Essays on Health Economics: Health consequences of working conditions, obesogenic environments, and exposure to air pollution

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I, Nicolás Humberto Libuy Ríos, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the work.

Abstract

This thesis aims to answer the question of how socio-economic and environmental factors affect health and healthy behaviours by evaluating the impact of working conditions, air pollution and obesogenic environments. Using rich longitudinal data from Chile and the UK, throughout the three chapters in this thesis, I provide causal evidence on key policy-relevant parameters in three topics in Health Economics.

The first essay studies the impact of reducing the standard workweek duration from 48 to 45 hours, resulting from the 2005 Chilean labour reform, on healthy behaviours and self-assessed health. Using a longitudinal difference-in-difference research design combined with propensity score matching, I find that the reform reduced smoking behaviours but did not impact self-assessed health. Furthermore, when I evaluate the heterogeneous effects, I find that the reform increased the probability of doing physical activity among women and workers without tertiary education.

Using Chilean longitudinal data, the second essay studies the association between air pollution, health at birth and cognitive performance during childhood. I use an instrumental variable strategy that exploits changes in lifetime exposure to air pollution resulting from variation in the geographical location, the timing of birth, the timing of the cognitive test, and exposure to thermal inversions– an atmospheric phenomena that increase concentrations of air pollution at ground level. I find that higher levels of air pollution during pregnancy harm health at birth and during childhood, and are detrimental to cognitive performance, especially among children with respiratory problems.

The third essay evaluates whether proximity to fast food restaurants affects childhood obesity rates in the UK. Using the Millennium Cohort Study linked with highly granular geographic microdata, I find that living near fast food restaurants is associated with a higher Body Mass Index and more body fat. I further provide evidence that the supply of fast food near schools during secondary school increases obesity.

Impact Statement

This thesis provides insights into how three national and international policy-relevant topics, working conditions, air pollution and obesogenic environments, impact on health throughout life.

Workweek duration: The literature in economics documents an adverse effect of working prolonged hours on health in developed nations dating back to the 1960s. In light of this evidence, many European nations have passed legislation that has steadily reduced the workweek to current standards. However, such a trend has not been observed in developing countries, leading to a workforce that have not yet received the health benefits of a shorter workweek. The findings of the first essay, that a reduction from 48 to 45 hours in the standard workweek in Chile improved healthy behaviours, expand the literature, providing evidence for Chile, a useful case study for countries who have a workforce with worsening underlying health conditions than developed nations. Beyond advancing the academic literature, the results in this essay are relevant for governments who are discussing the economic benefit of reducing working hours. It opens up the discussion about evaluating labour reforms in relation to outcomes that are not directly targeted, specifically among more vulnerable groups.

Air Pollution: The association between air pollution and health has been studied intensively in recent decades; however, a new focus has emerged in the economic literature, which is on evaluating its effects on broader human capital outcomes. The second essay in this thesis expands this literature by providing evidence of the harmful impact of lifetime exposure to air pollution on both health at birth and cognitive performance during childhood. The empirical strategy used in the essay allows for estimating parameters that are exempt from endogeneity problems that are common in the literature, which could be used to evaluate the economic cost of air quality in developing countries. Cost-benefit analyses of policies that reduce urban air pollution do not usually take into account its effect on cognitive deterioration at early ages. Furthermore, the finding that air pollution deteriorates cognitive performance during childhood will be beneficial to policymakers and practitioners working in the education sector, since they highlight the consequences of air pollution exposure for the learning process of children.

Obesogenic environments: The 'obesity epidemic' among adolescents in the UK and its longlasting effects throughout life have been a significant concern in recent years. The future financial pressure on the health system due to a larger overweight population will be a problem not only in the UK but also worldwide. In the evidence presented in the third essay, I discuss the role of obesogenic environments near homes and schools in explaining changes in Body Mass Index and body fat during childhood and adolescence. The finding that the availability of fast food restaurants around children's homes and schools increases obesity rates shows a potential mechanism through which the current high obesity rate among adolescents could be tackled. Furthermore, it provides evidence for the current policy discussion about banning new fast food restaurants near schools.

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Declaration

- Chapters 1, 2, 3 and 5 are single-authored by Nicolás Humberto Libuy Ríos
- Chapter 4 is a joint work work with Emla Fitzsimons, George Ploubidis and David Church.

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Chapter 1

Introduction

Evaluating how public policies and exposure to risky environments impact people's health has been of great interest in recent years. In part, this interest stems from the overwhelming evidence that health is determined by the social environment in which people grow up. Aspects such as adequate child development, having enough resources to live a good quality life, having good working conditions, and living in healthy and safe environment determine the health of the population (Marmot, 2020, 2010). Furthermore, there exists a consensus that the inequities in social environments throughout people's lives also determine inequities in health and unhealthy behaviours.

This thesis puts people's health and their evolution throughout life at the centre of the discussion. Through the different chapters, I study the impact that labour market policies have on people's health, as well as the harmful effects associated with exposure to unhealthy environments. I base my analysis on longitudinal, mainly nationally representative samples – administrative and geographic microdata – combined with strong econometric methods to estimate causal impacts and answer critical policy questions of our time. Additionally, by focusing on the period from childhood to adulthood, my thesis emphasises the relevance of studying health throughout life as a whole and not only at a particular moment in time.

A growing body of evidence has singled out early childhood as a particularly critical period because it is when the foundations of later development and healthier life are built (Heckman, 2008). This has led to an explosion in the literature that seeks to identify the elements that affect the development of children, with a greater emphasis on how the investment of parents or the home environment affects the cognitive, socio-emotional development and health of children (Francesconi and Heckman, 2016). At the same time, among the factors that affect children's health, environmental risks, such as air pollution, are commonly identified as determinants of infant mortality and respiratory diseases (Currie et al., 2014). However, the literature has only recently begun to assess the detrimental effects that environmental risks have on other aspects of child development, such as cognitive performance (Marcotte, 2017).

In the transition from childhood to adolescence, healthy behaviours are partly affected by the time that children spend in school as well as how healthy the environments in which they interact (Cobb et al., 2015). Among the many factors that affect health during this period, great emphasis has been placed on studying how obesogenic environments, for example, having greater access to fast food restaurants, can impact on childhood obesity (Williams et al., 2013). Interest in evaluating this association comes from the rampant 'obesogenic pandemic' that has been documented in several countries over the past decades (Swinburn et al., 2011). If living in healthier environments is associated with behavioural changes that potentially help to reduce childhood obesity, then public policies that restrict the supply of these products have the potential to improve population health in the short and long term. The evidence around this question is inconclusive, as is the evidence on whether the most vulnerable households are most affected by living in unhealthy environments.

