,040 were classified as recurrent caregivers which equates to 2.4% of the overall sample which is the same proportion as in the complete case LCA. Therefore, the LCA of the imputed data did not add much value to the analysis and was not further pursued.

Appendix 8.4: Change in relationship between caregiver and care recipient

Table A8.6 Change in caregiver-recipient relationship for analysis of multiple transitions (n=25,049)

Observed transitions*				Latent Classes*			
Categories	**No change in relationship**	**Change in relationship**	**Change in number of care recipients**	**Categories**	**No change in relationship**	**Change in relationship**	**Change in number of care recipients**
Overall	61.2%	8.6%	30.3%	**Overall**	61.2%	8.6%	30.3%
Non-caregiver	100.0%	0%	0%	**No care**	96.2%	2.3%	1.4%
Emerging	72.4%	2.5%	24.7%	**Emerging-short**	59.3%	10.0%	30.7%
				Emerging-long	36.6%	11.0%	52.4%
Temporary	88.6%	2.4%	8.9%	**Temporary**	55.8%	15.9%	28.3%
Long-term	35.2%	3.2%	61.6%	**Long-term**	29.9%	4.2%	65.9%
Former	73.1%	2.8%	24.1%	**Former-short**	60.6%	12.0%	27.4%
				Former-long	39.5%	8.5%	52.0%
Multiple transitions / current no care	40.7%	18.6%	40.7%	**Recurrent**	23.3%	16.4%	60.3%
Multiple transitions / current care	31.4%	15.4%	53.2%				

*p<0.001; weighted and accounted for complex survey design

Appendix 8.5: Regression results for observed transitions

Table A8.7 Regression results for Observed Transitions for physical inactivity; logistic regression models predicting physical inactivity across latent caregiving intensity classes among UKHLS participants (n=25,049), showing pooled Odds Ratios from multiple imputation (m=10) and accounting for complex survey design and household-level clustering. Results are shown for three models: PA1b (unadjusted), PA2b (adjusted for walking at baseline), and PA3b (adjusted for selected covariates).

		Model PA1b		Model PA2b		Model PA3b	
	Physical inactivity	**OR**	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**
OBSERVED TRANSITIONS	Non-caregiver	1.00	-	1.00	-	1.00	-
	Emerging	0.87	(0.77, 0.99)	0.87	(0.76, 0.99)	0.79	(0.69, 0.91)
	Temporary	1.04	(0.96, 1.14)	1.04	(0.95, 1.14)	0.91	(0.83, 1)
	Long-term	1.20	(0.99, 1.47)	1.21	(0.99, 1.48)	0.90	(0.72, 1.11)
	Former	1.34	(1.18, 1.51)	1.34	(1.19, 1.51)	1.07	(0.94, 1.22)
	Multiple transitions/current no care	1.13	(1.03, 1.25)	1.14	(1.04, 1.26)	0.95	(0.86, 1.05)
	Multiple transitions / current care	1.01	(0.91, 1.13)	1.03	(0.92, 1.14)	0.89	(0.8, 1.0)
Walking at baseline	0 days			1.00	-	1.00	-
	1-2 days			0.60	(0.55, 0.64)	0.79	(0.72, 0.86)
	3-4 days			0.53	(0.47, 0.58)	0.69	(0.62, 0.77)
	5-6 days			0.49	(0.44, 0.54)	0.65	(0.58, 0.73)
	Every day			0.45	(0.41, 0.5)	0.55	(0.5, 0.62)
Age group at baseline	Early adulthood (16-29)					1.00	-
	Early mid-adulthood (30-49)					1.15	(1.03, 1.29)
	Late mid-adulthood (50-64)					1.34	(1.2, 1.51)
	Late adulthood (65+)					2.12	(1.83, 2.45)
Sex	Men					1.00	-
	women					1.67	(1.57, 1.79)
Education	No Qualification					1.00	-
	A-Level, GCSE, other qualification					0.81	(0.73, 0.91)
	Degree or other higher qualification					0.72	(0.63, 0.81)

		Model PA1b		Model PA2b		Model PA3b	
	Physical inactivity	**OR**	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**
Ethnicity	White					1.00	-
	black					1.07	(0.88, 1.3)
	Indian					1.24	(0.96, 1.62)
	Pakistani/ Bangladeshi					1.70	(1.34, 2.15)
	other Asian/other					1.23	(0.98, 1.55)
Occupational Class	Not employed					1.00	-
	Management & professional					0.99	(0.81, 1.21)
	intermediate					0.88	(0.72, 1.08)
	routine					1.06	(0.86, 1.29)
Income quintiles	1 (low)					1.00	-
	2					0.93	(0.83, 1.05)
	3					0.93	(0.83, 1.05)
	4					0.84	(0.74, 0.94)
	5 (high)					0.73	(0.65, 0.83)
Working status	Not employed					1.00	-
	full-time employed					0.87	(0.71, 1.05)
	part-time employed					0.89	(0.74, 1.08)
Number of children in household	0					1.00	-
	1					0.96	(0.85, 1.07)
	2					0.79	(0.69, 0.9)
	3 or more					1.03	(0.84, 1.28)
Cohabiting at baseline	Single, divorced, widowed					1.00	-
	married or cohabiting					1.00	(0.91, 1.11)
	1					1.00	-
	2					0.87	(0.76, 0.99)
	3-4					0.88	(0.76, 1.01)
	5 or more					0.76	(0.63, 0.91)
	GHQ At baseline					1.02	(1.01, 1.02)
Self-rated general health	Good or excellent					1.00	-
	fair or poor					1.37	(1.21, 1.55)
	sf12_base					0.98	(0.97, 0.98)

		Model PA1b		Model PA2b		Model PA3b	
	Physical inactivity	**OR**	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**
Wave outcome observed	UKHLS 7					1.00	-
	UKHLS 9					0.91	(0.76, 1.08)
	UKHLS 11					1.09	(0.92, 1.29)
	UKHLS 13					0.99	(0.87, 1.13)

Table A8.8 Regression results for Observed Transitions for fruit and vegetable consumption; linear regression models predicting average daily fruit and vegetable intake across latent caregiving intensity classes among UKHLS participants (n=25,049), showing pooled coefficient estimates from multiple imputation (m=10) and accounting for complex survey design and household-level clustering. Results are shown for three models: DIET1b (unadjusted), DIET2b (adjusted for fruit and vegetable intake at baseline), and DIET3b (adjusted for selected covariates).

		Model DIET1b		**Model DIET2b**		**Model DIET3b**	
	Fruit and vegetable consumption	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**
OBSERVED TRANSITIONS	Non-caregiver	Ref.	-	Ref.	-	Ref.	-
	Emerging	0.1	(-0.1, 0.2)	0.0	(-0.1, 0.1)	0.0	(-0.1, 0.1)
	Temporary	0.1	(0, 0.2)	0.0	(-0.1, 0.1)	0.0	(-0.1, 0.1)
	Long-term	0.0	(-0.2, 0.2)	0.0	(-0.2, 0.2)	0.0	(-0.2, 0.2)
	Former	0.3	(0.1, 0.4)	0.1	(0, 0.3)	0.1	(0, 0.2)
	Multiple transitions/current no care	0.2	(0.1, 0.3)	0.1	(0, 0.2)	0.1	(0, 0.2)
	Multiple transitions / current care	0.2	(0.1, 0.3)	0.1	(0, 0.2)	0.1	(0, 0.2)
Portions fruit / vegetable at baseline	0			Ref.	-	Ref.	-
	1-3			2.1	(1.9, 2.3)	1.7	(1.5, 1.9)
	4			3.2	(3, 3.4)	2.7	(2.5, 2.9)
	5 or more			4.0	(3.8, 4.2)	3.4	(3.2, 3.7)
Age group at baseline	Early adulthood (16-29)					Ref.	-
	Early mid-adulthood (30-49)					0.1	(0, 0.2)
	Late mid-adulthood (50-64)					0.3	(0.2, 0.4)
	Late adulthood (65+)					0.2	(0, 0.3)
Sex	Men					Ref.	-
	women					0.2	(0.1, 0.2)
Education	No Qualification					Ref.	-
	A-Level, GCSE, other qualification					0.3	(0.2, 0.4)
	Degree or other higher qualification					0.7	(0.6, 0.8)

		Model DIET1b		Model DIET2b		Model DIET3b	
	Fruit and vegetable consumption	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**
Ethnicity	White					Ref.	-
	black					0.0	(-0.2, 0.2)
	Indian					-0.1	(-0.3, 0.1)
	Pakistani/ Bangladeshi					-0.5	(-0.8, -0.3)
	other Asian/other					0.3	(0.1, 0.5)
Occupational Class	Not employed					Ref.	-
	Management & professional					-0.3	(-0.5, -0.1)
	intermediate					-0.3	(-0.5, -0.1)
	routine					-0.5	(-0.7, -0.3)
Income quintiles	1 (low)					Ref.	-
	2					0.0	(-0.1, 0.1)
	3					0.1	(0, 0.2)
	4					0.2	(0.1, 0.3)
	5 (high)					0.4	(0.3, 0.5)
Working status	Not employed					Ref.	-
	full-time employed					0.3	(0.1, 0.4)
	part-time employed					0.4	(0.2, 0.6)
Number of children in household	0					Ref.	-
	1					-0.1	(-0.2, 0)
	2					0.0	(-0.1, 0.1)
	3 or more					-0.2	(-0.4, 0)
Cohabiting at baseline	Single, divorced, widowed					Ref.	-
	married or cohabiting					0.2	(0.1, 0.3)
Number of people living in the household	1					Ref.	-
	2					0.0	(-0.2, 0.1)
	3-4					0.0	(-0.1, 0.1)
	5 or more					0.0	(-0.1, 0.2)
	GHQ At baseline					0.0	(0, 0)
Self-rated general health	Good or excellent					Ref.	-
	fair or poor					-0.2	(-0.3, -0.1)
	UKHLS 7					Ref.	-

		Model DIET1b		Model DIET2b		Model DIET3b	
	Fruit and vegetable consumption	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**
Wave outcome observed	UKHLS 9					0.0	(-0.2, 0.1)
	UKHLS 11					0.0	(-0.1, 0.2)
	UKHLS 13					0.1	(0, 0.2)

Table A8.9 Regression results for Observed Transitions for Problematic Drinking; logistic regression models predicting problematic drinking across latent caregiving intensity classes among UKHLS participants (n=25,049), showing pooled odds ratio estimates from multiple imputation (m=10) and accounting for complex survey design and household-level clustering. Results are shown for three models: ALC1b (unadjusted), ALC2b (adjusted for drinks frequency at baseline), and ALC3b (adjusted for selected covariates).

		Model ALC1b		**Model ALC2b**		**Model ALC3b**	
	Problematic drinking	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
OBSERVED TRANSITIONS	Non-caregiver	1.00	-	1.00	-	1.00	-
	Emerging	0.89	(0.78, 1.02)	0.87	(0.75, 1.01)	0.86	(0.73, 1.01)
	Temporary	0.93	(0.85, 1.01)	0.86	(0.78, 0.95)	0.96	(0.87, 1.07)
	Long-term	0.80	(0.65, 0.97)	0.82	(0.65, 1.03)	0.86	(0.68, 1.11)
	Former	0.81	(0.71, 0.91)	0.71	(0.62, 0.81)	0.87	(0.75, 1)
	Multiple transitions/current no care	0.85	(0.77, 0.93)	0.76	(0.68, 0.85)	0.92	(0.82, 1.04)
	Multiple transitions / current care	0.85	(0.76, 0.94)	0.82	(0.73, 0.92)	0.87	(0.77, 0.99)
Walking at baseline	Non-drinker			1.00	-	1.00	-
	Monthly/weekly			5.08	(4.15, 6.21)	3.75	(3.04, 4.61)
	1-4 days/week			24.75	(20.33, 30.14)	23.09	(18.79, 28.36)
	5+ days a week			76.50	(61.28, 95.5)	97.79	(77.1, 124.04)
Age group at baseline	Early adulthood (16-29)					1.00	-
	Early mid-adulthood (30-49)					0.69	(0.61, 0.79)
	Late mid-adulthood (50-64)					0.43	(0.38, 0.49)
	Late adulthood (65+)					0.18	(0.15, 0.21)
Sex	Men					1.00	-
	women					1.55	(1.44, 1.67)
Education	No Qualification					1.00	-
	A-Level, GCSE, other qualification					1.12	(0.98, 1.28)
	Degree or other higher qualification					1.06	(0.92, 1.23)
Ethnicity	White					1.00	-

		Model ALC1b		Model ALC2b		Model ALC3b	
	Problematic drinking	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
	black					0.60	(0.46, 0.77)
	Indian					0.39	(0.29, 0.54)
	Pakistani/ Bangladeshi					0.19	(0.1, 0.36)
	other Asian/other					0.63	(0.47, 0.85)
Occupational Class	Not employed					1.00	-
	Management & professional					1.01	(0.8, 1.28)
	intermediate					0.91	(0.72, 1.15)
	routine					1.00	(0.79, 1.26)
Income quintiles	1 (low)					1.00	-
	2					1.12	(0.98, 1.29)
	3					1.28	(1.11, 1.46)
	4					1.42	(1.24, 1.63)
	5 (high)					1.61	(1.4, 1.86)
Working status	Not employed					1.00	-
	full-time employed					0.88	(0.69, 1.11)
	part-time employed					1.04	(0.83, 1.3)
Number of children in household	0					1.00	-
	1					1.24	(1.09, 1.41)
	2					1.48	(1.27, 1.72)
	3 or more					1.01	(0.78, 1.32)
Cohabiting at baseline	Single, divorced, widowed					1.00	-
	married or cohabiting					1.04	(0.93, 1.17)
	1					1.00	-
	2					1.17	(1, 1.36)
	3-4					1.21	(1.03, 1.42)
	5 or more					1.24	(0.99, 1.54)
	GHQ At baseline					1.00	(1, 1.01)
Self-rated general health	Good or excellent					1.00	-
	fair or poor					0.74	(0.66, 0.83)
Wave outcome observed	UKHLS 7					1.00	-
	UKHLS 9					0.91	(0.73, 1.14)

		Model ALC1b		Model ALC2b		Model ALC3b	
	Problematic drinking	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
	UKHLS 11					0.65	(0.53, 0.8)
	UKHLS 13					0.58	(0.5, 0.68)

Table A8.10 Regression results for Observed Transitions for Smoking; logistic regression models predicting smoking status across latent caregiving intensity classes among UKHLS participants (n=25,049), showing pooled odds ratio estimates from multiple imputation (m=10) and accounting for survey weights and household-level clustering. Results are shown for three models: SMOK1b (unadjusted), SMOK2b (adjusted for smoking status at baseline), and SMOK3b (adjusted for selected covariates).

		Model SMOK1b		**Model SMOK2b**		**Model SMOK3b**	
		Odds Ratio	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
OBSERVED TRANSITIONS	Non-caregiver	1.00	-	1.00	-	1.00	-
	Emerging	1.07	(0.87, 1.31)	0.91	(0.7, 1.19)	0.90	(0.68, 1.19)
	Temporary	1.08	(0.95, 1.23)	0.93	(0.79, 1.1)	1.06	(0.89, 1.26)
	Long-term	1.40	(1.08, 1.83)	1.15	(0.83, 1.6)	1.01	(0.7, 1.43)
	Former	0.94	(0.78, 1.13)	1.06	(0.83, 1.34)	1.23	(0.95, 1.58)
	Multiple transitions/current no care	1.06	(0.92, 1.22)	0.95	(0.79, 1.13)	1.11	(0.92, 1.35)
	Multiple transitions / current care	1.26	(1.08, 1.47)	1.19	(0.98, 1.46)	1.36	(1.1, 1.67)
Smoking at baseline	Non-smoker			1.00	-	1.00	-
	Ex-smoker			3.42	(2.68, 4.36)	4.16	(3.26, 5.3)
	Current smoker			96.44	(77.39, 120.18)	92.71	(74.44, 115.46)
Age group at baseline	Early adulthood (16-29)					1.00	-
	Early mid-adulthood (30-49)					0.77	(0.63, 0.94)
	Late mid-adulthood (50-64)					0.70	(0.56, 0.86)
	Late adulthood (65+)					0.27	(0.21, 0.36)
Sex	Men					1.00	-
	women					0.88	(0.77, 1)
Education	No Qualification					1.00	-
	A-Level, GCSE, other qualification					0.76	(0.63, 0.91)
	Degree or other higher qualification					0.53	(0.43, 0.66)
Ethnicity	White					1.00	-
	black					1.30	(0.88, 1.93)

		Model SMOK1b		Model SMOK2b		Model SMOK3b	
		Odds Ratio	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
	Indian					0.65	(0.39, 1.08)
	Pakistani/ Bangladeshi					0.98	(0.63, 1.5)
	other Asian/other					1.89	(1.15, 3.12)
Occupational Class	Not employed					1.00	-
	Management & professional					0.80	(0.51, 1.27)
	intermediate					0.83	(0.52, 1.31)
	routine					0.99	(0.64, 1.53)
Income quintiles	1 (low)					1.00	-
	2					0.91	(0.75, 1.1)
	3					0.95	(0.77, 1.16)
	4					0.81	(0.65, 1.01)
	5 (high)					0.65	(0.51, 0.82)
Working status	Not employed					1.00	-
	full-time employed					0.82	(0.52, 1.29)
	part-time employed					0.82	(0.53, 1.27)
Number of children in household	0					1.00	-
	1					1.10	(0.89, 1.36)
	2					0.92	(0.73, 1.17)
	3 or more					0.62	(0.41, 0.93)
Cohabiting at baseline	Single, divorced, widowed					1.00	-
	married or cohabiting					0.74	(0.62, 0.88)
	1					1.00	-
	2					0.92	(0.74, 1.14)
	3-4					1.12	(0.88, 1.43)
	5 or more					1.57	(1.12, 2.21)
	GHQ At baseline					1.00	(0.99, 1.01)
Self-rated general health	Good or excellent					1.00	-
	fair or poor					1.05	(0.89, 1.23)
Wave outcome observed	UKHLS 7					1.00	-
	UKHLS 9					0.83	(0.62, 1.1)

		Model SMOK1b		Model SMOK2b		Model SMOK3b	
		Odds Ratio	95% CI	Odds Ratio	95% CI	Odds Ratio	95% CI
	UKHLS 11					0.69	(0.52, 0.9)
	UKHLS 13					0.45	(0.37, 0.55)

Appendix 8.6: Regression results of latent classes

Table A8.11 Regression results for LCA for physical inactivity; logistic regression models predicting physical inactivity across latent caregiving intensity classes among UKHLS participants (n=25,049), showing pooled Odds Ratios from multiple imputation (m=10) and accounting for complex survey design and household-level clustering. Results are shown for three models: PA1a (unadjusted), PA2a (adjusted for walking at baseline), and PA3a (adjusted for selected covariates).

		Model PA1a		**Model PA2a**		**Model PA3a**	
	Physical inactivity	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
Latent Class	No care	1.00	-	1.00	-	1.00	-
	Temporary	1.08	(0.96, 1.21)	1.06	(0.95, 1.19)	0.91	(0.81, 1.03)
	Former long	1.41	(1.21, 1.64)	1.43	(1.23, 1.66)	1.13	(0.96, 1.33)
	Recurrent	0.8	(0.65, 0.97)	0.8	(0.65, 0.97)	0.65	(0.53, 0.81)
	Emerging-short	0.99	(0.87, 1.13)	1	(0.88, 1.14)	0.99	(0.86, 1.14)
	Former-short	1.12	(1, 1.25)	1.12	(1, 1.26)	0.94	(0.83, 1.06)
	Long-term	1.16	(1.02, 1.33)	1.17	(1.03, 1.34)	0.94	(0.81, 1.08)
	Emerging long	1.04	(0.9, 1.2)	1.06	(0.91, 1.23)	0.95	(0.81, 1.11)
Walking at baseline	0 days			1.00	-	1.00	-
	1-2 days			0.59	(0.55, 0.64)	0.79	(0.72, 0.86)
	3-4 days			0.52	(0.47, 0.58)	0.69	(0.61, 0.76)
	5-6 days			0.49	(0.44, 0.55)	0.65	(0.58, 0.73)
	Every day			0.45	(0.41, 0.5)	0.55	(0.5, 0.62)
Age group at baseline	Early adulthood (16-29)					1.00	-
	Early mid-adulthood (30-49)					1.14	(1.02, 1.28)
	Late mid-adulthood (50-64)					1.34	(1.2, 1.51)
	Late adulthood (65+)					2.12	(1.83, 2.45)
Sex	Men					1.00	-
	women					1.67	(1.56, 1.78)
Education	No Qualification					1.00	-
	A-Level, GCSE, other qualification					0.81	(0.73, 0.91)
	Degree or other higher qualification					0.72	(0.63, 0.81)

		Model PA1a		Model PA2a		Model PA3a	
	Physical inactivity	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
Ethnicity	White					1.00	-
	black					1.07	(0.88, 1.3)
	Indian					1.25	(0.96, 1.62)
	Pakistani/ Bangladeshi					1.71	(1.35, 2.16)
	other Asian/other					1.23	(0.98, 1.55)
Occupational Class	Not employed					1.00	-
	Management & professional					0.99	(0.81, 1.21)
	intermediate					0.88	(0.72, 1.08)
	routine					1.06	(0.86, 1.29)
Income quintiles	1 (low)					1.00	-
	2					0.94	(0.83, 1.05)
	3					0.93	(0.83, 1.05)
	4					0.84	(0.74, 0.95)
	5 (high)					0.74	(0.65, 0.83)
Working status	Not employed					1.00	-
	full-time employed					0.86	(0.71, 1.05)
	part-time employed					0.89	(0.74, 1.08)
Number of children in household	0					1.00	-
	1					0.96	(0.85, 1.07)
	2					0.79	(0.69, 0.9)
	3 or more					1.03	(0.83, 1.28)
Cohabiting at baseline	Single, divorced, widowed					1.00	-
	married or cohabiting					1.00	(0.9, 1.11)
Household size	1					1.00	-
	2					0.87	(0.76, 0.99)
	3-4					0.88	(0.76, 1.01)
	5 or more					0.76	(0.63, 0.91)
	GHQ At baseline					1.02	(1.01, 1.02)
Self-rated general health	Good or excellent					1.00	-
	fair or poor					1.37	(1.22, 1.55)
	sf12_base					0.98	(0.97, 0.98)

		Model PA1a		Model PA2a		Model PA3a	
	Physical inactivity	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
Wave outcome observed	UKHLS 7					1.00	-
	UKHLS 9					0.91	(0.76, 1.08)
	UKHLS 11					1.08	(0.91, 1.29)
	UKHLS 13					0.99	(0.87, 1.13)

Table A8.12 Regression results for LCA for fruit and vegetable consumption; linear regression models predicting average daily fruit and vegetable intake across latent caregiving intensity classes among UKHLS participants (n=25,049), showing pooled coefficient estimates from multiple imputation (m=10) and accounting for complex survey design and household-level clustering. Results are shown for three models: DIET1a (unadjusted), DIET2a (adjusted for fruit and vegetable intake at baseline), and DIET3a (adjusted for selected covariates).

		Model DIET1a		**Model DIET2a**		**Model DIET3a**	
	Fruit and vegetable consumption	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**
Latent Class	No care	Ref.	-	Ref.	-	Ref.	-
	Temporary	0.1	(0, 0.2)	0.0	(-0.1, 0.2)	0.1	(-0.1, 0.2)
	Former long	0.2	(0.1, 0.4)	0.1	(-0.1, 0.2)	0.1	(-0.1, 0.2)
	Recurrent	0.2	(0, 0.4)	0.1	(-0.1, 0.3)	0.1	(-0.1, 0.3)
	Emerging-short	0.2	(0.1, 0.4)	0.2	(0, 0.3)	0.1	(0, 0.2)
	Former-short	0.2	(0.1, 0.4)	0.1	(0, 0.2)	0.1	(0, 0.2)
	Long-term	0.1	(-0.1, 0.2)	0.0	(-0.1, 0.1)	0.0	(-0.1, 0.1)
	Emerging long	0.1	(-0.1, 0.2)	0.0	(-0.1, 0.2)	0.0	(-0.2, 0.1)
Portions fruit / vegetable at baseline	0			Ref.	-	Ref.	-
	1-3			2.0	(1.8, 2.3)	1.7	(1.5, 1.9)
	4			3.2	(2.9, 3.4)	2.7	(2.5, 2.9)
	5 or more			4.0	(3.8, 4.2)	3.4	(3.2, 3.7)
Age group at baseline	Early adulthood (16-29)					Ref.	-
	Early mid-adulthood (30-49)					0.1	(0, 0.2)
	Late mid-adulthood (50-64)					0.3	(0.2, 0.4)
	Late adulthood (65+)					0.2	(0, 0.3)
Sex	Men					Ref.	-
	women					0.2	(0.1, 0.2)
Education	No Qualification					Ref.	-
	A-Level, GCSE, other qualification					0.3	(0.2, 0.4)
	Degree or other higher qualification					0.7	(0.6, 0.8)
Ethnicity	White					Ref.	-
	black					0.0	(-0.2, 0.2)

		Model DIET1a		Model DIET2a		Model DIET3a	
	Fruit and vegetable consumption	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**
	Indian					-0.1	(-0.3, 0.1)
	Pakistani/ Bangladeshi					-0.5	(-0.8, -0.3)
	other Asian/other					0.3	(0.1, 0.5)
Occupational Class	Not employed					Ref.	-
	Management & professional					-0.3	(-0.5, -0.1)
	intermediate					-0.3	(-0.5, -0.1)
	routine					-0.5	(-0.7, -0.3)
Income quintiles	1 (low)					Ref.	-
	2					0.0	(-0.1, 0.1)
	3					0.1	(0, 0.2)
	4					0.2	(0.1, 0.3)
	5 (high)					0.4	(0.3, 0.5)
Working status	Not employed					Ref.	-
	full-time employed					0.3	(0.1, 0.4)
	part-time employed					0.4	(0.2, 0.6)
Number of children in household	0					Ref.	-
	1					-0.1	(-0.2, 0)
	2					0.0	(-0.1, 0.1)
	3 or more					-0.2	(-0.4, 0)
Cohabiting at baseline	Single, divorced, widowed					Ref.	-
	married or cohabiting					0.2	(0.1, 0.3)
Number of people living in the household	1					Ref.	-
	2					0.0	(-0.2, 0.1)
	3-4					0.0	(-0.1, 0.1)
	5 or more					0.0	(-0.1, 0.2)
	GHQ At baseline					0.0	(0, 0)
Self-rated general health	Good or excellent					Ref.	-
	fair or poor					-0.2	(-0.3, -0.1)
Wave outcome observed	UKHLS 7					Ref.	-
	UKHLS 9					0.0	(-0.2, 0.1)
	UKHLS 11					0.0	(-0.1, 0.2)

	Model DIET1a		Model DIET2a		Model DIET3a	
Fruit and vegetable consumption	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**	**Coeff.**	**95% CI**
UKHLS 13					0.1	(0, 0.2)

Table A8.13 Regression results for LCA for Problematic Drinking; logistic regression models predicting problematic drinking across latent caregiving intensity classes among UKHLS participants (n=25,049), showing pooled odds ratio estimates from multiple imputation (m=10) and accounting for complex survey design and household-level clustering. Results are shown for three models: ALC1a (unadjusted), ALC2a (adjusted for drinks frequency at baseline), and ALC3a (adjusted for selected covariates).

		Model ALC1a		**Model ALC2a**		**Model ALC3a**	
	Problematic drinking	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
Latent Class	No care	1.00	-	1.00	-	1.00	-
	Temporary	0.89	(0.79, 1)	0.86	(0.75, 0.97)	0.97	(0.84, 1.11)
	Former long	0.86	(0.74, 1)	0.76	(0.64, 0.9)	0.90	(0.75, 1.07)
	Recurrent	0.74	(0.61, 0.89)	0.67	(0.54, 0.83)	0.75	(0.59, 0.94)
	Emerging-short	0.92	(0.81, 1.05)	0.86	(0.74, 0.99)	0.88	(0.75, 1.03)
	Former-short	0.88	(0.78, 0.99)	0.80	(0.7, 0.91)	0.95	(0.83, 1.09)
	Long-term	0.82	(0.72, 0.93)	0.83	(0.72, 0.96)	0.87	(0.74, 1.01)
	Emerging long	0.92	(0.8, 1.07)	0.90	(0.76, 1.05)	0.91	(0.77, 1.08)
Walking at baseline	Non-drinker			1.00	-	1.00	-
	Monthly/weekly			5.08	(4.16, 6.21)	3.75	(3.04, 4.61)
	1-4 days/week			24.71	(20.3, 30.09)	23.10	(18.8, 28.37)
	5+ days a week			76.17	(61.02, 95.07)	97.86	(77.17, 124.1)
Age group at baseline	Early adulthood (16-29)					1.00	-
	Early mid-adulthood (30-49)					0.69	(0.6, 0.78)
	Late mid-adulthood (50-64)					0.43	(0.38, 0.49)
	Late adulthood (65+)					0.18	(0.15, 0.21)
Sex	Men					1.00	-
	women					1.55	(1.44, 1.67)
Education	No Qualification					1.00	-
	A-Level, GCSE, other qualification					1.12	(0.98, 1.28)
	Degree or other higher qualification					1.06	(0.92, 1.23)
Ethnicity	White					1.00	-
	black					0.60	(0.46, 0.77)

		Model ALC1a		Model ALC2a		Model ALC3a	
	Problematic drinking	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
	Indian					0.39	(0.29, 0.54)
	Pakistani/ Bangladeshi					0.19	(0.1, 0.36)
	other Asian/other					0.63	(0.47, 0.85)
Occupational Class	Not employed					1.00	-
	Management & professional					1.02	(0.8, 1.29)
	intermediate					0.91	(0.72, 1.15)
	routine					1.00	(0.79, 1.26)
Income quintiles	1 (low)					1.00	-
	2					1.12	(0.98, 1.29)
	3					1.28	(1.12, 1.47)
	4					1.42	(1.24, 1.63)
	5 (high)					1.61	(1.4, 1.86)
Working status	Not employed					1.00	-
	full-time employed					0.87	(0.69, 1.1)
	part-time employed					1.04	(0.83, 1.3)
Number of children in household	0					1.00	-
	1					1.24	(1.09, 1.41)
	2					1.48	(1.28, 1.72)
	3 or more					1.01	(0.78, 1.32)
Cohabiting at baseline	Single, divorced, widowed					1.00	-
	married or cohabiting					1.04	(0.93, 1.17)
	1					1.00	-
	2					1.16	(1, 1.35)
	3-4					1.20	(1.02, 1.41)
	5 or more					1.23	(0.99, 1.54)
	GHQ At baseline					1.00	(1, 1.01)
Self-rated general health	Good or excellent					1.00	-
	fair or poor					0.74	(0.66, 0.83)
Wave outcome observed	UKHLS 7					1.00	-
	UKHLS 9					0.92	(0.73, 1.15)
	UKHLS 11					0.66	(0.54, 0.8)

	Model ALC1a		Model ALC2a		Model ALC3a	
Problematic drinking	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
UKHLS 13					0.59	(0.5, 0.68)

Table A8.14 Regression results for LCA for Smoking; logistic regression models predicting smoking status across latent caregiving intensity classes among UKHLS participants (n=25,049), showing pooled odds ratio estimates from multiple imputation (m=10) and accounting for survey weights and household-level clustering. Results are shown for three models: SMOK1a (unadjusted), SMOK2a (adjusted for smoking status at baseline), and SMOK3a (adjusted for selected covariates).

		Model SMOK1a		**Model SMOK2a**		**Model SMOK3a**	
		Odds Ratio	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
Latent Class	No care	1.00	-	1.00	-	1.00	-
	Temporary	1.10	(0.92, 1.3)	1.08	(0.87, 1.34)	1.12	(0.89, 1.41)
	Former long	1.05	(0.84, 1.31)	1.12	(0.84, 1.5)	1.31	(0.96, 1.8)
	Recurrent	1.58	(1.22, 2.04)	1.50	(1.06, 2.12)	1.67	(1.17, 2.4)
	Emerging-short	0.94	(0.76, 1.16)	0.89	(0.69, 1.17)	0.99	(0.74, 1.32)
	Former-short	1.00	(0.84, 1.2)	0.98	(0.79, 1.22)	1.04	(0.83, 1.31)
	Long-term	1.18	(0.98, 1.43)	1.09	(0.86, 1.37)	1.05	(0.83, 1.34)
	Emerging long	1.15	(0.93, 1.44)	1.04	(0.8, 1.36)	1.08	(0.81, 1.43)
Smoking at baseline	Non-smoker			1.00	-	1.00	-
	Ex-smoker			3.41	(2.67, 4.34)	4.15	(3.26, 5.29)
	Current smoker			96.01	(77.03, 119.66)	92.52	(74.29, 115.22)
Age group at baseline	Early adulthood (16-29)					1.00	-
	Early mid-adulthood (30-49)					0.77	(0.63, 0.94)
	Late mid-adulthood (50-64)					0.70	(0.57, 0.87)
	Late adulthood (65+)					0.28	(0.21, 0.37)
Sex	Men					1.00	-
	women					0.88	(0.78, 1)
Education	No Qualification					1.00	-
	A-Level, GCSE, other qualification					0.76	(0.64, 0.92)
	Degree or other higher qualification					0.54	(0.43, 0.67)
Ethnicity	White					1.00	-
	black					1.29	(0.87, 1.93)

		Model SMOK1a		Model SMOK2a		Model SMOK3a	
		Odds Ratio	95% CI	Odds Ratio	95% CI	Odds Ratio	95% CI
	Indian					0.65	(0.39, 1.08)
	Pakistani/ Bangladeshi					0.98	(0.64, 1.5)
	other Asian/other					1.90	(1.16, 3.13)
Occupational Class	Not employed					1.00	-
	Management & professional					0.80	(0.51, 1.27)
	intermediate					0.83	(0.53, 1.31)
	routine					0.99	(0.64, 1.54)
Income quintiles	1 (low)					1.00	-
	2					0.91	(0.75, 1.1)
	3					0.94	(0.77, 1.16)
	4					0.81	(0.65, 1)
	5 (high)					0.64	(0.51, 0.81)
Working status	Not employed					1.00	-
	full-time employed					0.82	(0.52, 1.29)
	part-time employed					0.82	(0.53, 1.27)
Number of children in household	0					1.00	-
	1					1.09	(0.88, 1.34)
	2					0.91	(0.72, 1.16)
	3 or more					0.62	(0.42, 0.93)
Cohabiting at baseline	Single, divorced, widowed					1.00	-
	married or cohabiting					0.74	(0.62, 0.88)
	1					1.00	-
	2					0.91	(0.73, 1.13)
	3-4					1.13	(0.89, 1.44)
	5 or more					1.57	(1.12, 2.21)
	GHQ At baseline					1.00	(0.99, 1.01)
Self-rated general health	Good or excellent					1.00	-
	fair or poor					1.05	(0.89, 1.24)
Wave outcome observed	UKHLS 7					1.00	-
	UKHLS 9					0.83	(0.62, 1.1)

	Model SMOK1a		Model SMOK2a		Model SMOK3a	
	Odds Ratio	95% CI	Odds Ratio	95% CI	Odds Ratio	95% CI
UKHLS 11					0.69	(0.52, 0.9)
UKHLS 13					0.45	(0.37, 0.55)

Appendix 8.7: Regression results with longitudinal weights

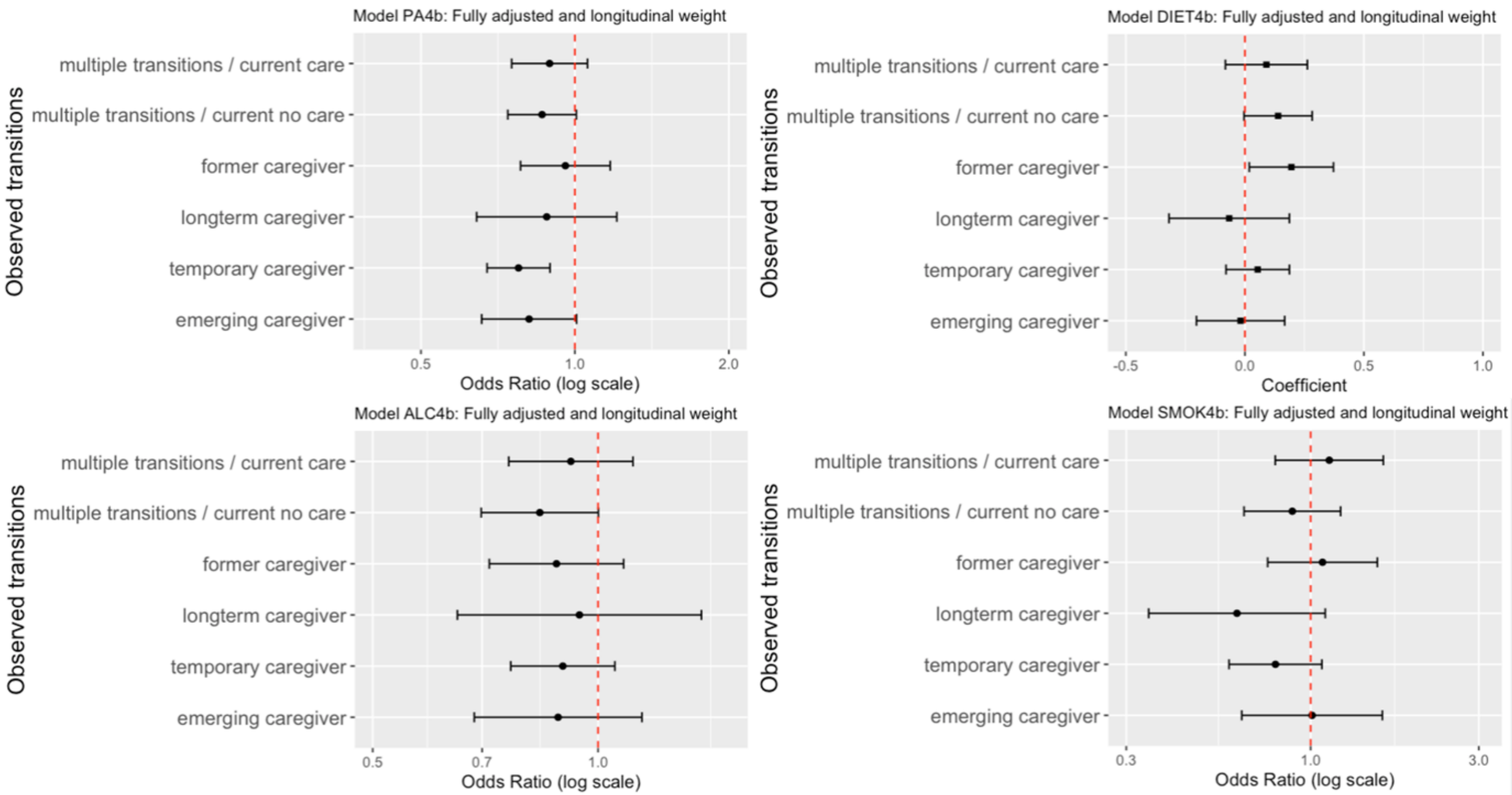


Figure A8.19 Sensitivity analysis with longitudinal weights for Observed Transitions for physical inactivity, fruit and vegetable consumption, problematic drinking, and smoking among UKHLS participants (n=25,049). The table presents the, incorporating longitudinal weights and pooled results on imputed data sets (m=10) and accounts for complex survey design and clustering at household level.