Later, during adulthood, working conditions have been identified as determinants of the population's health. On the one hand, providing access to good jobs and reducing long-term unemployment is key to improving people's living conditions and health. Much of the literature points to the negative health effects of unemployment, layoffs, and economic crises (Catalano et al., 2011; Ruhm, 2005; Schaller and Stevens, 2015; Sullivan and von Wachter, 2009; Sullivan and Wachter, 2009). On the other hand, the literature also shows that the quality of work, i.e. the cumulative effect of labour rights such as access to job security, an adequate salary, a good-work balance, safety and wellbeing, among other factors, can contribute to a healthier population (Cottini and Lucifora, 2013; Kivimki et al., 2015). Among the job characteristics associated with workers' health, the length of the working day has been at the centre of public debates, both due to its impact on the economy and because of the key role it has played in the discussion of workers' rights. This discussion has guided studies that evaluate the effects of long working hours on workers' health and, at the same time, has partly motivated reforms towards shorter working hours in various countries around the world (Sparks et al., 1997). While most of the evidence comes from industrialised countries, there is a lack of evidence for developing countries who typically face distinctive structural labour market conditions, as well as having deteriorated underlying population health.

By focusing on health throughout life, this thesis contributes to the health economics literature by providing new evidence on the impact of critical and understudied determinants of health. In particular, I evaluate how air pollution affects children's cognitive performance and infant health, how obesogenic environments affect the risk of being of excess weight, and how reductions in working hours affect healthy behaviours and self-assessed health. I examine these critical policy questions across different lifetime periods, from childhood to adulthood, and in both developing and developed nations. Throughout the chapters, I provide evidence that the negative impacts of air pollution, availability of fast food restaurants, and prolonged working hours on health and healthy behaviours are stronger among people with lower levels of education. This result points towards the importance of analysing further the detrimental effects of health inequalities throughout the lifecycle.

In chapter one, I study how the 2005 Chilean labour reform, which reduced the standard workweek from 48 to 45 hours, affected workers' healthy behaviours and self-assessed health. Understanding the relationship between long working hours and health has been the focus of a large body of research in recent decades, in which long working hours have been linked to chronic conditions as well as unhealthy behaviours. However, only a few studies have used plausible exogenous variations in workweek duration to assess this question, and when they do, most of the research focuses on developed countries. I fill this gap in the literature by using rich longitudinal data regarding workers from Chile and a research design that combines difference-in-difference methods with propensity score matching. In particular, I study how the compulsory reduction in the standard workweek duration – that occurred on 1^{st} January 2005 – impacted workers' smoking behaviours, physical activity and self-assessed health. The data shows that the reform caused a significant reduction in usual working hours, and, as mandated by the law, did not cause a decrease in labour earnings among affected workers.

Regarding the impacts on healthy behaviours, I find that the reform decreased the probability of smoking; however, I do not find impacts on the likelihood of doing physical activity. Similarly, no effects are found in relation to workers' self-assessed health. When I evaluate heterogeneous effects by gender and education level, the impacts on self-assessed health remain the same. However, the results indicate that the reform changed healthy behaviours, mainly among women and workers without tertiary education. Women affected by the reform reduced their probability of smoking and increased their likelihood of doing physical activity. Men and workers without tertiary education, in contrast, decreased only their smoking behaviours. These findings are in line with previous studies that have evaluated the impact of labour reforms in developed countries. This study contributes to the literature by providing new causal evidence for one of the developing countries, which, in contrast with developed nations, continue to have higher levels of workweek durations. Furthermore, the results demonstrate the importance of evaluating the broader effects of labour reforms on outcomes that are not directly targeted.

In chapter two, I study how air pollution is associated with health at birth and cognitive performance during childhood. The detrimental effects of air pollution on cognitive performance as well as on health at birth have previously been studied, leading to a large body of research in economics; however, most of this research has evaluated this question separately. On the one hand, this literature has provided evidence that exposure to air pollution is negatively associated with academic outputs such as maths or reading test scores. On the other hand, it has evaluated the impact of exposure to poor air quality on children's health throughout their lifetime. In this chapter, I connect the two areas of this literature by estimating the effect of air quality on both cognitive performance and health at birth using a rich longitudinal survey from Chile. The research design consists of an instrumental variable approach that exploits the known association between thermal inversions and air pollution. Thermal inversions occur when a layer of warmer air overlies a layer of cold air at the surface, reducing the vertical ventilation of air and resulting in higher concentrations of air pollution at ground level. To implement the research design, I combine data on daily air pollution from seven monitors throughout Santiago collected by the Chilean National Air Quality Information System (SINCA), daily temperature profile data from the Modern-Era Retrospective analysis for Research version 2 (MERRA-2) collected by the National Aeronautics and Space Administration (NASA), and data on daily weather conditions collected by the Chilean Meteorological Agency (CMA). I link these data with the Chilean Early Childhood Longitudinal Survey (ECLS) data to create measures of lifetime air pollution exposure. The analysis in this chapter reveals that exposure to poor air quality during pregnancy is connected with poor health outcomes at birth. In particular, the estimates show that higher levels of particulate matter 10 (PM10) pollution during pregnancy decrease birth weight, increase the probability of a low birth weight, shorten gestation, and increase the likelihood of having a premature child. I observe a similar pattern when I use the Air Quality Index, an index used by environmental agencies to rank the health risk of air pollution.

Regarding cognitive performance, I find that lifetime exposure to air pollution, measured from conception and during childhood, is negatively associated with Peabody Picture Vocabulary Test (PPVT) scores, a validated test used to measure how well children comprehend Spanish. Furthermore, the analysis shows that the impact of poor air quality on cognitive performance is larger among children with respiratory problems. This study contributes to the literature in several ways. First, it uses a credible exogenous variation (i.e. thermal inversions) together with high-quality longitudinal data. Second, by using the location and date of the cognitive evaluation, it improves on previous research by using a more accurate measure of exposure to air pollution. Third, the existing literature has many problems in representing developing countries, raising questions about the external validity of the current evidence. This chapter fills that gap by providing new evidence in the context of Chile, a middle-income country that, during the last decades, has consistently reduced its levels of urban air pollution.

Finally, in chapter three, I study whether proximity to fast food restaurants affects childhood obesity rates. The relevance of this research question arises from the surge in childhood obesity that we have witnessed in the last decade. Public health measures have failed to reverse the obesity epidemic that is now present all over the world (Swinburn et al., 2011). Evidence in the UK shows that younger generations are becoming obese at early ages and staying obese into adulthood, with 28% of children aged 2 to 15 being either overweight or obese. Meanwhile, the fast food retail industry in the UK is, by all accounts, booming, with fast food restaurants accounting for more than a quarter of all eateries in England (BBC, 2018). This evidence contrasts with an estimated 6.1 billion NHS financial burden associated with people who are overweight and obesity-related ill health (PHE, 2017).

The analysis in this chapter aims to overcome potential biases observed in cross-sectional studies by using the longitudinal structure of the Millennium Cohort Study (MCS) and estimating individual fixed effects models using data from ages 7, 11, and 14. I link data from the Ordnance Survey's Points of Interest (PoI) Dataset to characterise children's obesogenic environments around their home and their school. I use the PoI dataset, which contains geocoded stores and food facilities across Great Britain, to characterise longitudinal changes in the obesogenic environment of children. The analysis of the data shows that living near fast food restaurants is associated with a higher Body Mass Index (BMI) and more body fat. These results are driven by the negative association between the obesogenic environment and BMI among children whose parents achieved level three or below in their National Vocational Qualifications, exacerbating health inequalities. I further provide evidence that the supply of fast food near schools during secondary school increases obesity. This chapter adds new evidence from the UK to the limited – mainly US-based – literature that attempts to estimate the causal effect of fast foods on childhood obesity.

Chapter 2

The impact of reducing working hours on healthy behaviours

2.1 Introduction

During the last decades, a growing body of literature has documented robust correlational evidence between long working hours and health outcomes such as chronic diseases (Kivimki et al., 2015; van der Hulst, 2003; Virtanen et al., 2012a),[1] poor lifestyle habits (Taris et al., 2011),[2] mental health problems[3] and well-being deterioration (Cottini and Lucifora, 2013). According to estimates made by the World Health Organization (WHO), cardiovascular diseases, which have been linked with working long hours, are responsible for colossal health and economic costs. In particular, they are estimated to cause the death of 17.7 million people every year (31% of global death), 10% of the Disability-Adjusted Life Years lost in low- and middle-income countries, and 18% in high-income countries. Similarly, unhealthy behaviours associated with working prolonged hours, such as tobacco consumption and physical inactivity are among the five leading global risks for mortality (WHO, 2009).

[1] Among the non-communicable diseases studied in the literature are diabetes and cardiovascular conditions.

[2] Among the poor lifestyle habits studied in the literature are smoking, inadequate diet, and sedentary lifestyle.

[3] Among the mental health conditions studied in the literature are stress and fatigue (Ono et al., 1991; Spurgeon et al., 1997), sleeping problems, anxiety, irritability, and Self-Assessed Health (SAH).

There are at least two general mechanisms through which long working hours could lead to health deterioration. First, the physiological perspective[4] points out that working long hours do not allow the psychobiological systems to fully recover[5], thereby increasing the amount of additional effort needed during work to perform a task (Askenazy, 2004; Brenner et al., 2004; Demerouti and Bakker, 2007). The cumulative effect of lack of time to fully recover is thought to affect the physiological process that is associated with chronic health problems, such as an increase in blood pressure, hormone excretion and sympathetic nervous system activity (Taris et al., 2011). Second, the behavioural view proposes that unhealthy habits and lifestyle choices of people exposed to long working hours, such as smoking, drinking, lack of physical activity, and high intake of saturated fat and calories, are responsible for poor health outcomes. Regardless of the mechanisms through which long working hours affect workers' health, studies in various disciplines have consistently found correlational evidence that working long hours impair a wide variety of subjective and objective health outcomes.

The evidence regarding the negative association between working long hours and health has been challenged by studies that have argued that reducing working hours or job displacement might worsen workers' health. A reduction in working hours could aggravate workers' health through the indirect effect on future earnings and career progression (Black et al., 2015; Eliason, 2012; Francesconi and Bardasi, 2000; Schaller and Stevens, 2015; Sullivan and von Wachter, 2009). Additionally, the correlation between health and income is generally positive (Deaton, 2003a), challenging the mechanisms through which a reduction in working hours may cause improvements in terms of healthy habits. Separating the causal effect of working long hours from income effects is an important empirical issue that has not been resolved in most of the evidence published in recent decades. Additionally, some arguments in the literature point out that a reduction in working hours may cause stress for a subpopulation of workers. For example, in the context of a model where

[4]See Sluiter et al. (2003) and Wang et al. (2011)

[5]Internal recovery is the worker's capacity to recover during working hours, and external recovery is the worker's capacity to recover outside of office hours (Taris et al., 2011).

workers compete within the firm, Sánchez (2017) argues that by working long hours individuals signal that they are hard-working, a trait that is unobserved by the firm, increasing the probability of future promotion and career success. Therefore, a reform that reduces the maximum standard working hours may reduce competition for promotion via working hours, which might jeopardize future income and career progress, potentially harming workers' health.

Despite this research question's relevance, there have been only a few attempts to provide causal evidence about it. Ahn (2016) and Berniell and Bietenbeck (2017) study the labour reforms in South Korea and France respectively, and both find that working long hours is associated with risky behaviours (i.e. smoking, drinking and a sedentary lifestyle). Cygan-Rehm and Wunder (2018) study changes in the statutory workweek regulations in the German public sector and find that long working hours had adverse consequences for subjective well-being and objective health measures, such as the number of doctor visits. The results from studies on the labour reforms implemented in Portugal and France are mixed. On the one hand, Sánchez (2017) find evidence that a reduced workweek has a positive effect on Self-Assessed Health (SAH) for female workers in France; however, no effect was found for workers in Portugal. This contrasts with Lepinteur (2018), who found that reduced working hours increase job and leisure satisfaction in both countries. This chapter contributes new evidence to this growing and scarce literature in economics, which aims to identify the causal effect of long working hours on workers' health using quasi-experimental research designs.