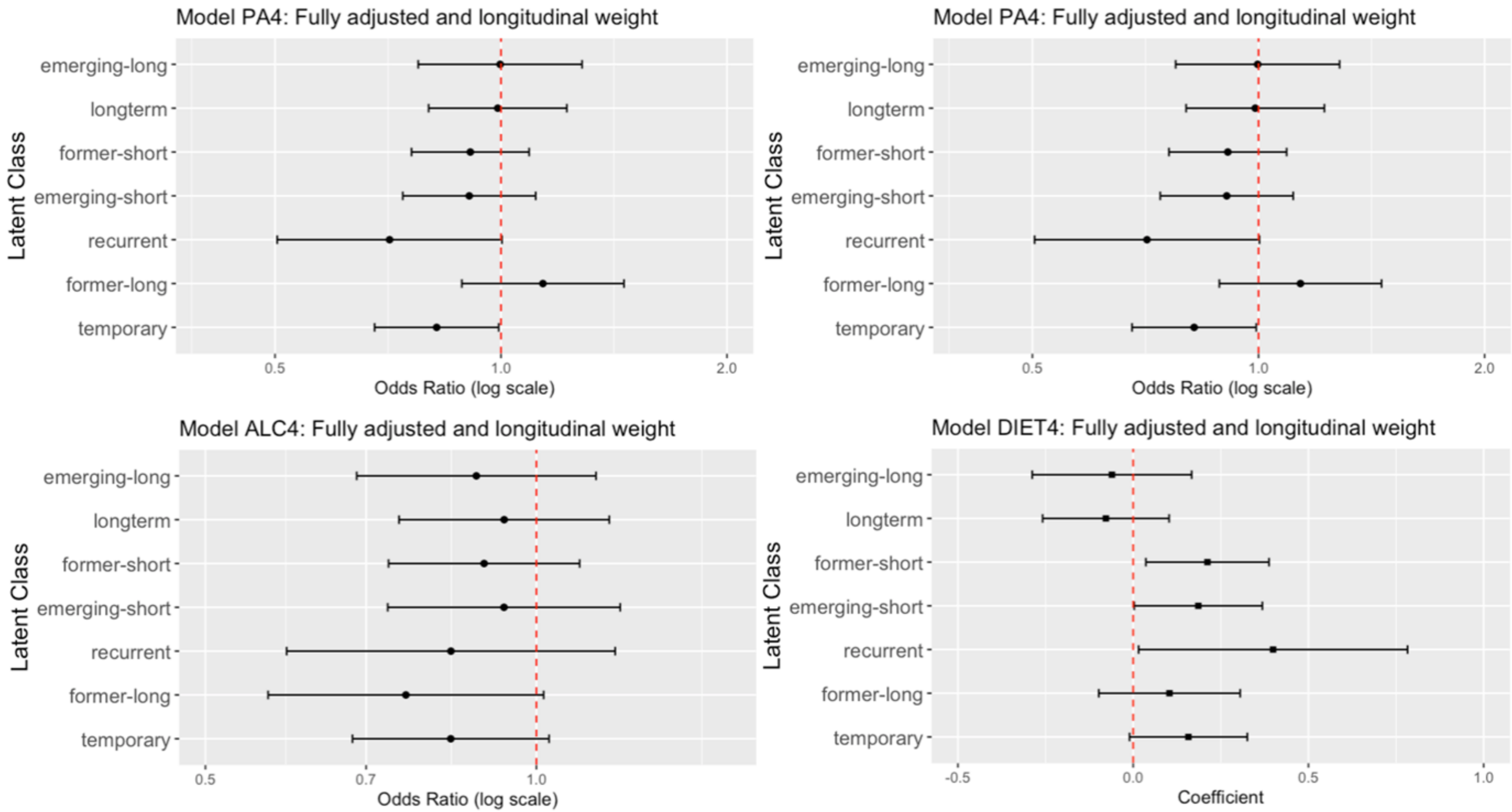


Figure A8.20 Sensitivity analysis with longitudinal weights for LCA for physical inactivity, fruit and vegetable consumption, problematic drinking, and smoking among UKHLS participants (n=25,049). The table presents the, incorporating longitudinal weights and pooled results on imputed data sets (m=10) and accounts for complex survey design and clustering at household level.

Appendix 8.8: Complete case analysis of Observed Transitions

Table A8.15 Descriptive statistics for Observed Transitions (n=25,049), based on complete cases. Estimates account for complex survey design and clustering at the household level.

	Unweighted n = 25,049		**Weighted proportions**							
Complete Cases	**level**	**n(%)**	**Non-caregiver**	**emerging**	**temporary**	**Long-term**	**former**	**Multiple / no care**	**Multiple / care**	**p**
			10,926	1,270	3,42	474	1,488	2,607	2,050	
Outcome										
Fruit and vegetable consumption	Mean(sd)	3.59 (2.21)	3.5 (2.2)	3.6 (2.2)	3.6 (2.2)	3.5 (2.1)	3.8 (2.2)	3.8 (2.3)	3.7 (2.3)	<0.001
	Missing	442 (1.8)								
Physical activity	Active	10538 (42.1)	45.9%	49.3%	44.9%	41.3%	38.8%	42.9%	45.7%	<0.001
	Inactive	13704 (54.7)	54.1%	50.7%	55.1%	58.7%	61.2%	57.1%	54.3%	
	Missing	807 (3.2)								
Problematic drinking	No	13291 (53.1)	50.7%	53.8%	52.6%	56.3%	56.0%	55.3%	55.1%	<0.001
	Yes	11194 (44.7)	49.3%	46.2%	47.4%	43.7%	44.0%	44.7%	44.9%	
	Missing	564 (2.3)								
Smoking	Non-smoker	22017 (87.9)	88.4%	87.7%	87.6%	84.4%	89.0%	87.8%	85.8%	<0.001

	Unweighted n = 25,049		**Weighted proportions**							
Complete Cases	**level**	**n(%)**	**Non-caregiver**	**emerging**	**temporary**	**Long-term**	**former**	**Multiple / no care**	**Multiple / care**	**p**
	Smoker	3015 (12.0)	11.6%	12.3%	12.4%	15.6%	11.0%	12.2%	14.2%	
	Missing	17 (0.1)								
Health behaviour at baseline										
Walking at baseline	none		25.3%	25.1%	26.4%	27.9%	25.3%	25.4%	23.5%	0.10
	1-2 days	6741 (26.9)	37.1%	37.8%	34.6%	30.7%	38.5%	35.0%	37.5%	
	3-4 days	8928 (35.6)	13.2%	13.6%	13.8%	12.2%	12.1%	13.1%	13.7%	
	5-6 days	3272 (13.1)	10.1%	9.0%	9.4%	10.8%	9.3%	11.0%	9.4%	
	Every day	2467 (9.8)	14.3%	14.4%	15.8%	18.5%	14.8%	15.6%	15.9%	
	Missing	3615 (14.4)								
Daily fruit and vegetable consumption at baseline	0 portions	209 (0.8)	0.9%	0.8%	0.8%	1.8%	0.5%	0.8%	1.2%	<0.001
	1-3 portions	14663 (58.5)	60.4%	57.0%	56.7%	58.0%	54.5%	53.6%	54.2%	
	4 portions	4519 (18.0)	18%	17.5%	18.5%	18.9%	18.3%	18.8%	20.3%	
	5+ portions	5613 (22.4)	20.7%	24.8%	24.0%	21.3%	26.7%	26.8%	24.2%	
	Missing	45 (0.2)								
	never smoked	11565 (46.2)	46.3%	43.7%	42.2%	39.4%	43.8%	40.9%	43.1%	0.02

	Unweighted n = 25,049		Weighted proportions							
Complete Cases	**level**	**n(%)**	**Non-caregiver**	**emerging**	**temporary**	**Long-term**	**former**	**Multiple / no care**	**Multiple / care**	**p**
Smoking status at baseline	ex-smoker	8859 (35.4)	36.1%	36.1%	37.7%	37.6%	40.7%	39.8%	36.8%	
	current smoker	4623 (18.5)	17.7%	20.1%	20.0%	23.0%	15.6%	19.3%	20.1%	
	Missing	2 (0.0)								
Drinks frequency at baseline	no drinks	2754 (11.0)	10.2%	9.9%	10.2%	13.4%	10.5%	10.4%	10.2%	<0.001
	monthly or weekly	7384 (29.5)	33.4%	34.9%	32.8%	35.0%	31.8%	31.7%	34.6%	
	1-4 per week	9371 (37.4)	44.0%	42.1%	41.8%	37.8%	41.9%	43.2%	42.4%	
	5+ per week	2865 (11.4)	12.4%	13.2%	15.2%	13.8%	15.8%	14.8%	12.9%	
	Missing	2675 (10.7)								
Covariates										
Age group at baseline	Early adulthood (16-29)	4343 (17.3)	26.5%	14.7%	15.4%	5.5%	9.4%	10%	11.4%	<0.001
	Early mid-adulthood (30-49)	9785 (39.1)	36.8%	45.5%	36.3%	42.8%	25.6%	34.4%	41.3%	
	Late mid-adulthood (50-64)	7039 (28.1)	21.8%	26.9%	30.5%	36.0%	41.6%	37.5%	34.2%	
	Late adulthood (65+)	3882 (15.5)	14.9%	12.9%	17.8%	15.7%	23.3%	18.0%	13.1%	
Sex	men	10748 (42.9)	50.8%	44.1%	44.1%	35.9%	41.7%	44.7%	40.9%	<0.001

	Unweighted n = 25,049		**Weighted proportions**							
Complete Cases	**level**	**n(%)**	**Non-caregiver**	**emerging**	**temporary**	**Long-term**	**former**	**Multiple / no care**	**Multiple / care**	**p**
	women	14301 (57.1)	49.2%	55.9%	55.9%	64.1%	58.3%	55.3%	59.1%	
	Missing	0								
Education	No qualification	3129 (12.5)	10.9%	10.3%	11.6%	17.0%	13.2%	12.5%	10.8%	<0.001
	A-Level, GCSE, other qualification	12854 (51.3)	51.9%	52.2%	53.4%	51.3%	52.3%	53.8%	50.4%	
	Degree or other higher qualification	9013 (36.0)	37.2%	37.4%	35.0%	31.7%	34.6%	33.7%	38.8%	
	Missing	53 (0.2)								
Ethnicity	white	22060 (88.1)	92.5%	94.6%	94.1%	94.7%	96.4%	94.8%	94.5%	<0.001
	black	848 (3.4)	2.0%	1.2%	1.6%	1.4%	0.8%	1.1%	1.6%	
	Indian	662 (2.6)	2.0%	1.4%	1.5%	1.6%	1.1%	1.1%	1.5%	
	Pakistani/Bangladeshi	807 (3.2)	1.2%	1.3%	1.2%	1.7%	0.8%	1.4%	1.3%	
	other Asian/other	662 (2.6)	2.4%	1.5%	1.5%	0.6%	0.9%	1.5%	1.2%	
	Missing	10 (0.0)								
	not employed	10064 (40.2)	38.2%	35.2%	38.7%	54.7%	46.2%	40.7%	36.2%	<0.001

	Unweighted n = 25,049		Weighted proportions							
Complete Cases	**level**	**n(%)**	**Non-caregiver**	**emerging**	**temporary**	**Long-term**	**former**	**Multiple / no care**	**Multiple / care**	**p**
Occupational Class	Management & professional	6706 (26.8)	29.3%	30.5%	27.6%	17.5%	22.6%	26.0%	29.0%	
	intermediate	3475 (13.9)	13.9%	15.6%	13.7%	10.9%	12.9%	14.5%	14.7%	
	routine	4609 (18.4)	18.5%	18.7%	20.1%	16.9%	18.2%	18.8%	20.1%	
	Missing	195 (0.8)								
Income quintiles	1 (low)	4173 (16.7)	15.0%	15.3%	14.5%	14.0%	13.5%	15.5%	15.0%	<0.001
	2	4669 (18.6)	16.9%	19.9%	18.8%	24.8%	20.1%	19.7%	19.5%	
	3	4803 (19.2)	19.4%	19.8%	18.6%	25.0%	16.8%	19.4%	18.5%	
	4	5398 (21.5)	22.1%	19.5%	22.3%	19.0%	23.4%	21.6%	20.6%	
	5 (high)	5978 (23.9)	26.6%	25.5%	25.8%	17.1%	26.1%	23.8%	26.4%	
	Missing	28 (0.1)								
Employment status	not in paid employment	9335 (37.3)	33.9%	33.0%	36.0%	50.5%	43.6%	37.9%	33.5%	<0.001
	full-time employed	11440 (45.7)	50.1%	49.9%	46.3%	33.7%	39.4%	43.9%	46.8%	
	part-time employed	4272 (17.1)	16.0%	17.1%	17.7%	15.8%	17.0%	18.2%	19.7%	
	Missing	2 (0.0)								

	Unweighted n = 25,049		**Weighted proportions**							
Complete Cases	**level**	**n(%)**	**Non-caregiver**	**emerging**	**temporary**	**Long-term**	**former**	**Multiple / no care**	**Multiple / care**	**p**
Number of children living in the household	0	17557 (70.1)	71.5%	66.9%	73.8%	68.7%	82.6%	75.6%	70.6%	<0.001
	1	3310 (13.2)	13.3%	15.0%	11.2%	13.0%	8.6%	11.2%	13.2%	
	2	3048 (12.2)	11.6%	14.2%	10.8%	12.2%	6.2%	9.8%	11.8%	
	3+	1134 (4.5)	3.6%	3.9%	4.2%	6.1%	2.5%	3.4%	4.4%	
	Missing	0								
Cohabiting status	single, separated, widowed	8205 (32.8)	39.4%	27.8%	31.0%	23.4%	27.9%	29.5%	27.5%	<0.001
	married or cohabiting	16840 (67.2)	60.6%	72.2%	69.0%	76.6%	72.1%	70.5%	72.5%	
	Missing	4 (<0.1)								
Self-rated general health	excellent, very good or good	18843 (75.2)	85.9%	83.9%	83.3%	76.1%	82.2%	8.2%	82.1%	<0.001
	fair or poor	3711 (14.8)	14.1%	16.1%	16.7%	23.9%	17.8%	17.8%	17.9%	
	Missing	2495 (10.0)								
Household size	1	3465 (13.8)	15.6%	9.7%	14.2%	4.3%	11.2%	13.8%	10.7%	<0.001
	2	8944 (35.7)	32.0%	36.1%	38.2%	39.6%	46.3%	41.2%	35.1%	

	Unweighted n = 25,049		Weighted proportions							
Complete Cases	**level**	**n(%)**	**Non-caregiver**	**emerging**	**temporary**	**Long-term**	**former**	**Multiple / no care**	**Multiple / care**	**p**
	3-4	9785 (39.1)	41.6%	44.5%	37.5%	43.2%	34.8%	36.2%	42.9%	
	5+	2855 (11.4)	10.8%	9.6%	10.1%	12.9%	7.7%	8.7%	11.3%	
	Missing	0								
Age	Mean(sd)	46.58 (16.56)	43.5 (18.1)	46.4 (15.3)	48.4 (16.5)	50.6 (13.1)	53.2 (15.4)	50.8 (14.9)	48.1 (14.2)	<0.001
	Missing	0								
GHQ	Mean(sd)	11.08 (5.35)	10.7 (5.10)	11.3 (5.5)	11.1 (5.2)	12.5 (6.1)	11.2 (5.3)	11.4 (5.5)	11.5 (5.4)	<0.001
	Missing	2,713 (10.8%)								
SF12	Mean(sd)	50.65 (10.34)	51.7 (9.8)	50.7 (10.0)	50.4 (10.5)	48.8 (10.8)	49.8 (10.4)	49.8 (10.6)	50.2 (10.6)	<0.001
	Missing	4,026 (16.1%)								

Table A8.16 Complete Case Analysis for Observed Transitions: regression results for physical inactivity; logistic regression models predicting physical inactivity across latent caregiving intensity classes among UKHLS participants (n=20,030) using complete case analysis. The table presents odds ratios from three models: PACC1 (unadjusted), PACC2 (adjusted for walking at baseline), and PACC3 (adjusted for selected covariates). The reference category is the 'low outside' caregiving intensity class. The analysis accounts for complex survey design and clustering at the household level.

		Model PA1CC		**Model PA2CC***		**Model PA3CC****	
	Physical inactivity	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
OBSERVED TRANSITIONS	Non-caregiver	1.00	-	1.00	-	1.00	-
	Emerging	0.88	(0.77, 1.01)	0.87	(0.76, 1.91)	0.79	(0.68, 0.92)
	Temporary	1.06	(0.97, 1.16)	1.05	(0.96, 1.15)	0.92	(0.83, 1.01)
	Long-term	1.23	(0.99, 1.52)	1.22	(0.98, 1.52)	0.93	(0.73, 1.17)
	Former	1.35	(1.19, 1.54)	1.36	(1.19, 1.56)	1.09	(0.95, 1.25)
	Multiple / no care	1.11	(1.01, 1.23)	1.12	(1.01, 1.24)	0.93	(0.84, 1.04)
	Multiple / care	1.05	(0.94, 1.17)	1.07	(0.96, 1.19)	0.92	(0.81, 1.03)

*adjusted for health behaviour at baseline; ** adjusted for adjusted health behaviour at baseline for age group, sex, education, ethnicity, occupational class, income quintiles, employment status, number of children in the household, cohabiting status, self-rated general health, household size, GHQ, and SF12 at baseline

Table A8.17 Complete Case Analysis for Observed Transitions: regression results for fruit and vegetable consumption; logistic regression models predicting physical inactivity across latent caregiving intensity classes among UKHLS participants (n=21,697) using complete case analysis. The table presents odds ratios from three models: DIETCC1 (unadjusted), DIETCC2 (adjusted for baseline fruit and vegetable consumption), and DIETCC3 (adjusted for selected covariates). The reference category is the 'low outside' caregiving intensity class. The analysis accounts for complex survey design and clustering at the household level.

		Model DIET1CC		**Model DIET2CC***		**Model DIET3CC*****	
	Fruit and vegetable consumption	**Coefficient**	**95% CI**	**Coefficient**	**95% CI**	**Coefficient**	**95% CI**
OBSERVED TRANSITIONS	Non-caregiver	Ref.	-	Ref.	-	Ref.	-
	Emerging	0.1	(-0.1/0.2)	0.0	(-0.1/0.1)	0.0	(-0.1/0.1)
	Temporary	0.1	(0.0?0.2)	0.0	(-0.1/0.1)	0.0	(-0.1/0.1)
	Long-term	0.0	(-0.2/0.2)	0.0	(-0.2/0/2)	0.0	(-0.1/0.2)
	Former	0.3	(0.1/0.4)	0.2	(0.0/0.3)	0.1	(0.0/0.2)
	Multiple / no care	0.3	(0.1/ 0.4)	0.1	(0.0/0.2)	0.1	(0.0/0.2)
	Multiple / care	0.2	(0.1/0.3)	0.1	(0.0/0.2)	0.1	(0.0/0.2)

*adjusted for health behaviour at baseline; *** adjusted for adjusted health behaviour at baseline for age group, sex, education, ethnicity, occupational class, income quintiles, employment status, number of children in the household, cohabiting status, self-rated general health, household size and GHQ at baseline.

Table A8.18 Complete Case Analysis for Observed Transitions: regression results for problematic drinking; logistic regression models predicting physical inactivity across latent caregiving intensity classes among UKHLS participants (n=21,475) using complete case analysis. The table presents odds ratios from three models: ALC1CC (unadjusted), ALC2CC (adjusted for drinks frequency at baseline), and ALC3CC (adjusted for selected covariates). The reference category is the 'low outside' caregiving intensity class. The analysis accounts for complex survey design and clustering at the household level.

		Model ALC1CC		**Model ALC2CC***		**Model ALC3CC*****	
	Problematic drinking	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
OBSERVED TRANSITIONS	Non-caregiver	1.00	-	1.00	-	1.00	-
	Emerging	0.88	(0.77, 1.00)	0.86	(0.74, 1.00)	0.90	(0.76, 1.06)
	Temporary	0.92	(0.84, 1.00)	0.85	(0.77, 0.94)	1.00	(0.90, 1.11)
	Long-term	0.81	(0.66, 0.98)	0.83	(0.66, 1.04)	0.96	(0.75, 1.23)
	Former	0.81	(0.72, 0.92)	0.72	(0.62, 0.82)	0.94	(0.81, 1.08)
	Multiple / no care	0.82	(0.75, 0.91)	0.74	(0.66, 0.83)	0.96	(0.86, 1.08)
	Multiple / care	0.84	(0.76, 0.93)	0.80	(0.72, 0.90)	0.91	(0.81, 1.03)

*adjusted for health behaviour at baseline; *** adjusted for adjusted health behaviour at baseline for age group, sex, education, ethnicity, occupational class, income quintiles, employment status, number of children in the household, cohabiting status, self-rated general health, household size and GHQ at baseline.

Table A8.19 Complete Case Analysis Observed Transitions: regression results for smoking; logistic regression models predicting physical inactivity across latent caregiving intensity classes among UKHLS participants (n=22,050) using complete case analysis. The table presents odds ratios from three models: SMOK1CC (unadjusted), SMOK2CC (adjusted for smoking status at baseline), and SMOK3CC (adjusted for selected covariates). The reference category is the 'low outside' caregiving intensity class. The analysis accounts for complex survey design and clustering at the household level.

		Model SMOK1CC		**Model SMOK2CC***		**Model SMOK3CC*****	
	Smoking	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**	**Odds Ratio**	**95% CI**
OBSERVED TRANSITIONS	Non-caregiver	1.00	-	1.00	-	1.00	-
	Emerging	1.05	(0.84, 1.31)	0.84	(0.68, 1.18)	0.91	(0.68, 1.21)
	Temporary	1.06	(0.93, 1.21)	0.93	(0.77, 1.08)	1.06	(0.89, 1.27)
	Long-term	1.36	(1.03, 1.79)	1.03	(0.79, 1.57)	1.06	(0.73, 1.53)
	Former	0.95	(0.79, 1.14)	0.79	(0.87, 1.39)	1.37	(1.07, 1.76)
	Multiple / no care	1.05	(0.90, 1.22)	0.90	(0.78, 1.12)	1.14	(0.94, 1.39)
	Multiple / care	1.28	(1.10, 1.49)	1.10	(0.99, 1.47)	1.42	(1.16, 1.74)

*adjusted for health behaviour at baseline; *** adjusted for adjusted health behaviour at baseline for age group, sex, education, ethnicity, occupational class, income quintiles, employment status, number of children in the household, cohabiting status, self-rated general health, household size and GHQ at baseline.