The study exploits the impact of the 2005 Chilean labour reform on health-related behaviours, such as tobacco use and physical activity, and workers' SAH. I focus my analysis on the compulsory reduction in standard weekly working hours from 48 to 45, which occurred on 1^{st} January 2005 and was part of a broader labour reform implemented in December 2001. The mixture of a labour market with a traditional long workweek and a population with a high prevalence of health conditions connected with prolonged working hours, such as cardiovascular diseases and sedentarism, makes the Chilean labour reform a relevant case to study. For instance, in 2014, cardiovascular diseases in Chile accounted for 27.5% of the total deaths, mainly at the expense of stroke and acute myocardial infarction (Ministry of Health, Chile).[6] And, according to the estimates from the last National Health Survey in 2017-2018, 33.4% of adults smoke and 86.7% of adults have a sedentary lifestyle.[7]

The analysis in this chapter is based on the first three surveys of the Chilean Social Protection Survey (SPS), which is a large nationally representative longitudinal study designed to evaluate the Chilean pension system (Arenas et al., 2006). To estimate the impact of the reduction in working hours, I use a difference-in-difference approach combined with matching (DiD-M). This method calculates the Average Treatment on workers affected by the reform (ATT) by essentially taking the difference between health outcomes before and after the compulsory reduction in working hours for treated workers, adjusted by the change experienced by workers in the control group over the same period. The DiD-M identifies ATT if the common support and parallel trend assumption hold. The former states that, conditional on observed individual characteristics, workers unaffected by the reform evolved from the pre- to the post-policy period in the same manner as affected workers would have evolved had they not been treated (Blundell and Costa Dias, 2009). Although the SPS does not allow me to assess the parallel trend assumption for health behaviours or SAH, it enables me to provide evidence that the parallel trends assumption holds for job-related characteristics linked to health. Additionally, I provide evidence that the compulsory nature of the reduction in standard working hours created a scenario in which treated workers experienced a sharp decrease in working hours while unaffected workers maintained a similar workweek to before the reform.

[6]Cardiovascular diseases (International Classification of Diseases: ICD-10 I00-I99) accounted for 28,064 deaths (the rate is 157.49/100,000 inhabitants), stroke accounted for 8,603 deaths (the rate is 48.28/100,000 inhabitants) and acute myocardial infarction accounted for 8,102 deaths (the rate is 45.47/100,000 inhabitants).

[7]According to Margozzini and Passi (2018), current tobacco use is 33,4% overall (4.6 millions of adults) and 37,8% and 29,1% among adult men and women respectively and 86.7% of adults use their leisure time for sedentary activities with the figures for men and women being 83,2% and 90,0% respectively.

I focus my analysis on workers aged 25-65 years at the first interview who were working at both the first and third SPS interviews. The treatment and control groups are defined using eligibility rules established by the law. In particular, the treatment group includes individuals who were working between 46-48 hours per week in the private sector in January 2002, while the control group includes employees of the public and private sector who were working 43-45 hours per week in January 2002. I provide a sensitivity analysis showing that the estimates are robust to alternative definitions of the treatment and control groups.

I find the reform caused a significant reduction in usual working hours, and, as mandated by the law, did not cause a decrease in labour earnings among affected workers. The decline in usual hours was more pronounced among men than women, and among workers without tertiary education than among individuals with some tertiary education. Regarding the impacts of the reform on health behaviours, I find the policy decreased the probability of smoking by around 7.7 percentage points. These results are larger among men and workers without tertiary education, in which I find a significant decline of 11.3 and 25.9 percentage points in the probability of tobacco use. Among women, I find that the reform decreased the probability of smoking by 6.2 percentage points. I also find that the reform decreased the probability of smoking five or more cigarettes per day by 9.9 percentage points. This finding holds for both those with low and high levels of education.

Concerning sedentary behaviours, the impact of the reform on the probability of doing physical activity shows no significant effect. However, I find that the reform increased the probability of doing exercise among women by 13.8 percentage points and increased the probability of doing exercise at least three times per week by 19.9 percentage points. The analysis reveals that the reform had beneficial effects on reducing unhealthy behaviours, particularly among women and workers with lower educational levels. These findings reinforce the results reported by Ahn (2016), who also find a positive health effect for women and workers with relatively low levels of education. In contrast, I do not find that the reform had an impact on SAH, nor, when I focus on specific sub-populations, challenging the findings of

Cygan-Rehm and Wunder (2018), that an additional hour of work deteriorate SAH.

This study makes several contributions to the existing literature. First, to the best of my knowledge, it provides the first causal evidence of the impact of reducing long working hours on health outcomes among workers in a developing country. The Chilean case is interesting for other nations that continue to have higher levels of weekly working hours relative to developed nations. Furthermore, the Chilean labour reform reduced the standard workweek duration without changing labour income, generating a unique scenario to evaluate its impacts on workers' health. Second, it adds to and corroborates previous results in the literature for specific subpopulations, such as women and low-educated workers. Third, taken together, the results demonstrate the importance of evaluating the broader effects of the reform on outcomes that are not directly targeted.

The remainder of this chapter proceeds as follows. Section 2.2 gives an overview of the literature that links working hours with health outcomes. Section 2.3 describes the labour reform in Chile and its historical context. Section 2.4 describes the data and presents evidence of the reform on usual hours and earnings. Section 2.5 discusses the empirical strategy. Section 2.6 provides estimates of the effects of the reduction in standard working hours on health outcomes. Section 2.7 presents the robustness analysis, and Section 2.8 concludes.

2.2 Literature review

How and why might long working hours affect health? The literature that assesses this question can be divided into two groups: on the one hand, studies that show that working long hours are negatively associated with several health outcomes, and on the other hand, quasi-experimental studies in the economics literature, which provide causal evidence showing that increased working hours lead to health deterioration. In this section, I discuss the previous empirical studies in both areas of the literature.

In a meta-analysis of 21 studies from 1965-1996, Sparks et al. (1997) find a mean correlation of 0.13 between measures of overall health and working hours. In their analysis, they split the studies into physiological and psychological health outcomes[8] and find a slightly higher correlation with physiological than psychological health outcomes. The authors argue that the weak but significant relationship between both, physiological and psychological measurement, and hours of work could be mediated by: the type of job, the working environment, age, individual control over work schedule and maladaptive behaviours – such as poor nutritional habits– smoking and drinking. Similarly, in a systematic review of 27 medical and psychological empirical studies from 1996 to 2001, van der Hulst (2003) present evidence about the relationship between long working hours and several health outcomes such as mortality, diagnosed disease[9], subjective health[10], physiological measures[11] and health-related behaviours.[12] The author finds that working long hours is associated with adverse health and argues that the evidence associated with physiological recovery mechanisms seems stronger than the evidence for behavioural life-style mechanisms. In particular, long working hours were found to be associated with cardiovascular disease, diabetes, illnesses leading to disability retirement, subjectively reported physical ill health, and subjective fatigue.

Cottini and Lucifora (2013) use an instrumental variable approach to study the detrimental effect of adverse working conditions on work-related mental health conditions using data from 15 European countries. They show that characteristics mainly associated with job demands (i.e. performing complex and intensive tasks or having restrictive job autonomy) and job hazards (i.e. handling dangerous materials or being exposed to temperature fluctuations) are correlated with mental health problems in the workplace. Furthermore, exposure to long working hours has been associated with higher levels of stress, fatigue, industrial injury and depressive

[8]Measures used in the physiological health meta-analysis included somatization, headaches, work accidents, myocardial infarction, coronary heart disease, and general physical health symptoms. The psychological health measures included hostility, depression, poor sleep, irritability/tension, problems with relationships, lack of concentration, tiredness, role strain, anxiety, frustration, exhaustion, insomnia, social dissatisfaction, mood symptoms and general mental stress.