Appendix 8.9: Analysis of missingness for the analysis of multiple transitions

Table A8.20 Frequency and proportion of missingness by outcome and covariates for eligible participants from UKHLS wave 2 to 13 for the analysis of multiple caregiving transitions on health behaviours.

Variable	N missing (n=25,049)	Percent missing
Outcomes		
Physical inactivity	807	3.2%
Fruit and vegetable consumption	442	1.8%
Problematic drinking	564	2.3%
smoking	17	0.1%
Baseline health behaviours		
Walking frequency	26	0.1%
Fruit and vegetable consumption at baseline	45	0.2%
Drinks frequency at baseline	2,675	10.7%
Smoking status at baseline	2	<0.0%
Covariates		
Age at baseline	0	0.0%
Sex	0	0.0%
Education	53	0.2%
Ethnicity	10	<0.1%
Occupational Class	195	0.8%
Income quintiles	28	0.1%
Working status	2	<0.1%
cohabiting status at baseline	4	<0.1%
Household size (categorical)	0	0.0%

Table A8.21 Analysis of missingness for analytical sample investigating multiple caregiving transitions for eligible participants from UKHLS wave 2 to 13 for the analysis of multiple caregiving transitions on health behaviours.

		Complete cases n= 19,274 (77.0%)	**Missing cases n= 5,775 (23.0%)**	**p**
Outcome				
Observed Transitions	Never caregiver	9,347 (76.8%)	2,830 (23.2%)	
	Emerging	1,127 (77.4%)	330 (22.6%)	
	Temporary	2,975 (77.5%)	862 (22.5%)	
	Long-term	420 (75.0%)	140 (25.0%)	
	Former	1,290 (77.9%)	366 (22.1%)	
	Multiple / no care	2,267 (76.2%)	706 (23.8%)	
	Multiple / care	1,848 (77.4%)	541 (22.6%)	0.65
Latent classes (LCA)	Non-caregiver	12,130 (77.0%	3,630 (23.0%)	
	Temporary	1,394 (75.2%)	459 (24.8%)	
	Former-long	783 (77.2%)	231 (22.8%)	
	Recurrent	446 (76.8%)	135 (23.2%)	
	Emerging-short	1,109 (77.4%)	323 (22.6%)	
	Former-short	1,444 (77.0%)	431 (23.0%)	
	Long-term	1,134 (77.9%)	321 (22.1%)	
	Emerging-long	834 (77.3%)	245 (22.7%)	0.75
Physical inactivity	Active	8,698 (82.5%)	1,840 (17.5%)	
	Inactive	10,576 (77.2%)	3,128 (22.8%)	<0.001
Diet (daily fruit and vegetable portions)	Mean(SD)	3.7 (2.2)	3.3 (2.2)	<0.001
Smoking status	Non-smoker	17,097 (77.7%)	4,920 (22.4%)	
	Current Smoker	2,177 (72.2%)	838 (27.8%)	<0.001
Problematic drinking	No	10,028 (75.5%)	3,263 (24.5%)	
	Yes	9,246 (82.6%)	1,948 (17.4%)	<0.001
Health behaviour at baseline				
Walking frequency at baseline	None	4,931 (73.2%)	1,810 (26.9%)	
	1-2 days	7,028 (78.7%)	1,900 (21.3%)	
	3-4 days	2,610 (79.8%)	662 (20.2%)	
	5-6 days	1,932 (78.3%)	535 (21.7%)	
	Every day	2,773 (76.7%)	842 (23.3%)	<0.001
Daily Fruit and vegetable frequency	0 portions	140 (67.0%)	69 (33.0%)	
	1-3 portions	11,055 (75.4%)	3,608 (24.6%)	
	4 portions	3,623 (80.2%)	896 (19.8%)	
	5+ portions	4,456 (79.4%)	1,157 (20.6%)	<0.001
Drinks frequency at baseline	No drinks	2,129 (77.3%)	625 (22.7%)	
	Monthly or weekly	6,330 (85.7%)	1,054 (14.3%)	
	1-4 per week	8,285 (88.4%)	1,086 (11.6%)	
	5+ per week	2,530 (88.3%)	335 (11.7%)	<0.001
Smoking status at baseline	Never smoked	8,814 (76.2%)	2,751 (23.8%)	
	Ex-smoker	7,090 (80.0%)	1,769 (20.0%)	
	Current Smoker	3,370 (72.9%)	1,253 (27.1%)	<0.001
Covariates				
Sex	Male	8,263 (76.9%)	2,485 (23.1%)	
	Female	11,011 (77.0%)	3,290 (23.0%)	0.83
Age group at baseline	16-29	3,334 (76.8%)	1,009 (23.2%)	
	30-49	7,542 (77.1%)	2,243 (22.9%)	
	50-64	5,559 (79.0%)	1,480 (21.0%)	
	65+	2,839 (73.1%)	1,043 (26.9%)	<0.001
Cohabiting status	Single/not-cohabiting	6,075 (74.0%)	2,130 (26.0%)	
	Married/cohabiting	13,199 (78.4%)	3,641 (21.6%)	<0.001
Education	No qualification	1,972 (63.0%)	1,157 (37.0%)	
	A-Level/GCSE/Other	9,937 (77.3%)	2,917 (22.7%)	
	Degree/Higher qualification	7,365 (81.7%)	1,648 (18.3%)	<0.001
Occupational class	Management/Professional	5,654 (84.3%)	2,710 (26.9%)	
	Intermediate	2,771 (79.7%)	704 (20.3%)	
	Routine	3,495 (75.8%)	1,114 (24.2%)	
	Not employed	7,354 (73.1%)	2,710 (26.9%)	<0.001

Being in paid employment	Full-time employed	9,111 (79.6%)	2,329 (20.4%)	
	Part-time employed	3,423 (80.1%)	849 (19.9%)	
	Not in paid employment	6,740 (72.2%)	2,595 (27.8%)	<0.001
Wealth quintiles	1 (low)	2,799 (67.1%)	1,374 (32.9%)	
	2	3,392 (72.7%)	1,277 (27.4%)	
	3	3,769 (78.5%)	1,034 (21.5%)	
	4	4,370 (81.0%)	1,028 (19.0%)	
	5 (high)	4,944 (82.7%)	1,034 (17.3%)	<0.001
Household size	1	2,506 (72.3%)	959 (27.7%)	
	2	7,054 (78.9%)	1,890 (21.1%)	
	3-4	7,668 (78.4%)	2,117 (21.6%)	
	5+	2, 046 (71.7%)	809 (28.3%)	<0.001
Number of children living in the household	0	13,569 (77.3%)	3,988 (22.7%)	
	1	2,535 (76.6%)	775 (23.4%)	
	2	2,356 (77.3%)	692 (22.7%)	
	3+	814 (71.8%)	320 (28.2%)	<0.001
General health	Good to excellent	16,343 (86.7%)	2,500 (13.3%)	
	Fair or poor	2,931 (70.0%)	780 (21.0%)	<0.001
GHQ	(Mean score)	11.0 (5.2)	11.6 (5.9)	<0.001
SF12-PCS	Mean score	50.7 (10.3)	49.7 (10.8)	<0.001
Age	Mean age	46.4 (16.3)	47.1 (17.3)	0.01

Appendix 8.10: Description of Observed Transitions variable

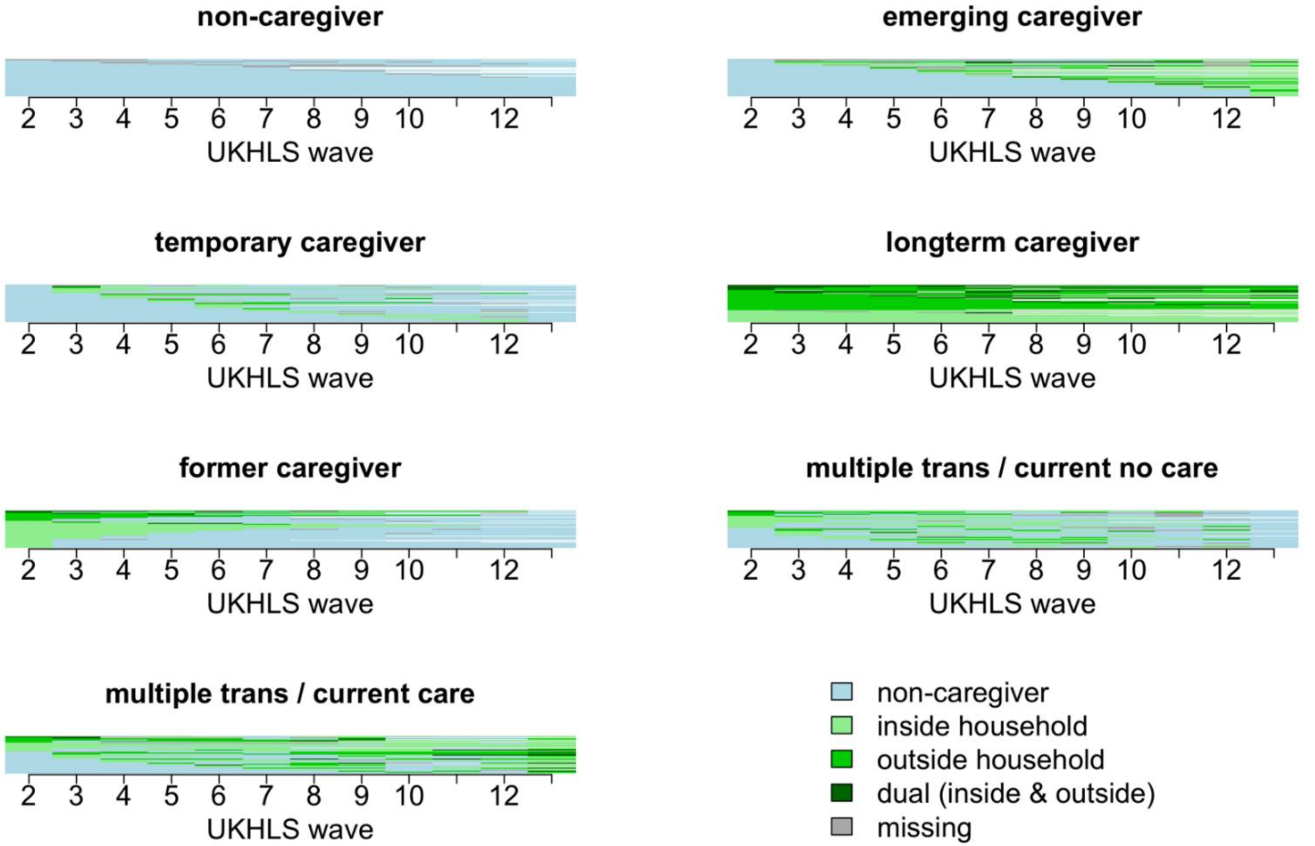


Figure A8.21 Sequence Index Plot for Observed Transition by place of care groups across UKHLS waves 2 to 13 (n=25,049). Each panel represents an Observed Transitions group.

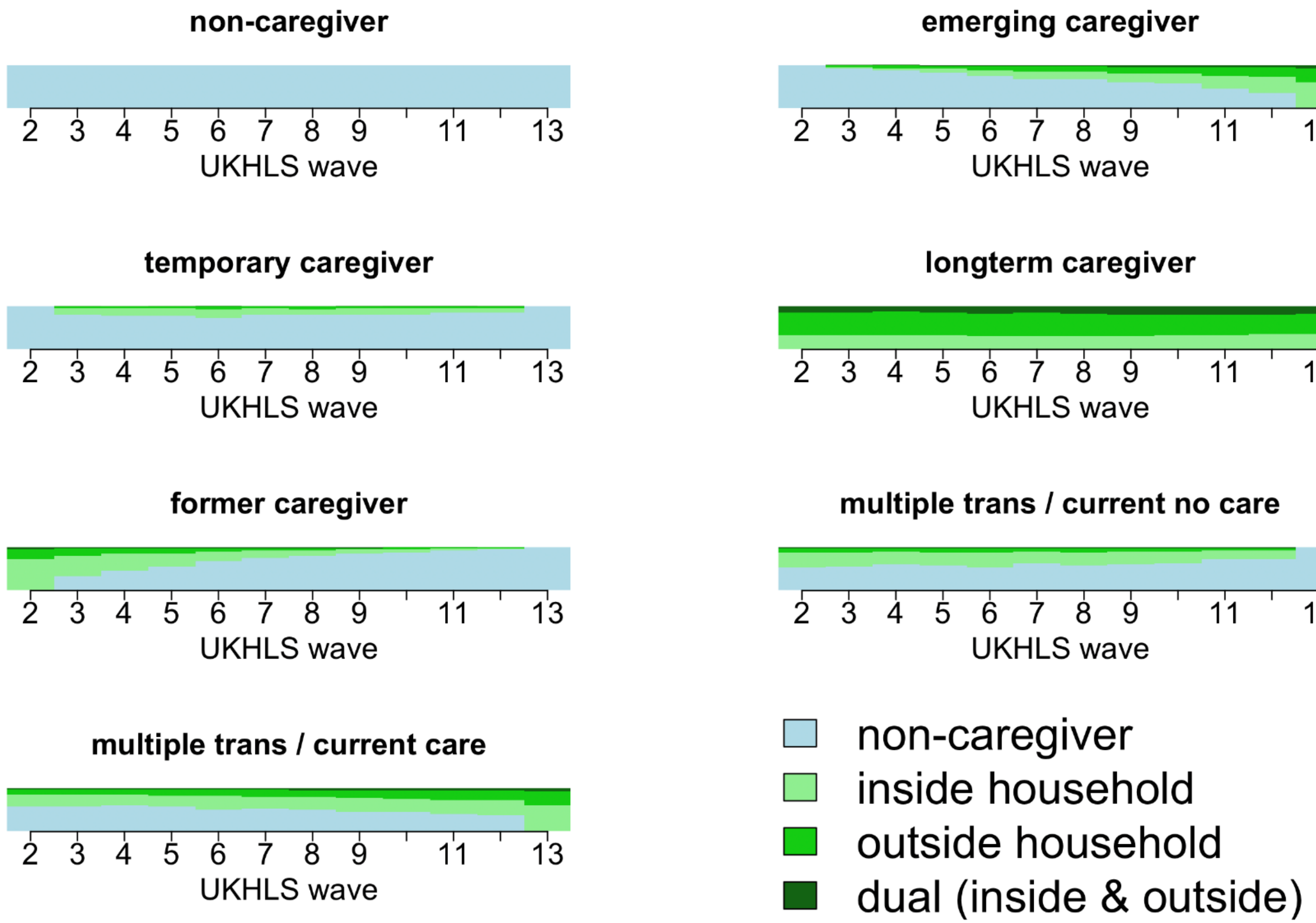


Figure A8.22 Sequence Distribution Plot for Observed Transitions by place of care groups across UKHLS waves 2 to 13 (n=25,049). Each panel represents an Observed Transitions group.

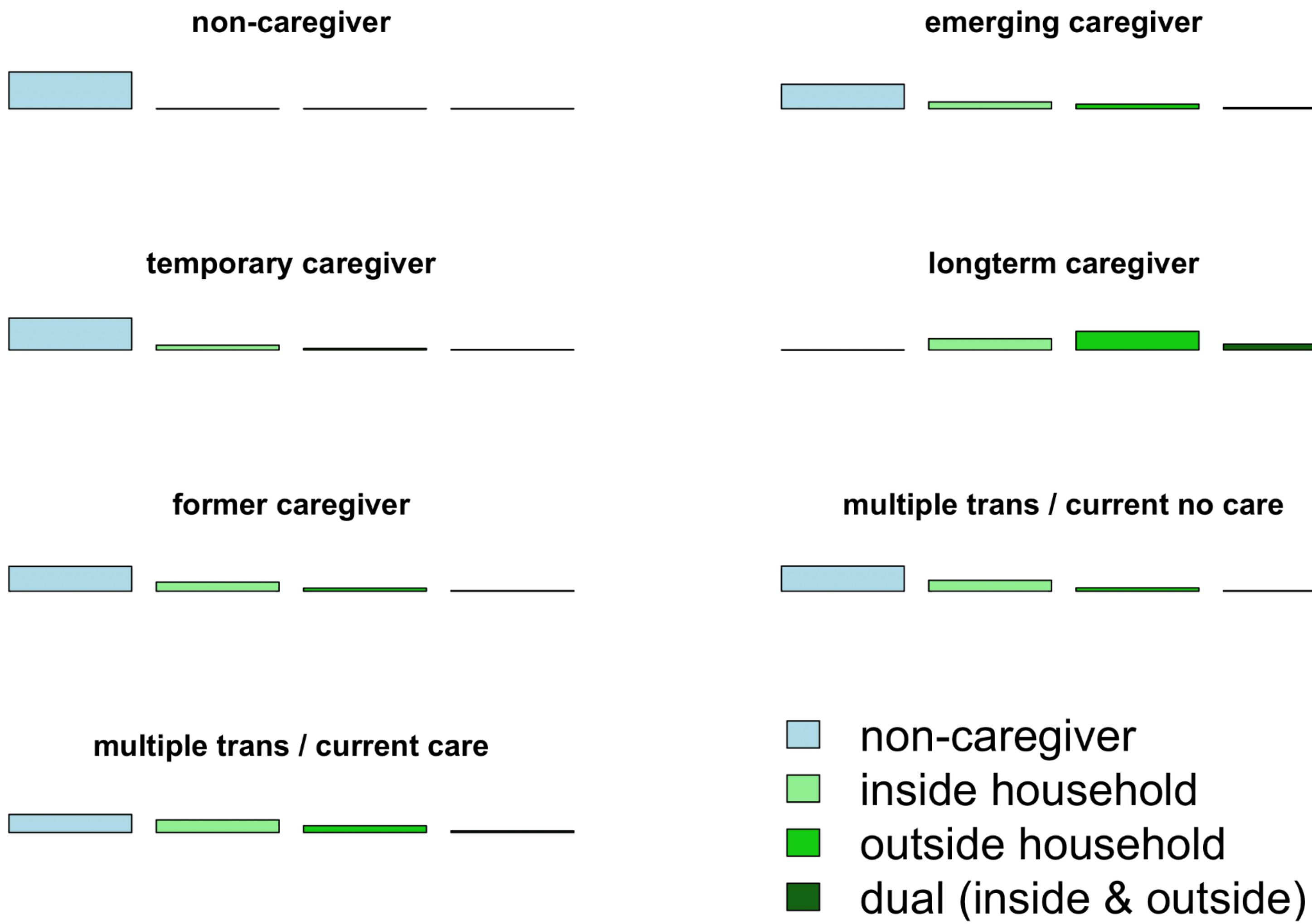


Figure A8.23 Sequence Modal Plot for Observed Transitions by place of care groups across UKHLS waves 2 to 13 (n=25,049). Each panel represents an Observed Transitions group.

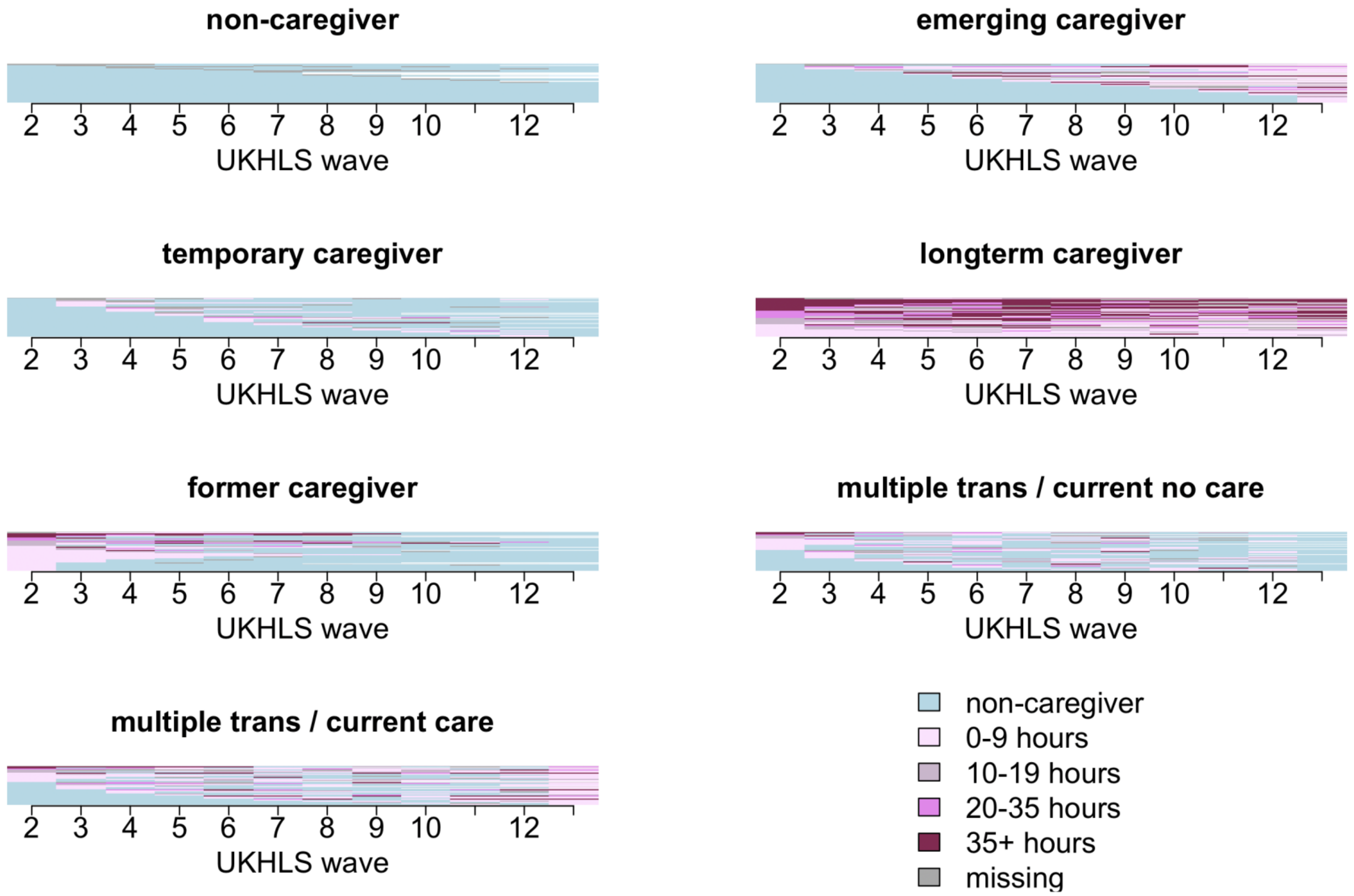


Figure A8.24 Sequence Index Plot for Observed Transitions by care hours across UKHLS waves 2 to 13 (n=25,049). Each panel represents an Observed Transition group.

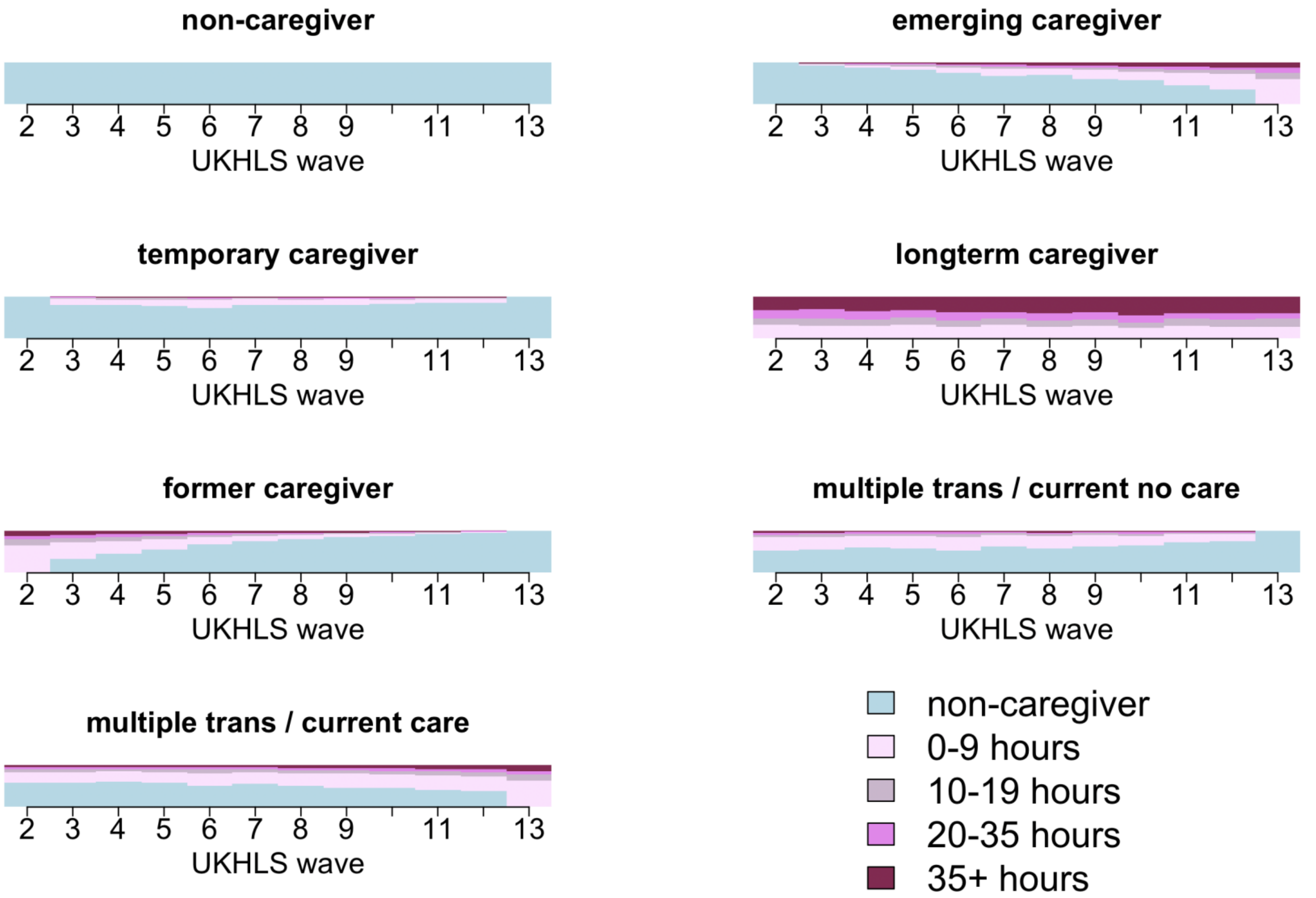


Figure A8.25 State Distribution Plot for Observed Transitions by care hours across UKHLS waves 2 to 13 (n=25,049). Each panel represents an Observed Transition group.

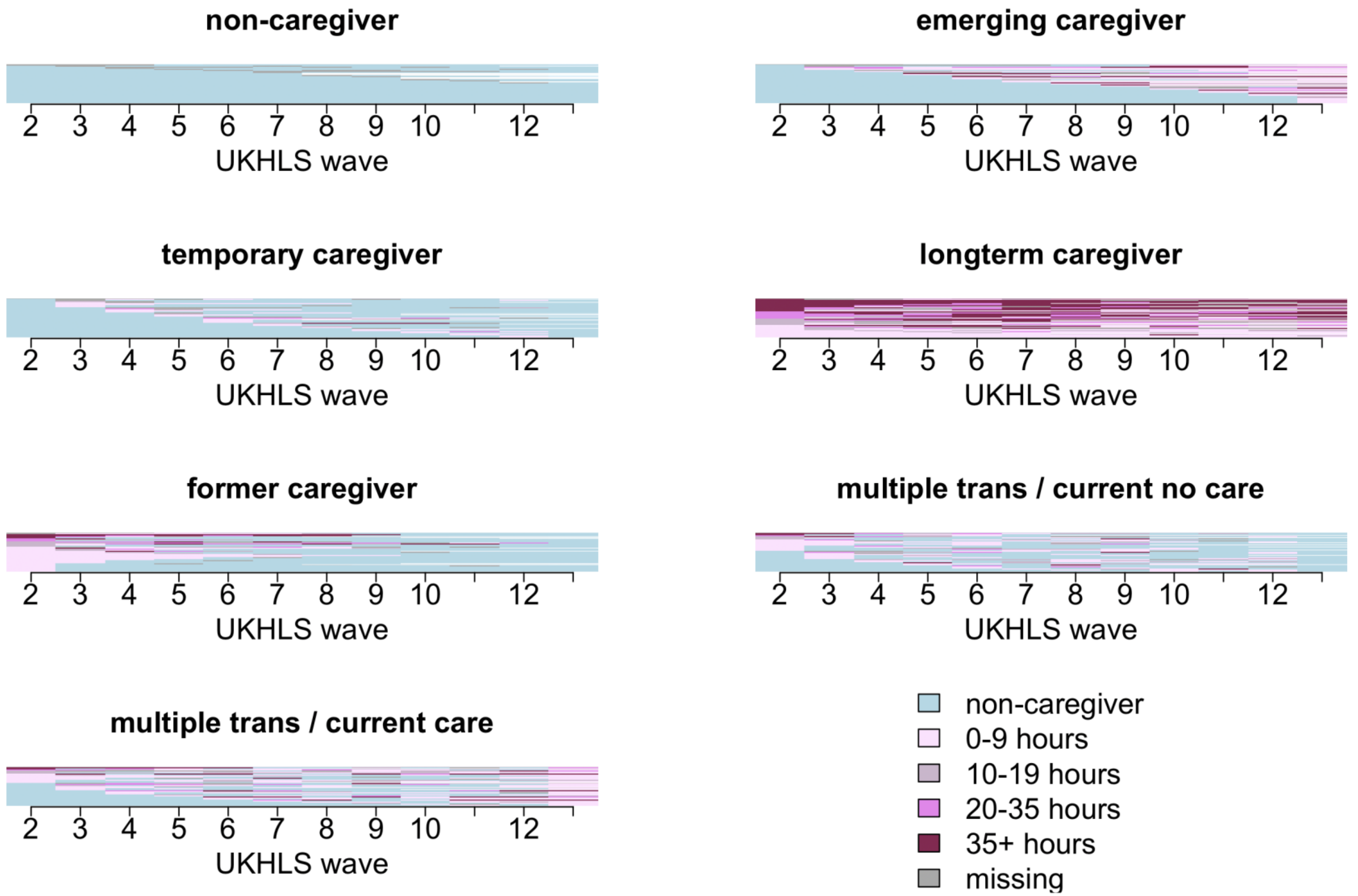


Figure A8.26 Sequence Index Plot for Observed Transitions by care hours across UKHLS waves 2 to 13 (n=25,049). Each panel represents an Observed Transition group.

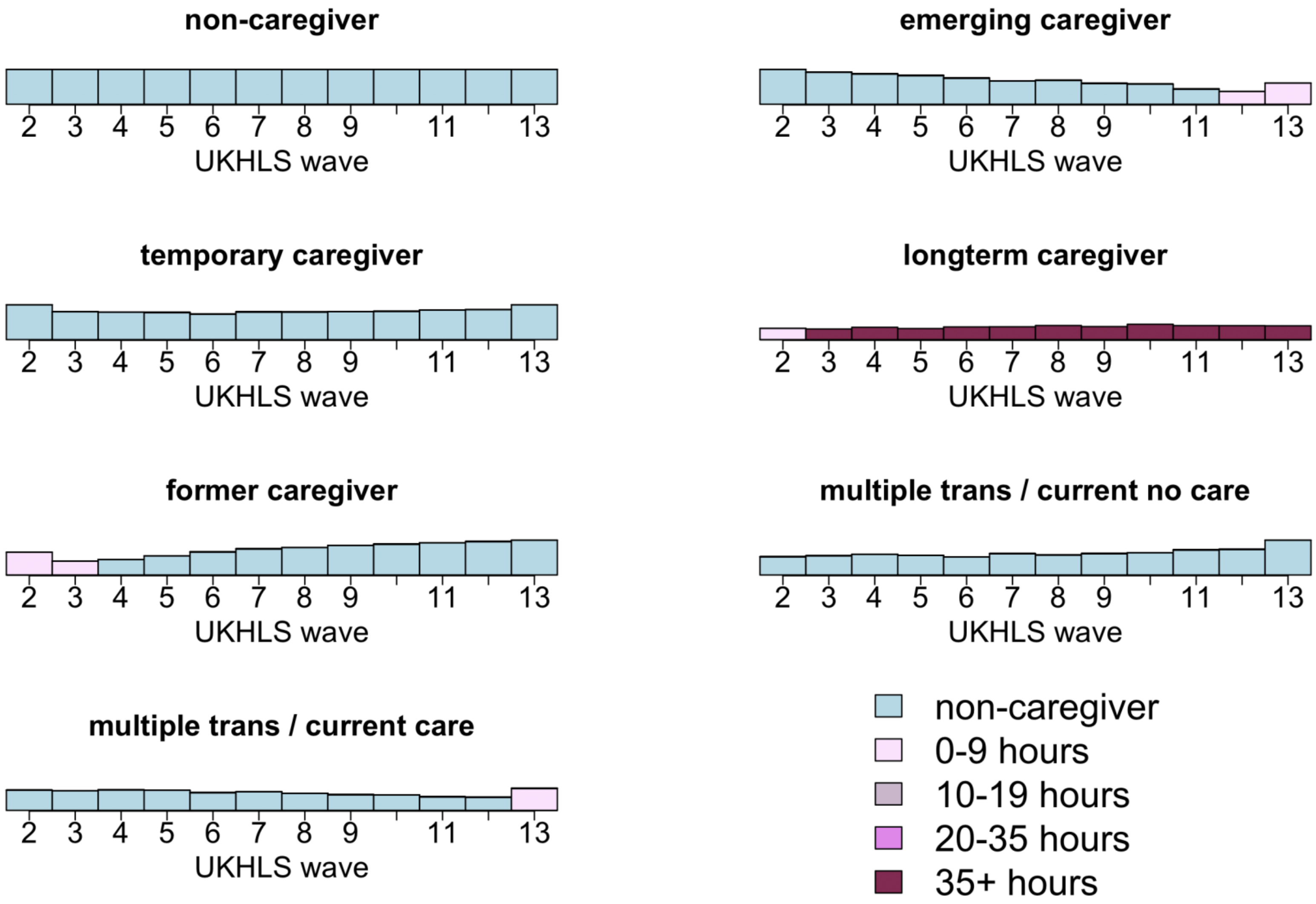


Figure A8.27 Sequence Modal State Plot for Observed Transitions by care hours across UKHLS waves 2 to 13 (n=25,049). Each panel represents an Observed Transition group.

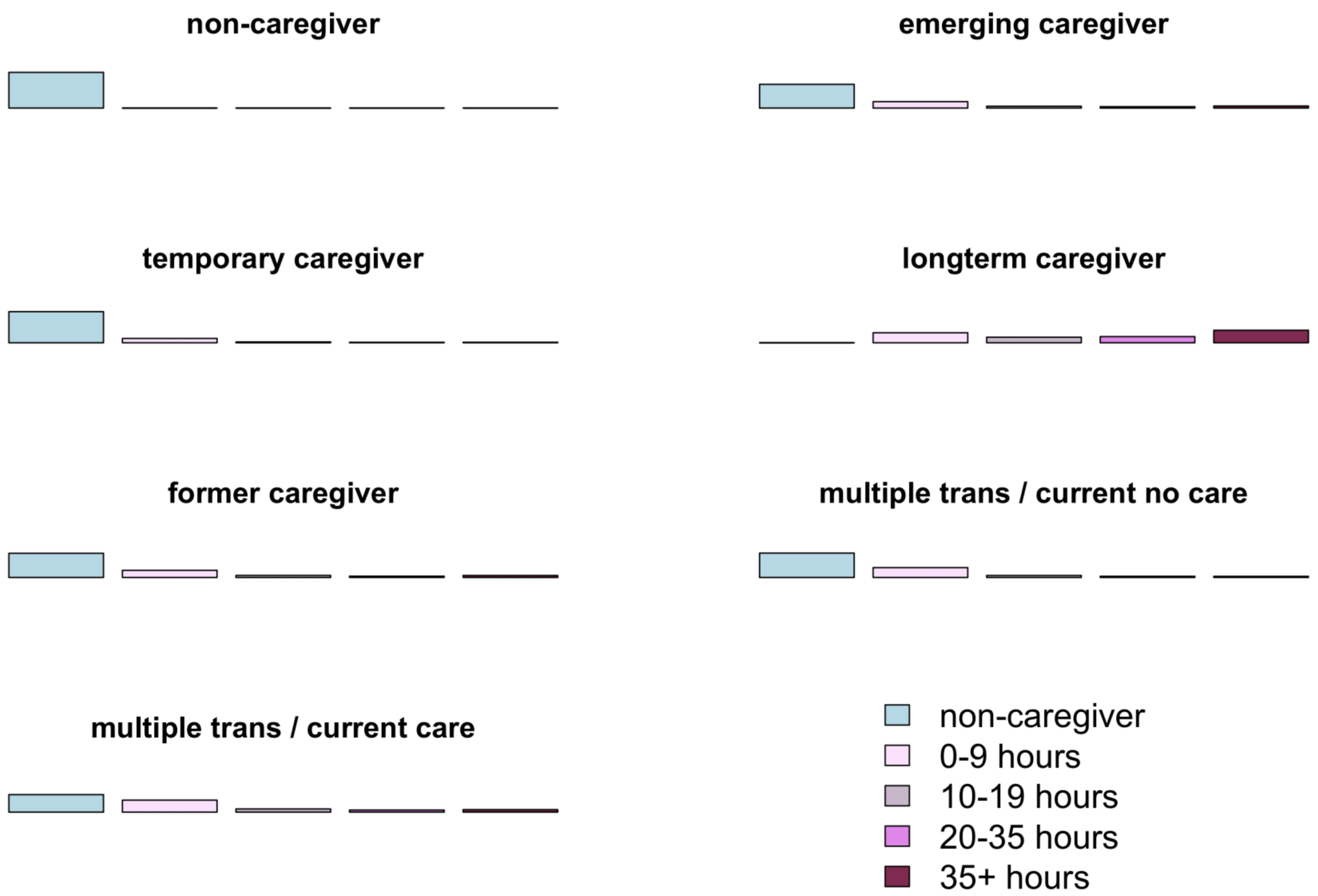


Figure A8.28 Sequence Modal Plot for Observed Transitions by care hours across UKHLS waves 2 to 13 (n=25,049). Each panel represents an Observed Transition group.

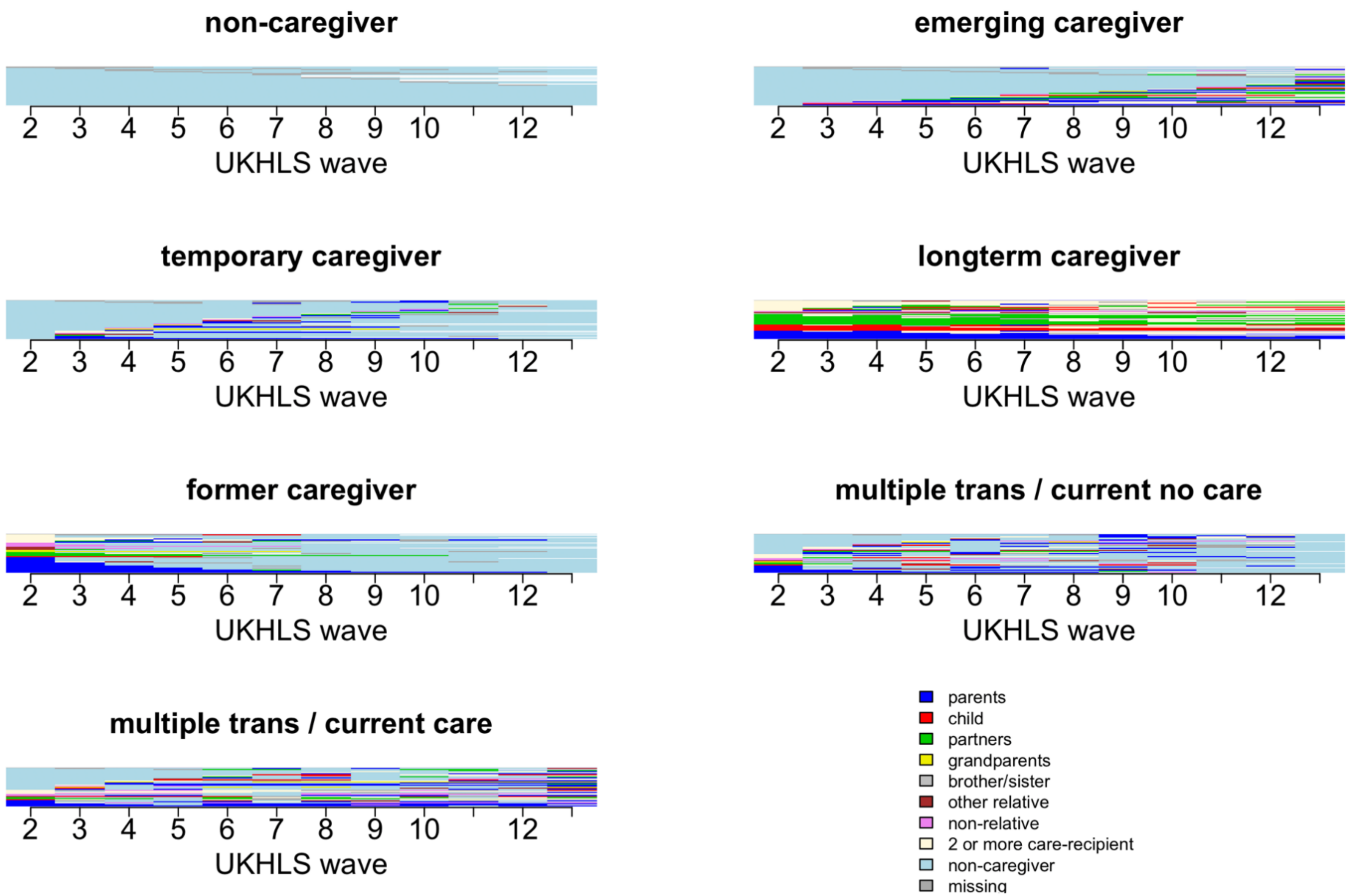


Figure A8.29 Sequence Index Plot for Observed Transitions by caregiver-recipient relationship across UKHLS waves 2 to 13 (n=25,049). Each panel represents an Observed Transitions group.