[9]They analysed diagnoses of cardiovascular diseases, hypertension, diabetes, and work disability.

[10]They analysed a general index of subjective health, psychological health, and physical health.

[11]They analysed cardiovascular, immunologic, and other biochemical indices.

[12]They analysed sleep hours, alcohol consumption, smoking, drugs, eating habits, exercise, and BMI/obesity.

symptoms (Geurts et al., 2009; Godin and Kittel, 2004; Kasl, 1998; Lundberg and Frankenhaeuser, 1999; Pikhart et al., 2004; Taris et al., 2011; Virtanen et al., 2012b).

The lack of causal evidence that has been emphasized in the meta-analyses published in the last decades is a major limitation in the literature (Cottini and Lucifora, 2013; Kivimki et al., 2015; Sparks et al., 1997; Virtanen et al., 2012a). However, recent studies using quasi-experimental designs have provided causal evidence for the effect of a prolonged workweek on several health outcomes. Ahn (2016) study the impact of a workweek reduction from 44 to 40 hours on health-related behaviours in South Korea by exploiting the timing and stepwise scheme of the labour reform implemented between 2004 and 2011. Using fixed effects instrumental variable methods, the author finds that a one hour decrease in the workweek reduce the probability of smoking by 0.86 percentage points and increase the probability of regular exercise by 0.72 percentage points. Additionally, the author finds that a one-hour reduction in the workweek increases the probability of drinking by 5.8 percentage points, which they argued could be associated with healthy and moderate drinking habits since no significant effect for frequent and daily drinking habits was found. Berniell and Bietenbeck (2017) use the reduction in working hours from 39 to 35 hours induced by the Aubry I and II French reform[13] to identify the causal effect on workers' health. They use a difference-in-differences and a lagged dependent variable specification, with and without instrumental variables, that exploits the employer-level variation in the adaptation of the reform. They focus their analysis on males and show that one additional hour of work increases the probability of smoking by 1.5-2.5 percentage points and reduces SAH by 0.04-0.08 percentage points on a scale from 0-10. The authors do not find a significant effect on workers' Body Mass Index (BMI). Similarly, Cygan-Rehm and Wunder (2018) use a fixed effects instrumental variable strategy that exploits moderates time and state-level changes in the statutory workweek in the German Public sector from 1985 through to 2014. They find that an increase of one additional hour is associated with a decrease of 0.059 scale points in SAH and increase the number of doctor

[13]The French reform included two round of labour reforms: Aubry I, passed in 1998, and Aubry II, passed in 2000.

visits in the last three months by 0.290. Studies that have evaluated the reduction in standard hours from 39 to 35 in France and from 44 to 40 in Portugal find mixed results. On the one hand, Sánchez (2017) finds that the reduction in working hours in France has a negative effect on SAH for young males; however, it has a positive effect on females. The author does not find any effect on health outcomes in Portugal. On the other hand, Lepinteur (2018) using a difference-in-differences method, finds that the reforms increase job and leisure satisfaction among affected workers in both countries.[14]

Overall, previous empirical studies provide a compelling case for the potentially detrimental effects of long working hours on workers' health. However, the evidence comes mainly from industrialized countries, which typically have a more formal labour market and a population with better underlying health than in the developing world. By focusing on the understudied Chilean labour reform, this study contributes to the literature in three areas. First, as explained in more detail in the next sections, the Chilean labour reform decreased working hours while remunerations were unchanged by the law. The Chilean case provides a unique scenario to evaluate the effect of hours separated from changes in labour income. Second, in the Chilean reform, the compulsory reduction in working hours was separated from the rest of the reform, which allows me to isolate the reduction in the standard workweek from other aspects of the policy. Third, it provides a unique case to study developing countries that still have a standard workweek that is far longer than that in developed countries.

2.3 The reduction in workweek hours

Since 1924, the labour workweek duration in Chile has been 48 hours, which is relatively high in comparison to OECD countries but similar to weekly hours in other non-OECD countries. The 48-hours scenario was substantially changed in the mid-2000s when the Socialist government of Ricardo Lagos implemented a labour

[14]While the impact of the reform on job satisfaction and leisure satisfaction for Portugal are 0.070 (SE: 0.028) and 0.130 (SE: 0.032), for France are 0.087 (SE: 0.042) and 0.154 (SE: 0.047) respectively.

reform that reduced the workweek duration to 45 hours. Still, in 2019, Chilean workers rank fourth in the ranking of weekly hours worked among OECD members, with an average of 42.8.[15] While in 2001 an average Chilean worker spent almost 10 hours more working than an average worker in OECD countries, in 2019 the same average gap narrowed to 5.8 hours (see Figure 2.1 and 2.2).[16]

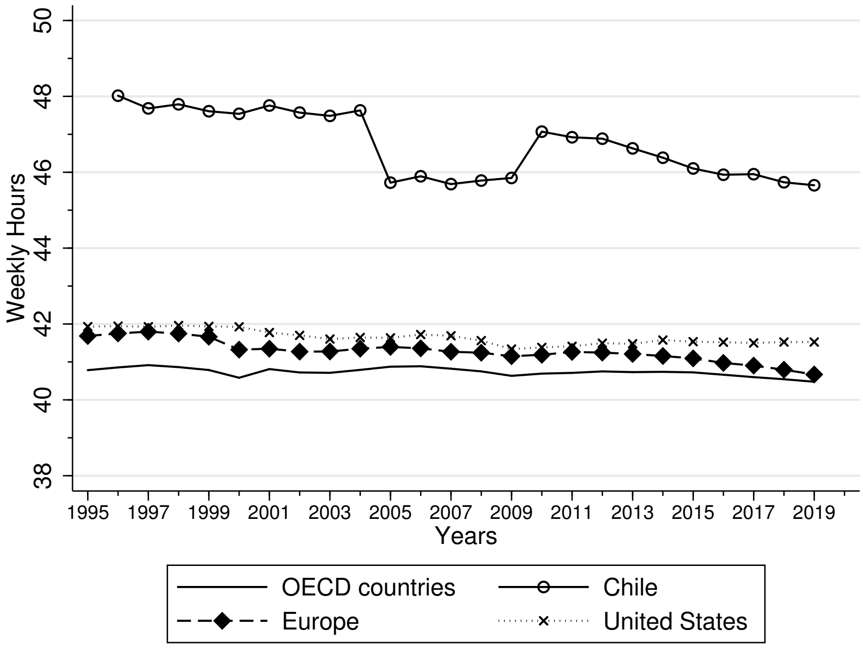

Figure 2.1: Average usual weekly hours worked on the main job: OECD

Notes: The figure shows the average usual weekly hours worked on the main full-time job from 1995 to 2019. It includes men and women of ages 15 or more. Full-time employment is defined by OECD according to a common definition of more than 30-weekly-usual hours worked in the main job. Source: Published in the OECD.Stats, https://data.oecd.org/.