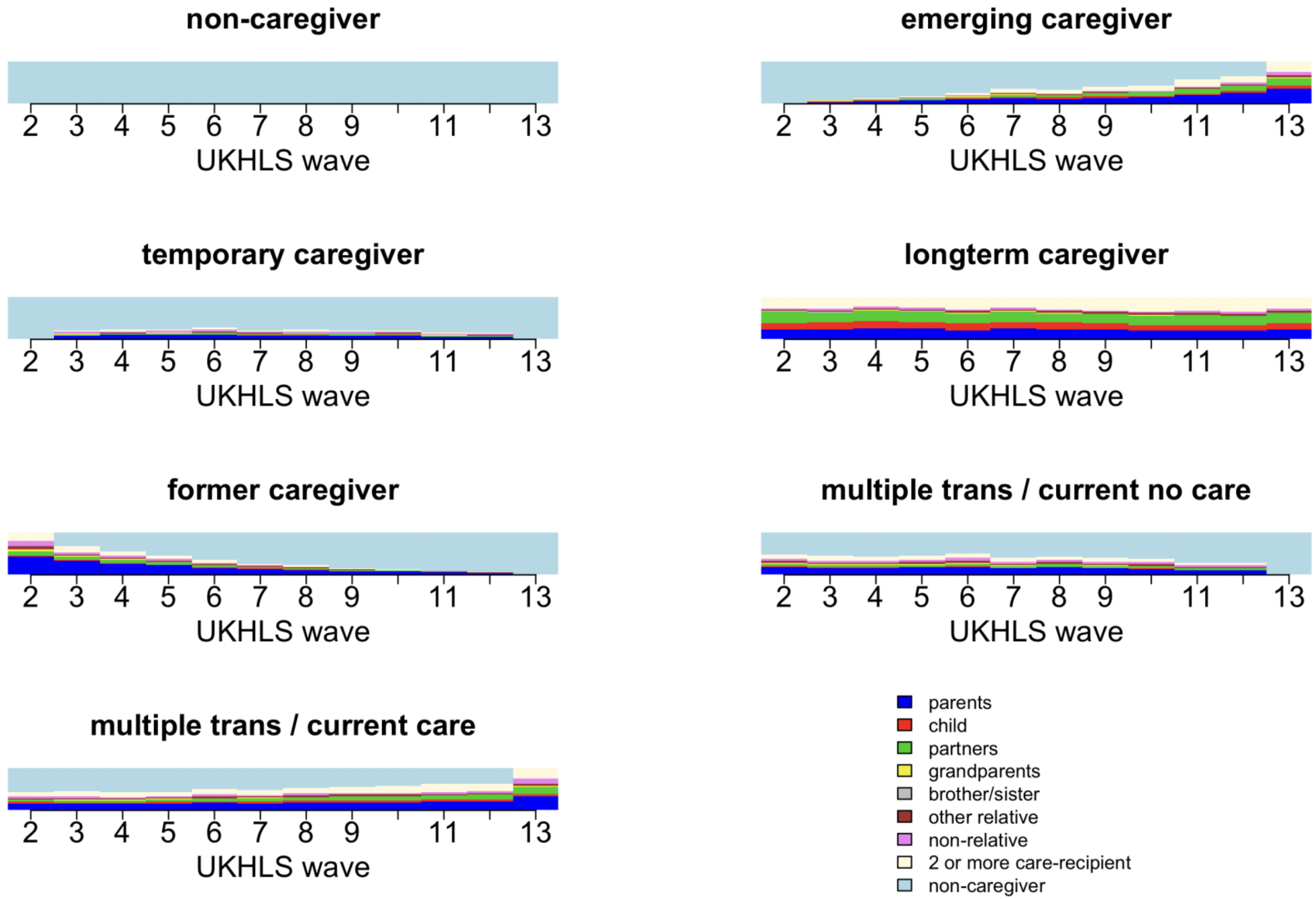


Figure A8.30 State Distribution Plot for Observed Transitions by caregiver-recipient relationship across UKHLS waves 2 to 13 (n=25,049). Each panel represents an Observed Transitions group.

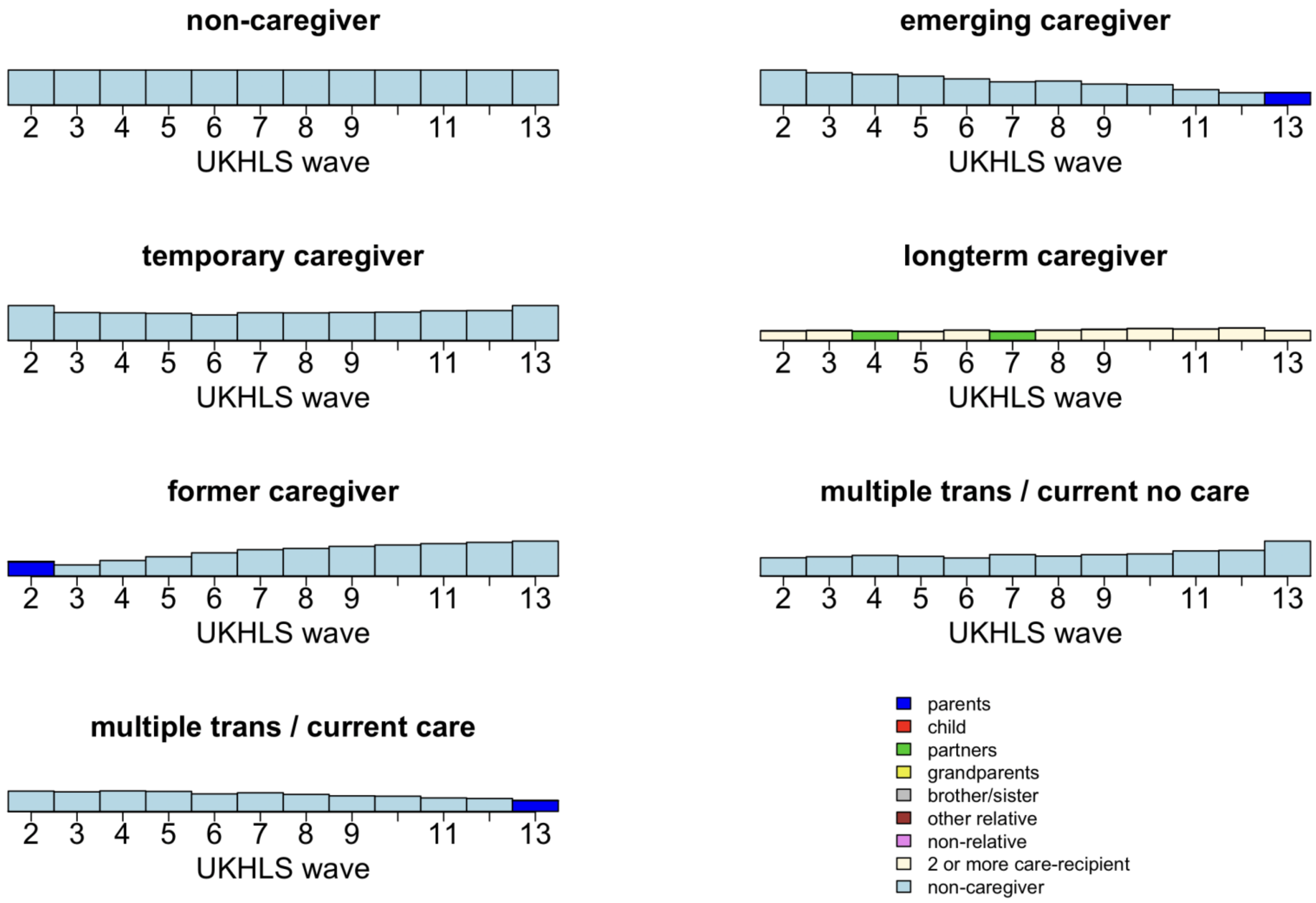


Figure A8.31 Sequence Modal State Plot for Observed Transitions by caregiver-recipient relationship across UKHLS waves 2 to 13 (n=25,049). Each panel represents an Observed Transitions group.

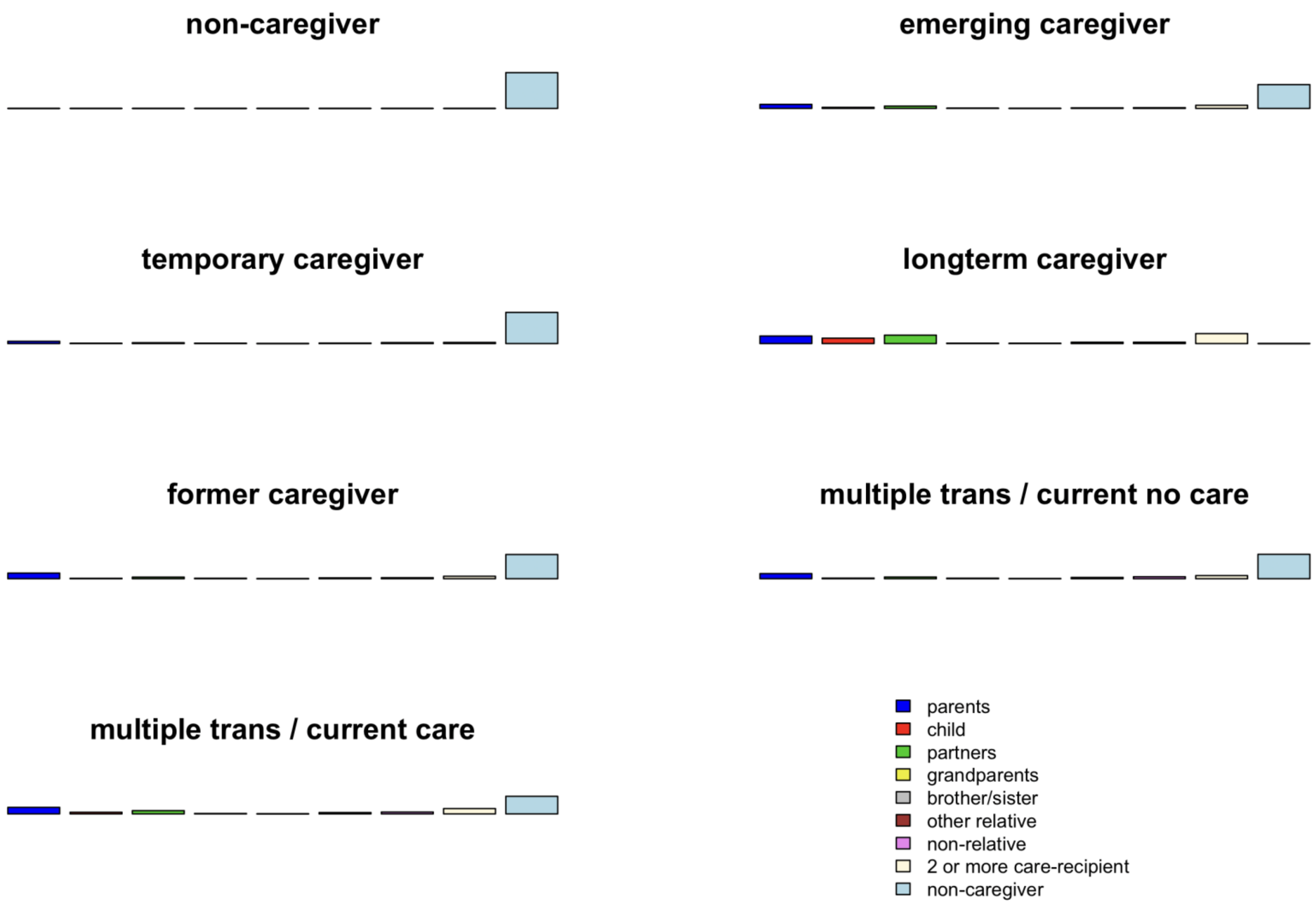


Figure A8.32 Sequence Modal Plot for Observed Transition by caregiver-recipient relationship across UKHLS waves 2 to 13 (n=25,049). Each panel represents an Observed Transitions group.

Appendix 8.11: Description of LCA

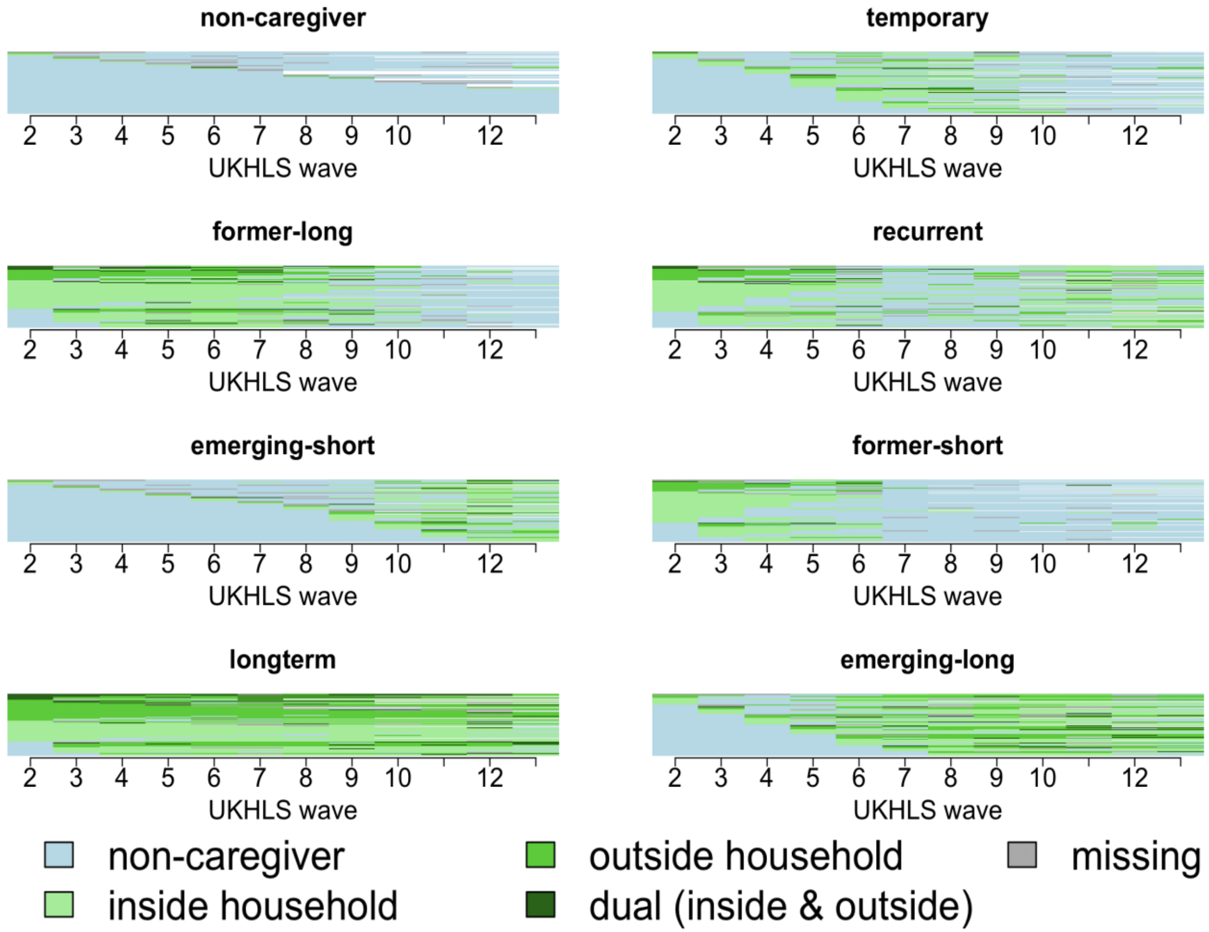


Figure A8.33 Sequence Index Plot for LCA eight-class solution by place of care across UKHLS waves 2 to 13 (n=25,049). Each panel represents a latent class.

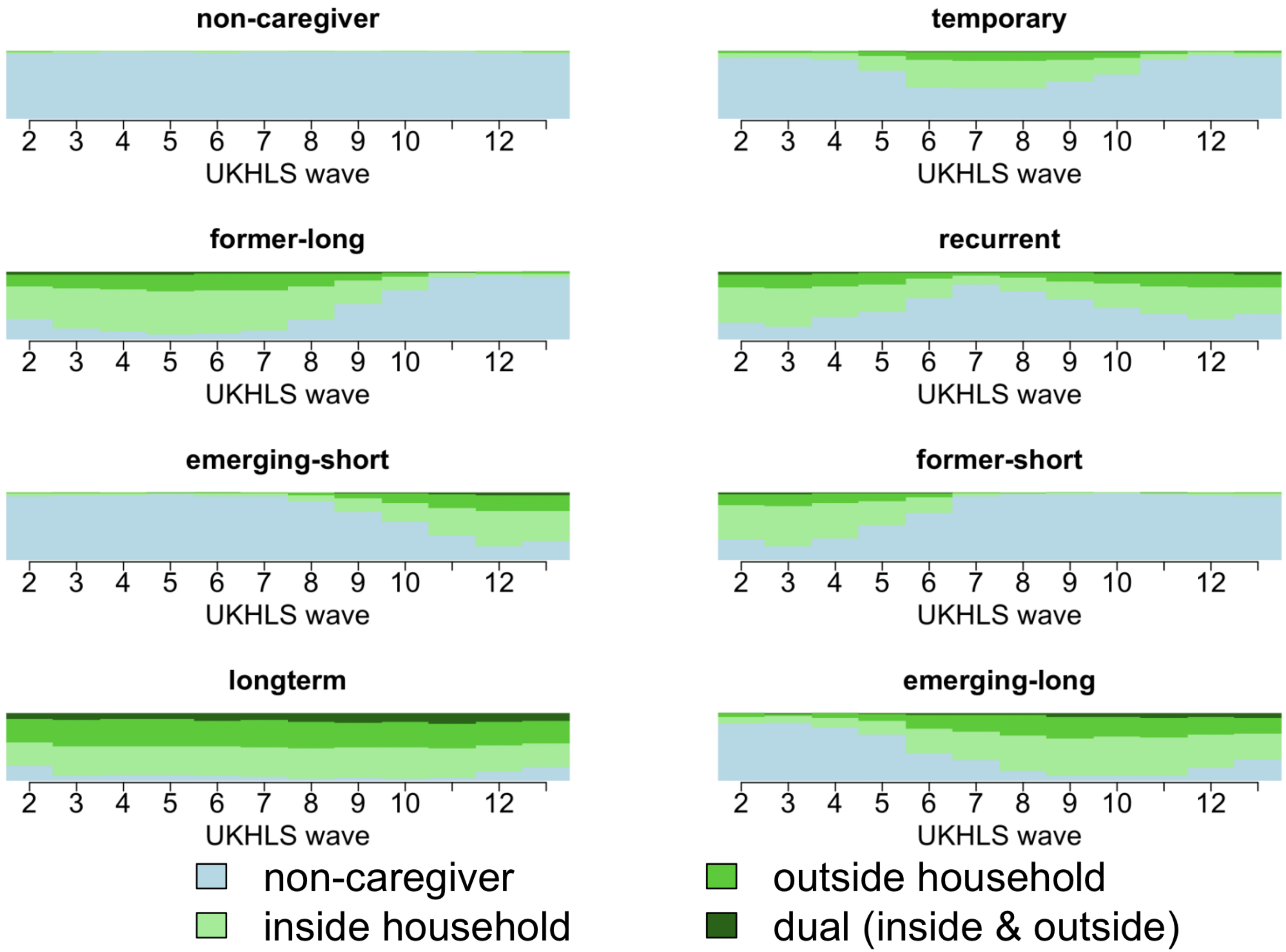


Figure A8.34 State Distribution Plot for LCA eight-class solution by place of care across UKHLS waves 2 to 13 (n=25,049). Each panel represents a latent class.

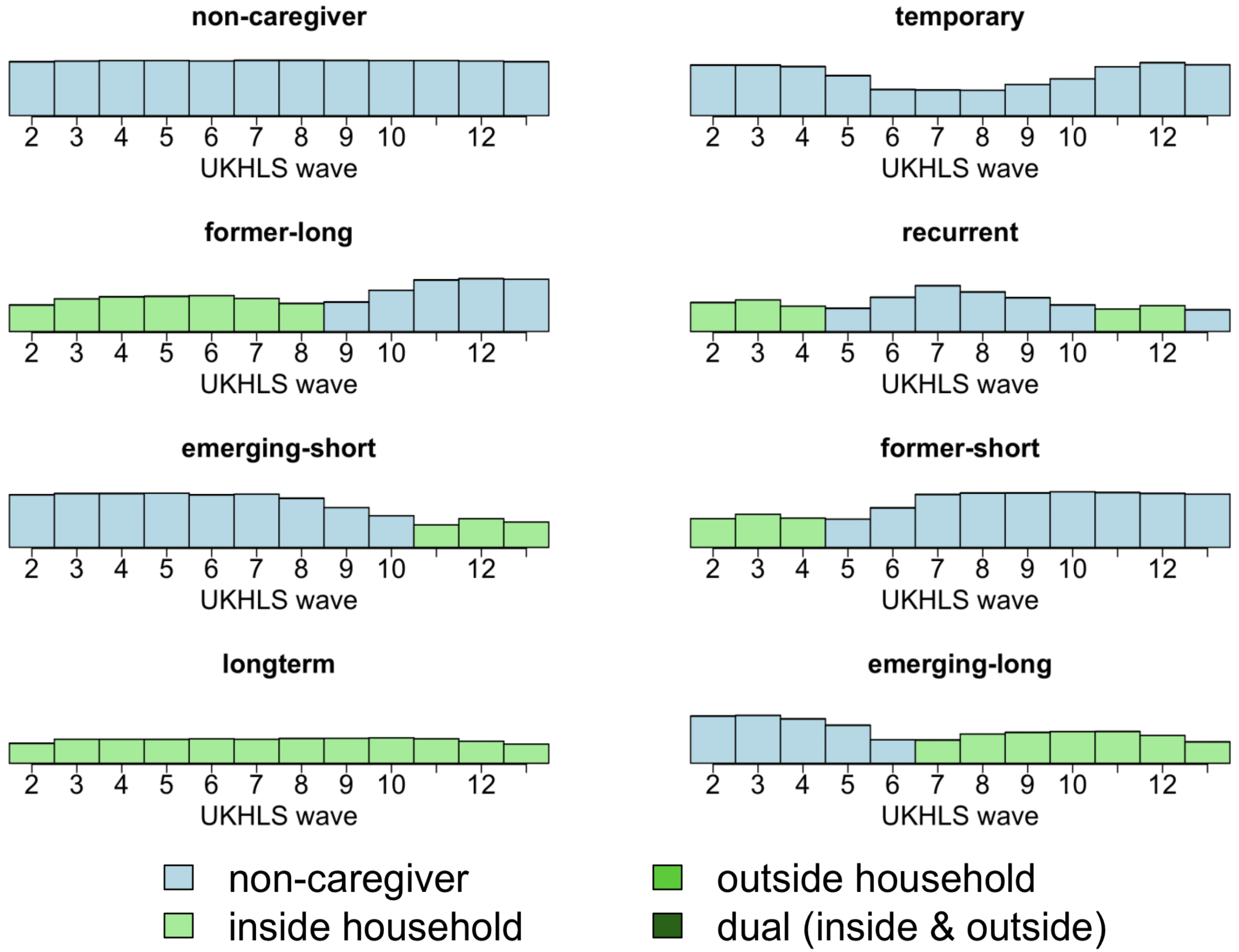


Figure A8.35 Sequence Modal State Plot for LCA eight-class solution by place of care across UKHLS waves 2 to 13 (n=25,049). Each panel represents a latent class.

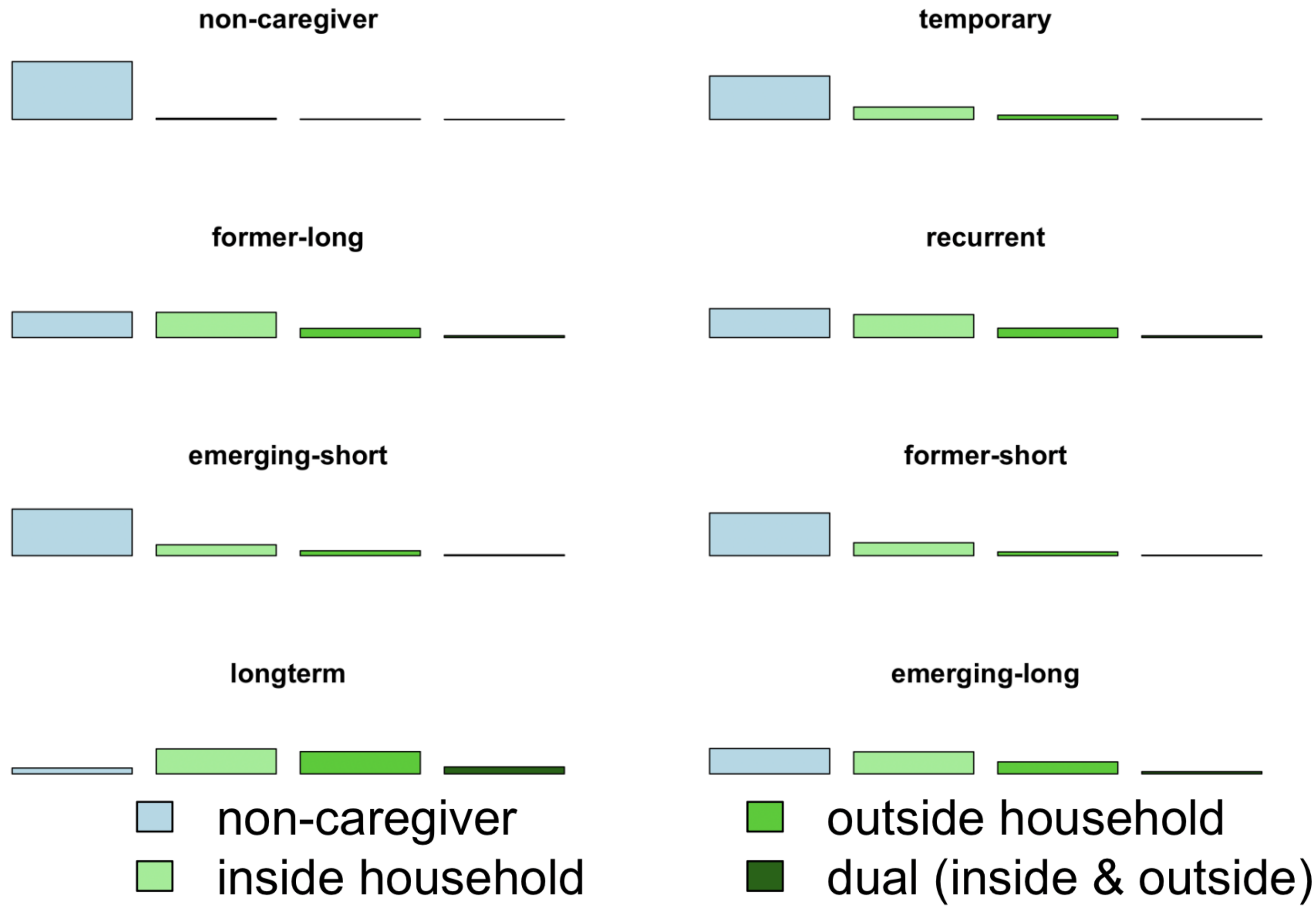


Figure A8.36 Sequence Modal Plot for LCA eight-class solution by place of care across UKHLS waves 2 to 13 (n=25,049). Each panel represents a latent class.

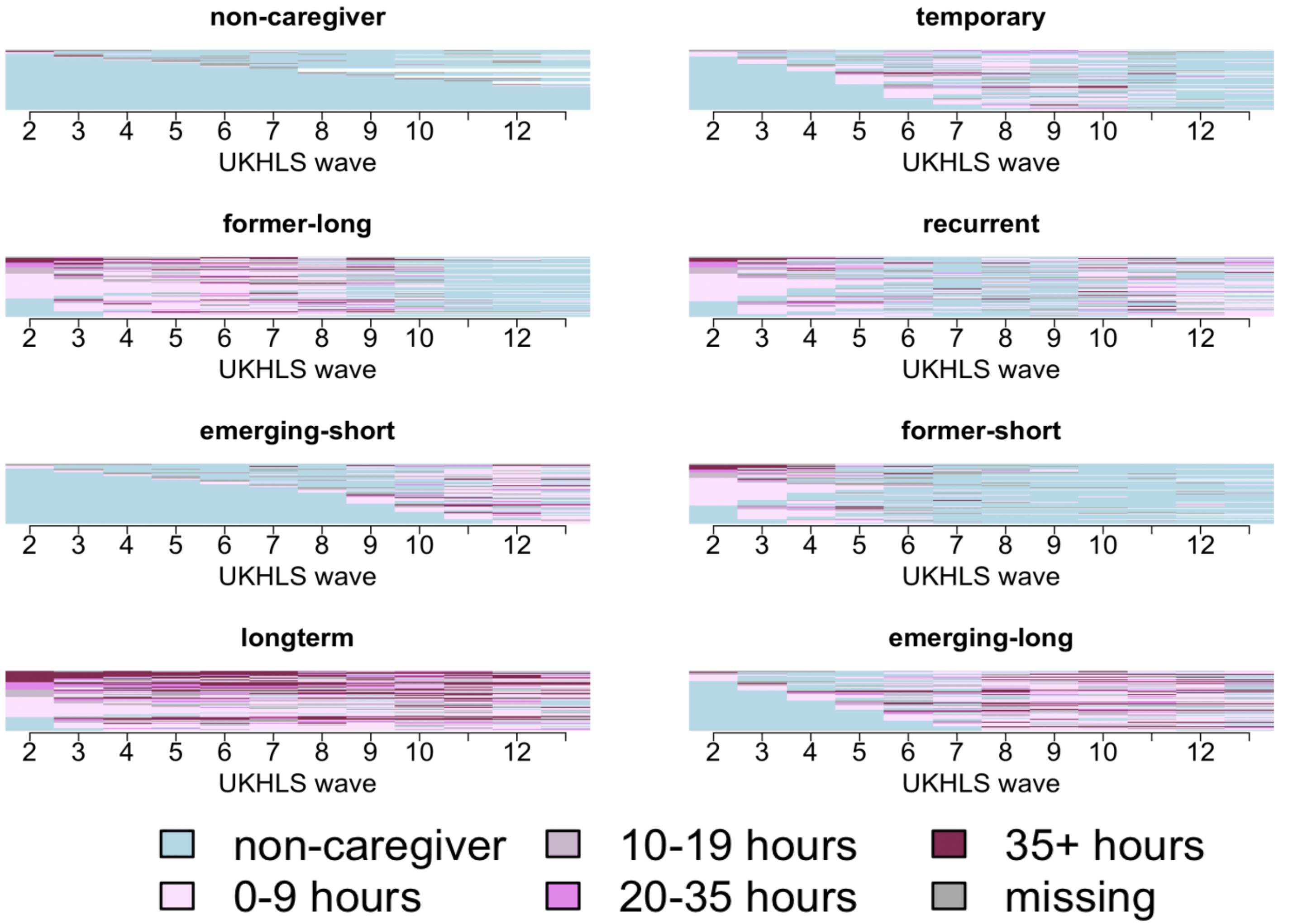


Figure A8.37 Sequence Index Plot for LCA eight-class solution by care hours across UKHLS waves 2 to 13 (n=25,049). Each panel represents a latent class.

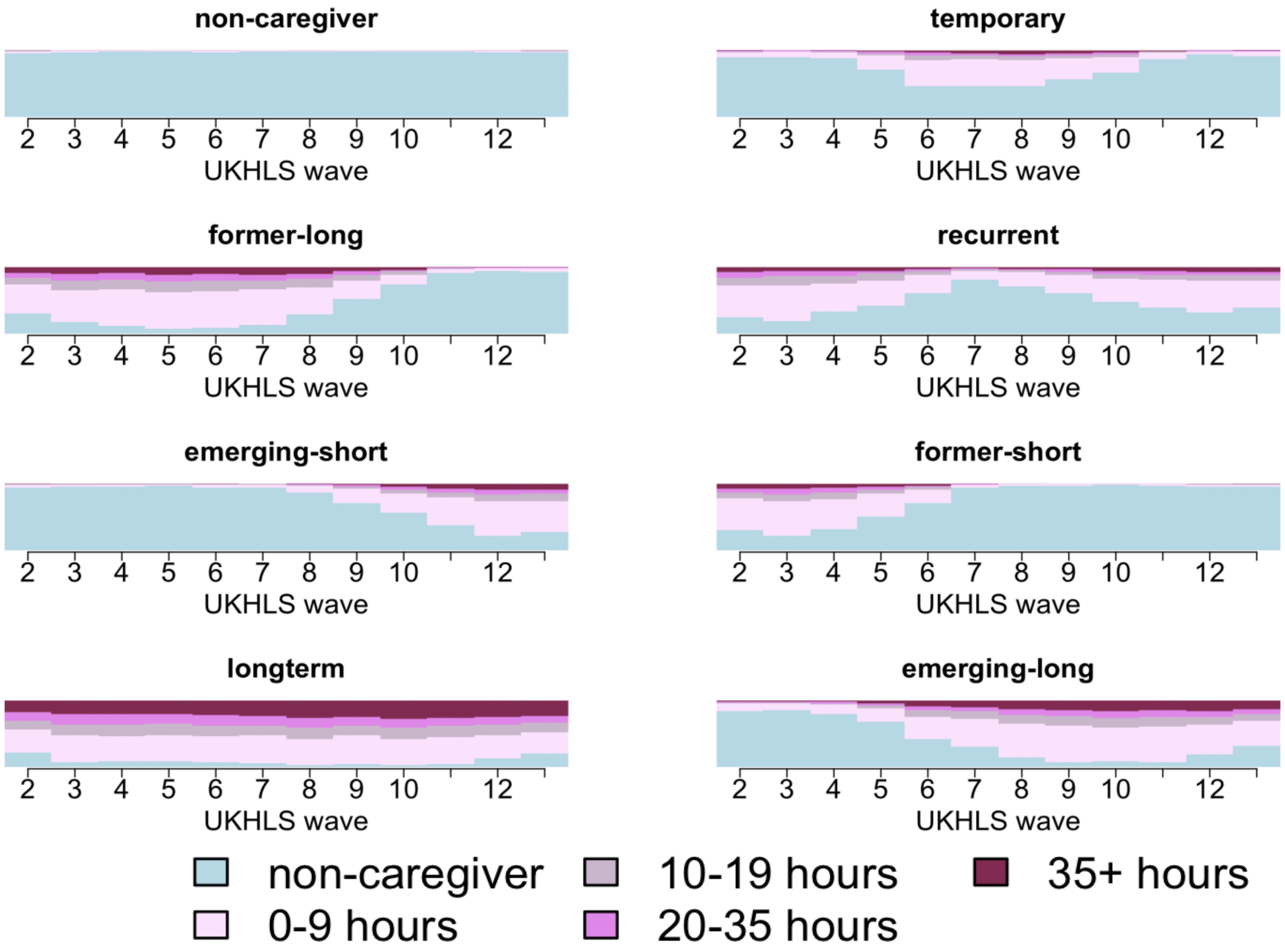


Figure A8.38 State Distribution Plot for LCA eight-class solution by care hours across UKHLS waves 2 to 13 (n=25,049). Each panel represents a latent class.

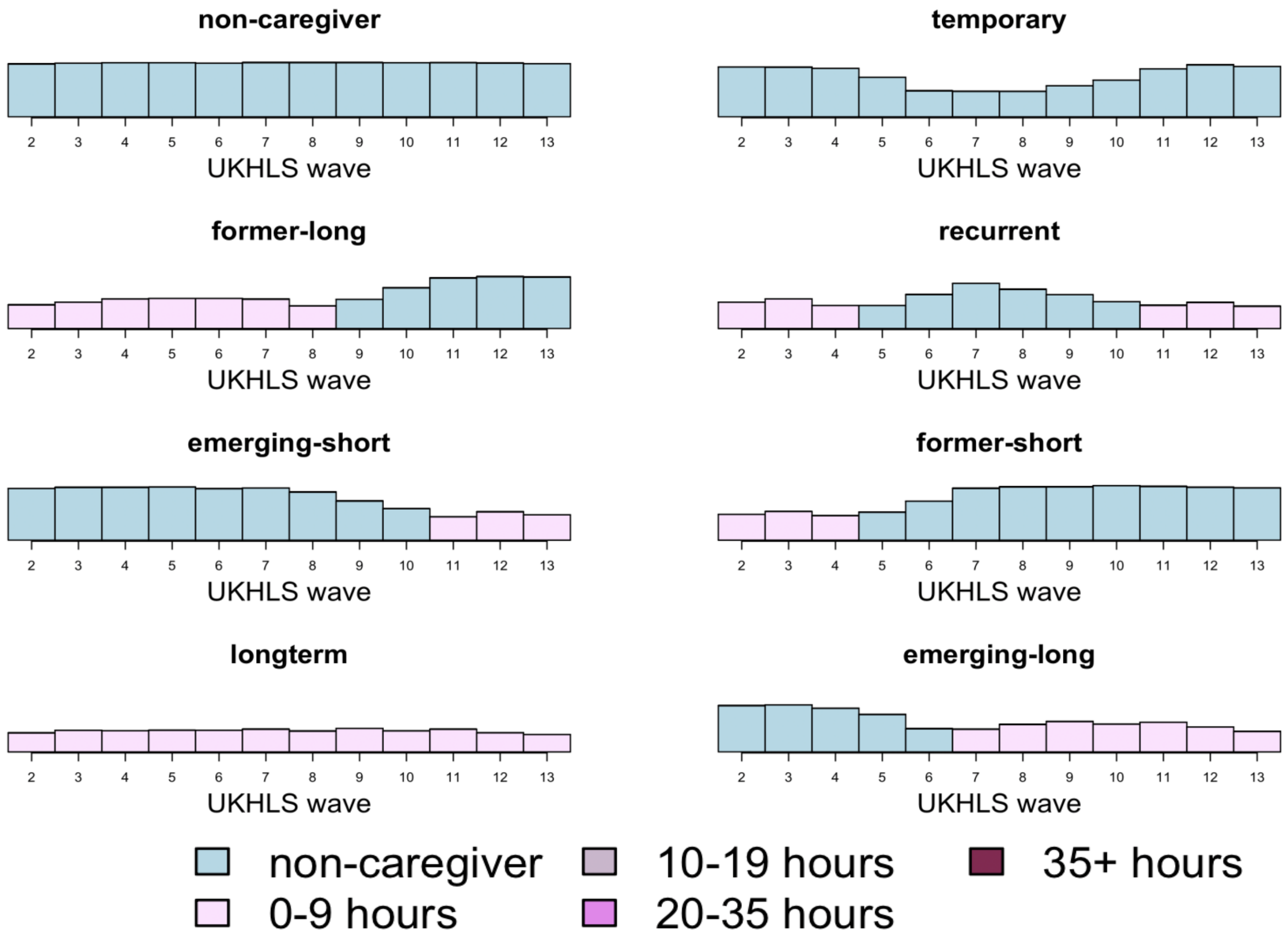


Figure A8.39 Sequence Modal State Plot for LCA eight-class solution by care hours across UKHLS waves 2 to 13 (n=25,049). Each panel represents a latent class.