The labour reform was put forward by the Chilean Government in March 2000 with the general objective of improving individual and collective labour relations. The law was passed in October 2001 and was almost entirely implemented in December 2001. The labour reform can be classified into two main domains (Sánchez, 2013). The first group of modifications to the law focused on changing the employer-employee relationship and the supervisory role of the Ministry of Labour. In particular, it reformed the procedures available to end contracts and

[15] The data can be found in: https://data.oecd.org/emp/hours-worked.htm

[16] According to OECD data, while the average weekly hours worked in Chile in 2001 and 2017 were 47.1 and 43.1 in OECD countries these figures were 37.3 and 36.6, respectively.

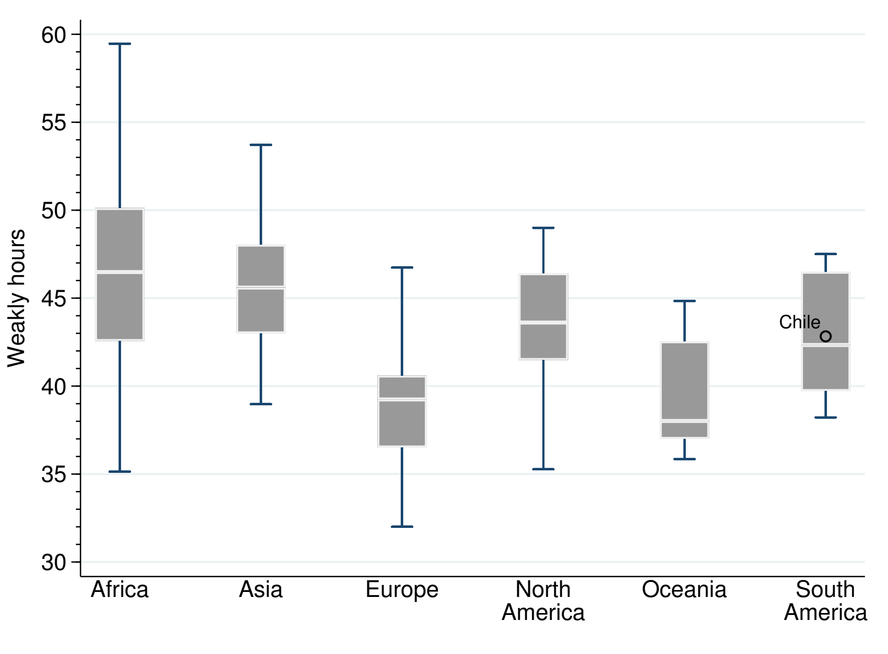

Figure 2.2: Average usual weekly hours worked on the main job by continent (ILO)

Notes: The figure shows the distribution of the mean weekly hours actually worked per employed person, by continent. For each country, the last available statistic reported to the the International Labour Organization Statistical Department (ILO-STAT) is used. Employment comprises men and women of working age (15 or more) included in the categories paid employment or self-employment. Details about concepts and definitions can be found in https://ilostat.ilo.org/resources/concepts-and-definitions/description-hours-of-work/. Source: https://ilostat.ilo.org/data/

the associated layoff cost; the exceptional distribution of working time in some industries; how firms and employees agree overtime hours; the collective bargaining procedures; specific working privileges; management limiting fines; and the supervision power of the Ministry of Labour. I describe these aspects of the reform in more detail in the Appendix. The second topic of the reform, and the most relevant for this study was the compulsory reduction in working hours from 48 to 45.

The modifications to the law were implemented nationwide starting in December 2001; however, the reduction in the standard workweek duration was mandated to be compulsory from 1^{st} January 2005. The law included a 3-year period to allow firms to adjust to the new regulation. During this period, adjustments related to working hours had to be made with the agreement of both employees and employers. In the event of no agreement before 1st January 2005, employers could unilaterally reduce working hours. Initially, the law was ambiguous about the change in remunerations; however, on 22^{nd} September 2004, the Ministry of Labour stated that regardless of the remuneration scheme (fixed, variable or mixed[17]), the employer must maintain the same remuneration of its workers as before the reform.[18]

In a nutshell, the Chilean labour reform had several relevant features. First, it allows me to isolate the effect of the reduction in working hours on health outcomes from other variables that could be associated with health-related behaviours and individuals' SAH, e.g. wages. Second, when compared with labour reforms in other countries, the Chilean case, with a historical long workweek duration prior to the implementation of the reform, is highly relevant for other countries, where the average workweek duration is still over 40 hours.

2.4 Data and descriptive evidence

In this section, I describe the survey and present descriptive statistics relating to the sample used in the primary analysis. First, I describe the health outcomes and covariates used in the empirical analysis. Second, I describe the timing of the labour reform and how it relates to the survey fieldwork period. I provide evidence that it is possible to use the first survey as the baseline period in the difference-in-difference analysis since no evidence of anticipatory behaviours was observed until late 2004. The empirical methodology, as well as the definitions of the control and treatment groups, are provided in Section 2.5.

2.4.1 The Chilean Social Protection Survey (SPS)

I use individual-level data from the first three surveys (2002, 2004 and 2006) of the longitudinal Chilean Social Protection Survey (SPS). The SPS is a nationally representative longitudinal survey designed to evaluate the Chilean pension system. The first wave was drawn from a sampling frame of affiliates in the pension system in 2001. The sampling frame covers affiliates to the pension system starting in January

[17]The ORD N.:4338/168 of the Ministry of Labour states that *"in the case of workers subject to fixed remuneration, the total amount must be maintained, while in the case of workers subject to exclusively variable remuneration, the employer must adjust, proportionally, the parameters that serve as a basis for calculating said stipends, or their value. Finally, concerning dependents affected by a mixed remuneration system, that is, consisting of a fixed salary and variable stipends, the employer must maintain the agreed salary amount and adjust the variable remuneration in the terms and with the objective already indicated"*

[18]Details about this can be found in the ORD N.:4338/168 form the Ministry of Labour.

1981 until August 2001, representing around three-quarters of the Chilean population aged 15 or more in 2001 (Arenas et al., 2006).[19] The data includes detailed and rich information on individuals' socio-demographic characteristics and labour market conditions. It also contains socio-demographic information from other individuals in the household. For the primary respondent, starting in January 1981 (or since the interviewees were 15 years old), the SPS collected retrospective information about the initial and final month of the following employment status: employed, unemployed, looking for a job for the first time or inactive. In addition to employment status, the survey also asked about the main occupation, industry and firm size, among other job characteristics. And, crucially useful to identify workers affected by the reform, the SPS collected the usual weekly hours worked at both the moment of the interview and retrospectively, i.e. it collected information before and after the labour reform was implemented. In sub-section 2.4.2, I describe in more detail the evolution of usual hours and labour statistics during the relevant period.

Additionally, the SPS provides rich information on health-related outcomes including Self-Assessed Health; frequency of exercise; smoking and drinking behaviours; diagnosis of different diseases, such as diabetes, heart problems, stroke, arthritis, and mental illness; weight, height and BMI; physical activity and participation in organisations (i.e. volunteer organisations or NGOs); an assessment about Activities of Daily Living (ADL) that ask whether the individual usually needs help from third parties to perform activities (i.e. doing intense exercise, walking long distances, climbing stairs, having a bath, getting dressed, eating and getting out of their bed); and hospitalisation and frequency of hospitalisation. Unfortunately, several of the health-related questions are not available for the period analysed, which is the reason why I restrict the analysis to Self-Assessed Health, frequency of exer-

[19] In the 2002 SPS sampling frame, the armed forces, which are covered by a separate pension system, were excluded. Importantly, in the SPS 2004, a sample of non-affiliated people was included, which allows for characterising the population excluded from the analysis in this chapter. As expected, the non-affiliated population are more likely to work in the informal sector and achieve lower education levels than the affiliated population. For instance, estimates from the SPS 2004 show that 14% of non-affiliates to the pension system had some tertiary education as compared with 20.2% of the affiliated group. Furthermore, the non-affiliated group has a younger age structure than affiliated workers. Around 15% of the non-affiliated group were aged18-25 while the same estimates for the affiliated population are only 4%.

cise and tobacco use.

To measure SAH, I use the question "Would you say that in general, your health is...?"[20] to create two binary variables. The first one indicates that the individual reported "Good", and the second one that the individual answered "Good" or "Very Good". While some concerns exist in the literature regarding the validity of SAH measurements (Crossley and Kennedy, 2002; Datta Gupta and Jrges, 2012; Layes et al., 2012), there is evidence that subjective measures of health are a good predictor of mortality, health care utilization and chronic diseases (Burstrm and Fredlund, 2001; Doiron et al., 2015; Idler and Benyamini, 1997). Moreover, international evidence about the predictive power of SAH measures in changes of several health conditions has also been found in 13 European countries (Becchetti et al., 2018), meaning that, despite its potential biases, SAH capture meaningful information about individuals' future health.

I use the question "Do you currently smoke?" to create a binary variable indicating whether the worker smoked at the moment of the interview and the question "How many cigarettes per week do you smoke?" to determine the number of cigarettes smoked per day. Additionally, I present the results using a binary variable indicating whether the worker smoked five or more cigarettes per day. To measure sedentary behaviour, I use the question "In the last month, how many times have you practised sports or some physical activity?". I label as "Some exercise" a dependent binary variable indicating whether the worker reported any frequency of physical activity. Additionally, I use two binary variables that capture whether the worker exercised at least once per week, and whether the individual exercised at least three times per week.

Table 2.1 displays the characteristics of workers used in the analysis, as well as for men and women, and workers with and without tertiary education. Around 40% of the sample smoked in the first survey, while 17% indicated that they smoked

[20]This question is answered on a 1 to 5 scale in the SPS 2002, and on a 1 to 6 scale in the SPS 2006. In the SPS 2002, 1 means "Very Good" and 5 means "Very Bad"; however, in 2006 the category "Excellent" was included to discriminate within the category "Very good", where 1 means "Excellent" and 6 means "Very Bad". To create a standard measure over time, I grouped the categories "Excellent" and "Very Good" in the SPS 2006

five or more cigarettes per day. The percentage of workers that smoked was larger among males (43%) than females (35%), but surprisingly similar by educational level. Regarding physical activity, around 38% indicated that they did some exercise and only 12% of workers exercised at least three times per week. Working women practised less exercise than men – 20% of women compared with 46% of men. The percentage of workers who indicated that their health was "Very Good" was 12%, while 76% of workers considered their health "Good" or "Very Good". The SAH figures are similar by gender and by education level.

In the matching method described in the next section, I use individual-level characteristics collected in the first survey. Table 2.2 shows variables that have previously been linked with working prolonged hours and that were measured before the reduction in working hours was compulsory. Workers were matched based on socio-demographic and job-related covariates. The demographic covariates included are sex, age, categorical variables indicating the highest level of education achieved, marital status, regional categories and two health-related variables. The health-related variables indicate whether workers attended a doctor due to an emergency consultation and whether they attended due to hospitalisation. The job covariates included in the analysis are the primary worker's occupation, industry, and unionisation status, all corresponding to January 2001. The main occupation was categorised following the Labour International Standard Classification of Occupations (ISCO) of the International Labour Organization.[21] Similarly, I include seven industry categories classified using the International Standard Classification of Industry.[22] Finally, in addition to job characteristics in January 2001, the number of months employed between December 1997 and December 2001 – just before the implementation of the reform – was used as an additional variable.

[21]The occupation categories included are professionals; technicians and associate professionals; clerical support workers; service and sales workers; skilled agricultural, forestry and sherry workers; craft and related trades workers; plant and machine operators, and assemblers; and elementary occupations.

[22]The industry categories included are agriculture, hunting, forestry, fishing, mining and quarrying; manufacturing; construction, electricity, gas and water supply; commerce, hotels and restaurants; transport and communications; financial intermediation; and public, social and personal services.