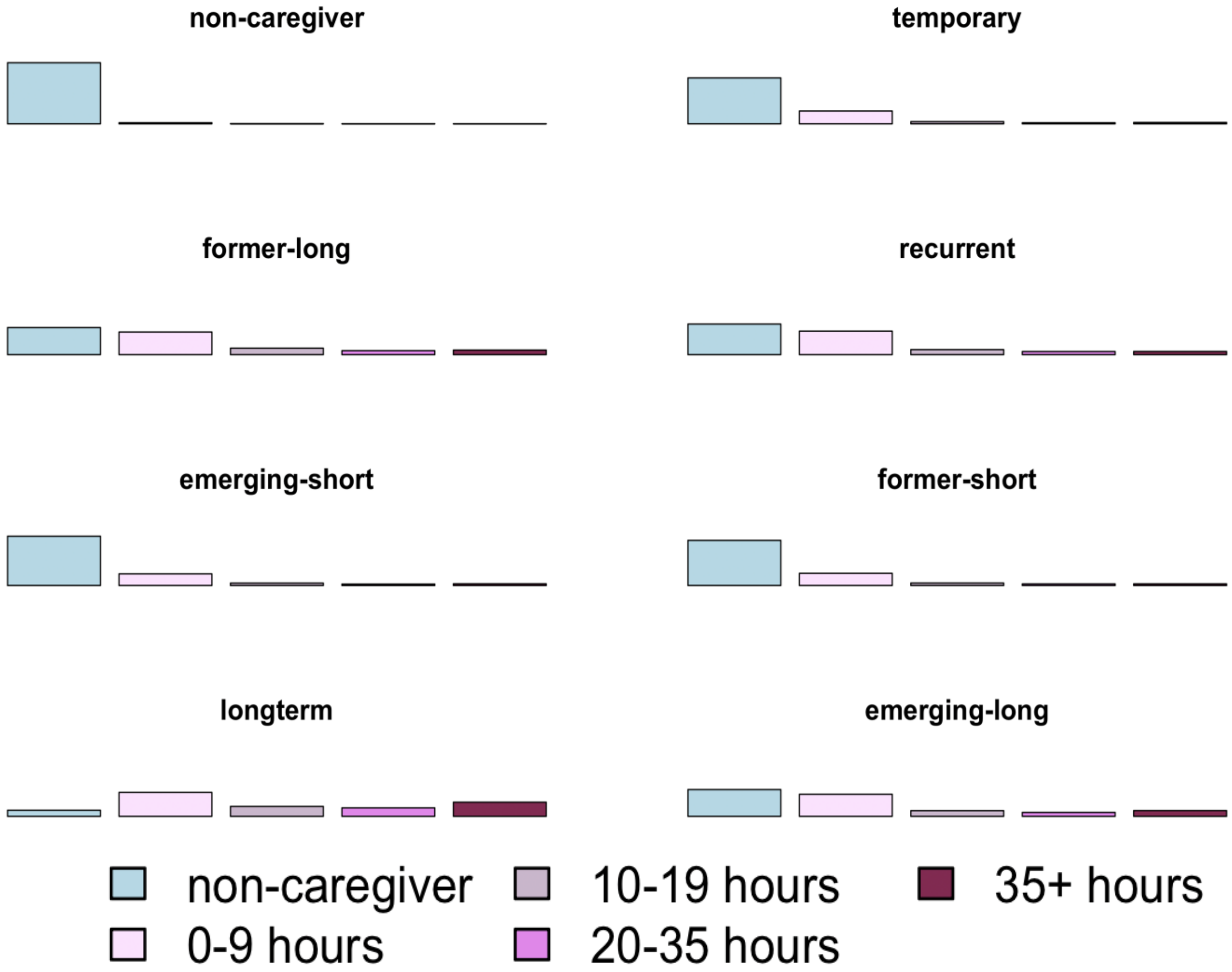


Figure A8.40 Sequence Modal Plot for LCA eight-class solution by care hours across UKHLS waves 2 to 13 (n=25,049). Each panel represents a latent class.

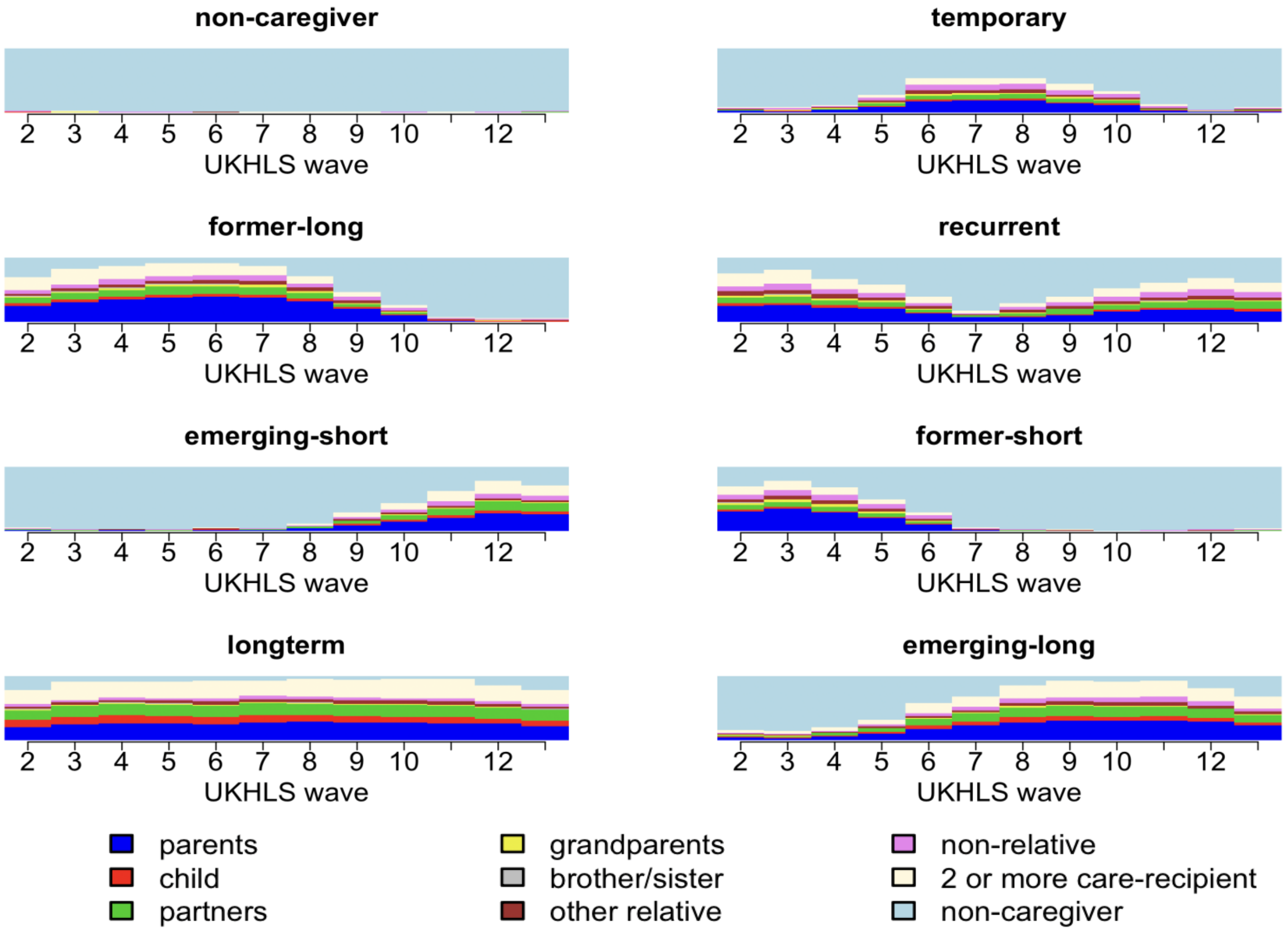


Figure A8.41 State Distribution Plot for LCA eight-class solution by caregiver-recipient relationship across UKHLS waves 2 to 13 (n=25,049). Each panel represents a latent class.

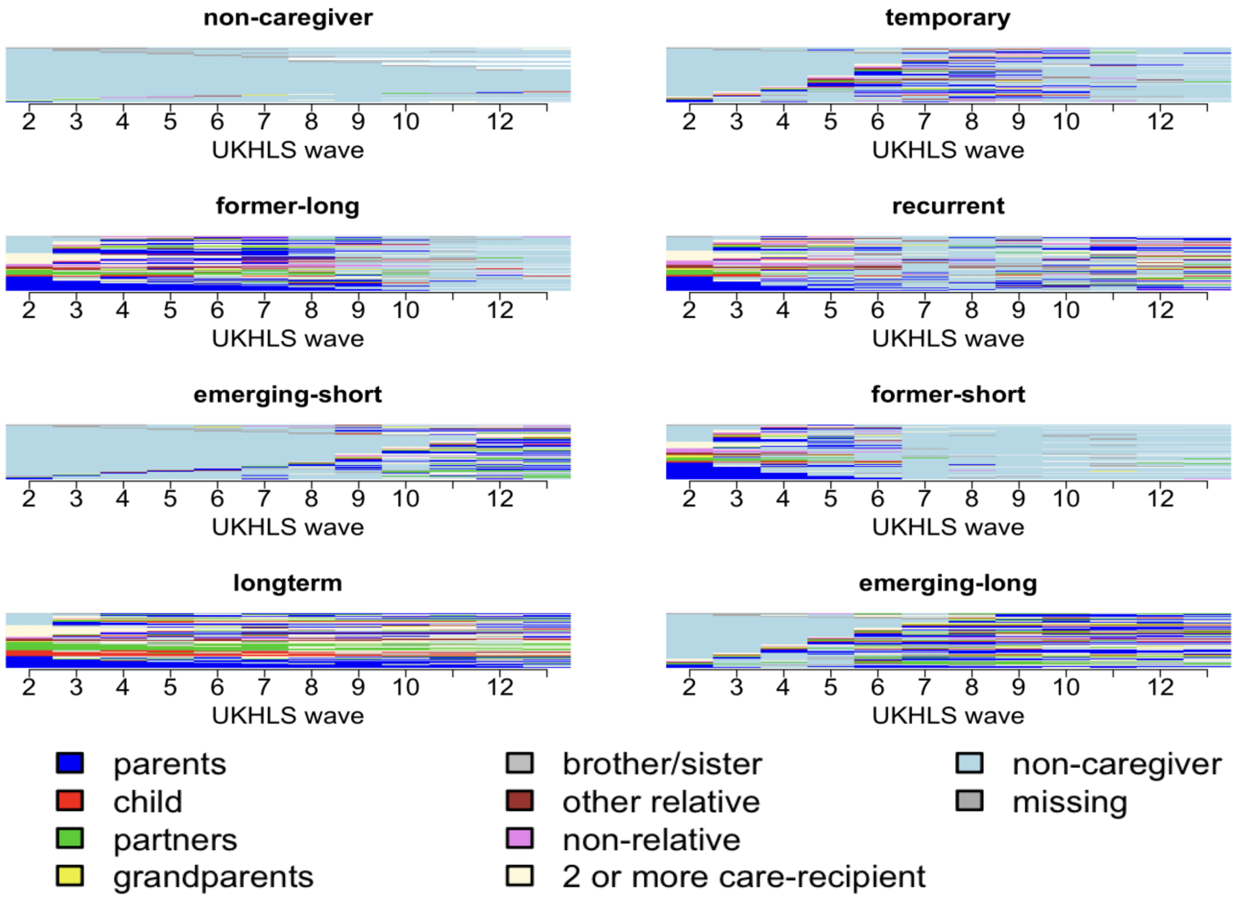


Figure A8.42 Sequence Index Plot for LCA eight-class solution by caregiver-recipient relationship across UKHLS waves 2 to 13 (n=25,049). Each panel represents a latent class).

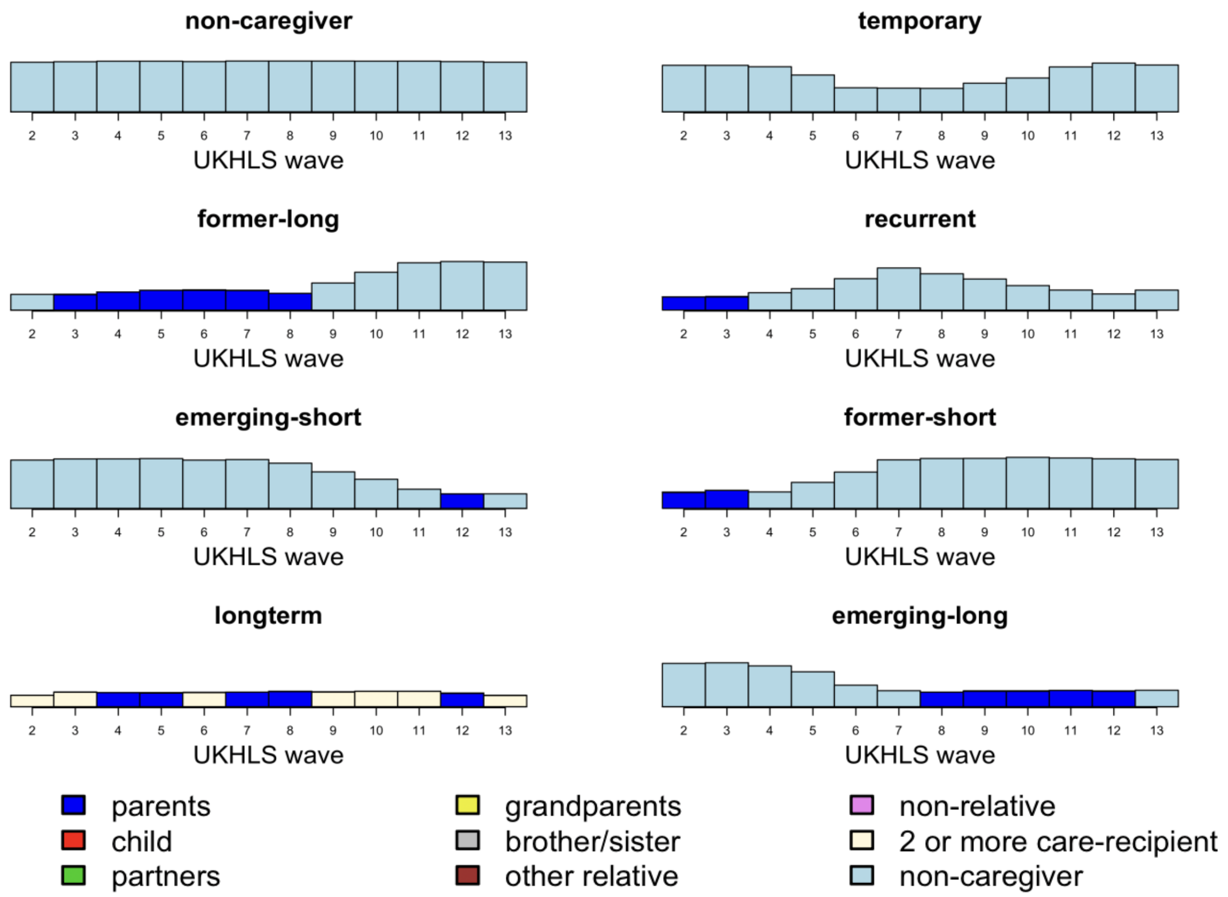


Figure A8.43 Sequence Modal State Plot for LCA eight-class solution by caregiver-recipient relationship across UKHLS waves 2 to 13 (n=25,049). Each panel represents a latent class.

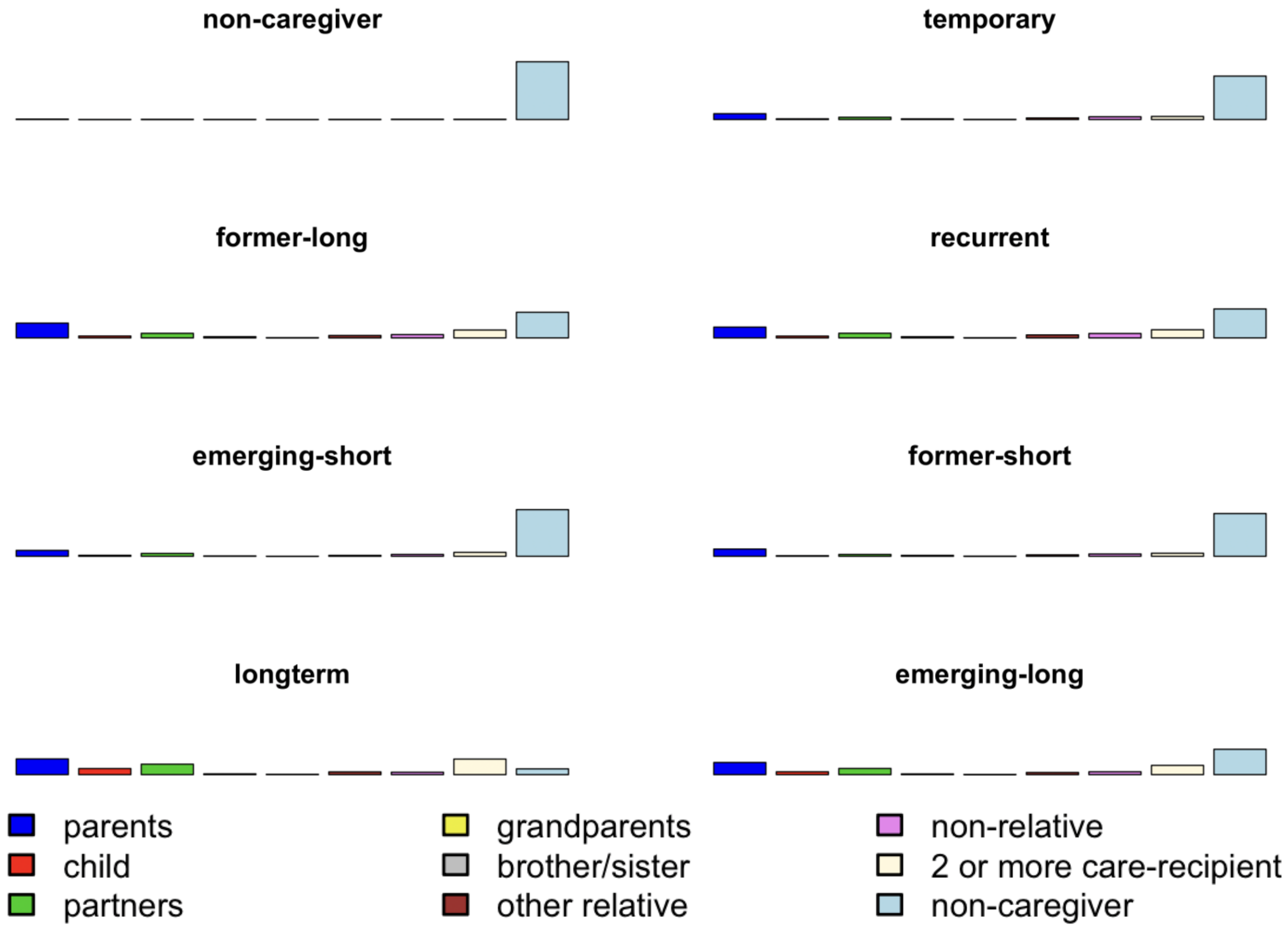


Figure A8.44 Sequence Modal Plot for LCA eight-class solution by caregiver-recipient relationship across UKHLS waves 2 to 13 (n=25,049). Each panel represents a latent class.

Appendix 8.12: Number of recommended imputations

Table A8.22 Number of recommended imputations, based on van Hippel's formula

Outcome	CV=0.10; alpha=0.05	CV=0.05; alpha=0.05
Physical inactivity	4	10
Fruit and vegetable consumption	2	4
Problematic drinking	3	7
Smoking	2	2

Appendix Chapter 9: Discussion & Conclusion

Appendix 9.1: Smoking status and entering caregiving

Table A9.1 Analysis of change in smoking status for the analysis entering caregiving, based on the propensity score matched sample (n=25,979) of eligible UKHLS participants from waves 5 to 13 who have been successfully matched.

Smoking status (n=25.979)		No transition into care	Transition into caregiving	p
Never smoked		79.9%	79.1%	
Always smoked		8.5%	9.2%	
Stopped smoking		9.1%	8.3%	
Started smoking		2.7%	3.3%	0.003

Based on a propensity score matched samples and entropy balance weight