Table 2.1: Summary statistics for variables used in analysis

		Gender		Education	
	Total	Men	Female	High school or less	More than high school
Panel A. Hours and labour income					
Hours	47.4	47.6	47.0	47.7	46.7
Log Labour Income	5.3	5.3	5.3	5.2	5.8
Panel B. Smoking and sedentary behaviours					
Smoking behaviours					
Current Smoker (%)	40.4	42.6	35.1	40.1	41.5
Smoke >= 5 cigarettes per day (%)	16.6	18.4	12.5	16.8	16.0
Number of Cigarettes per day	2.2	2.5	1.6	2.3	2.1
Sedentary behaviours					
Some Exercise (%)	38.3	46.0	19.7	38.5	37.6
Exercise at least once per week (%)	30.9	36.9	16.4	31.2	30.1
Exercise at least 3 times per week (%)	11.9	13.1	8.8	11.5	13.0
Panel C. Self Assesed Health					
Very Good (%)	11.9	11.6	12.4	10.0	17.4
Very Good or Good (%)	76.5	76.3	76.9	73.0	87.0
Male	70.8	-	-	76.5	53.8
Age	39.4	39.8	38.5	40.2	37.2
No education or pre school	0.7	0.9	0.2	-	-
First level or Differential level	26.4	32.2	12.4	-	-
Second level: Scientific-Humanist	31.0	31.4	29.9	-	-
Second level: Technical-Professional	16.8	16.4	17.8	-	-
Third level: Technical-Professional Institute	13.6	10.5	21.1	-	-
Third level: College or Postgraduate	11.5	8.6	18.6	-	-
Children ages 0-18 in household	1.1	1.2	1.0	1.2	1.0
Marital Status (%)					
Single	20.5	15.5	32.6	16.8	31.4
Regions (%)					
Metropolitan Region	43.2	41.9	46.5	39.9	53.0
North	10.6	10.6	10.6	11.6	7.5
Center	33.3	35.2	28.8	35.4	27.2
South	12.9	12.3	14.2	13.1	12.3
Occupation (%)					
Professionals	6.1	3.6	12.3	0.1	24.2
Technicians and associate professionals	8.4	7.5	10.6	2.8	25.1
Clerical support workers	16.9	11.2	30.7	13.8	26.1
Service and sales workers	13.9	9.4	24.9	15.7	8.4
Skilled agricultural forestry and fishery workers	6.3	8.4	1.3	8.2	0.7
Craft and related trades workers	16.9	22.4	3.5	20.4	6.4
Plant, machine operators and assemblers	12.7	16.0	4.6	15.9	3.1
Elementary occupations	15.6	18.0	9.8	20.2	1.7
Industry (%)					
Agriculture, Hunting, Forestry, Fishing, Mining and Quarrying	13.5	17.7	3.5	16.9	3.3
Manufacturing	21.0	23.3	15.3	24.0	11.7
Construction, Electricity, Gas and Water supply	9.9	13.2	1.9	11.2	5.9
Commerce, Hotels and Restaurants	18.8	15.0	27.9	19.6	16.1
Transport and Communications	6.2	7.1	3.8	5.8	7.3
Financial Intermediation	7.7	7.9	7.2	4.9	16.0
Public, Social and Personal Services	19.8	12.3	37.8	14.5	35.4
Months employed between Dec 1997 and Dec 2001	46.5	46.9	45.5	46.7	45.8
Unionized (%)	14.1	14.2	13.9	13.2	16.7
Attended the doctor for an emergency consultation (%)	16.1	16.7	14.8	16.9	13.8
Attended the doctor for hospitalization (%)	9.1	7.1	13.7	8.3	11.2
Observations	2,175	1,540	635	1,630	545

Notes: The table shows the mean characteristics of the sample used in the main analysis. It includes controls and treatment groups as defined in the main text.

As shown in Table 2.1, the average worker's age is 39 years, around 70% of the workers are men, 25% of workers have some tertiary education, and 20% are single. Most workers participate in industries related to manufacture, commerce, and public and social services. Overall, the distribution of job characteristics – occupation, industry, and union status – shows that the SPS gives a rich portrait of the working population in Chile before the implementation of the labour reform.

2.4.2 Timing of the reform and the SPS fieldwork period

In Figure 2.3, I show the timing of the reform, together with the SPS fieldwork period. The first and third survey fieldwork occurred, respectively, between May 2002 and January 2003, and between November 2006 and July 2007. The health outcomes used in the analysis were collected in the first and third waves of the SPS. Before moving to the difference-in-difference analysis, which I describe in the next section, it is essential to provide evidence that the announcement that occurred in December 2001 did not generate significant changes in the behaviours of workers until after the fieldwork of the first wave had ended. Anticipatory responses could have happened because, although the compulsory cut in working hours occurred in January 2005, firms and workers could adjust hours voluntarily between January 2002 and December 2004. However, changes in usual working hours, employment and wages during 2002 are implausible due to the long period of adjustment included in the law. Additionally, previous studies have found that such modifications were not observed until late 2004 (Sánchez, 2013). I provide similar evidence in the context of this study, which allows me to use the first wave of the SPS as the baseline period in the estimation of a difference-in-difference strategy.

In Figure 2.4, I show the distribution of usual working hours reported in the SPS for the private sector for selected years between 2000 and 2007. The figure shows that during the period when the law was discussed in the congress and after publication, the distribution of working hours remained highly concentrated at 48 hours per week. Later, while there was an increase in the proportion of workers who reported working 45 hours in 2004, the sharp decrease from 48 to 45 hours occurred in 2005. In 2007, when the third survey wave was collected, the distribution of usual

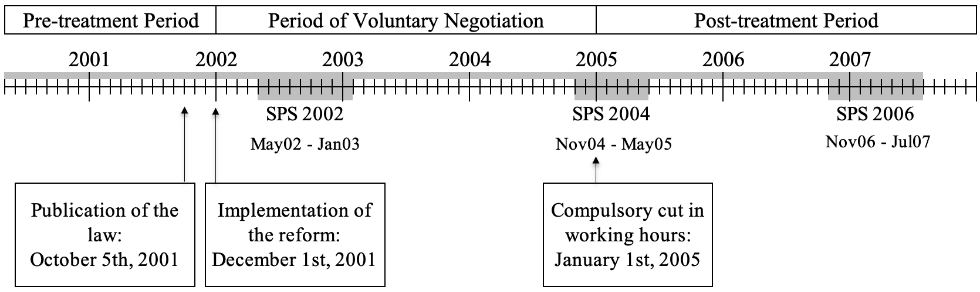

Figure 2.3: Timing of the Labour Reform

Notes: The figure shows the labour reform's timing and the fieldwork period of each SPS wave (thick grey lines). Three waves were conducted during the period, in 2002, 2004 and 2006. Retrospective information about employment such as working hours, occupation, industry, and other job characteristics, were asked at each wave (thin grey lines).

hours was highly concentrated at 45 hours, showing evidence that the reform had been fully implemented at that time. This result is consistent with the evolution of workweek hours shown in Figure 2.1, which use OECD data, and also with Figure 2.5, which uses SPS data. The latter figure shows the evolution of the mean and mode of usual working hours between 2000 and 2007, providing evidence that a sharp decline in hours was observed in January 2005.

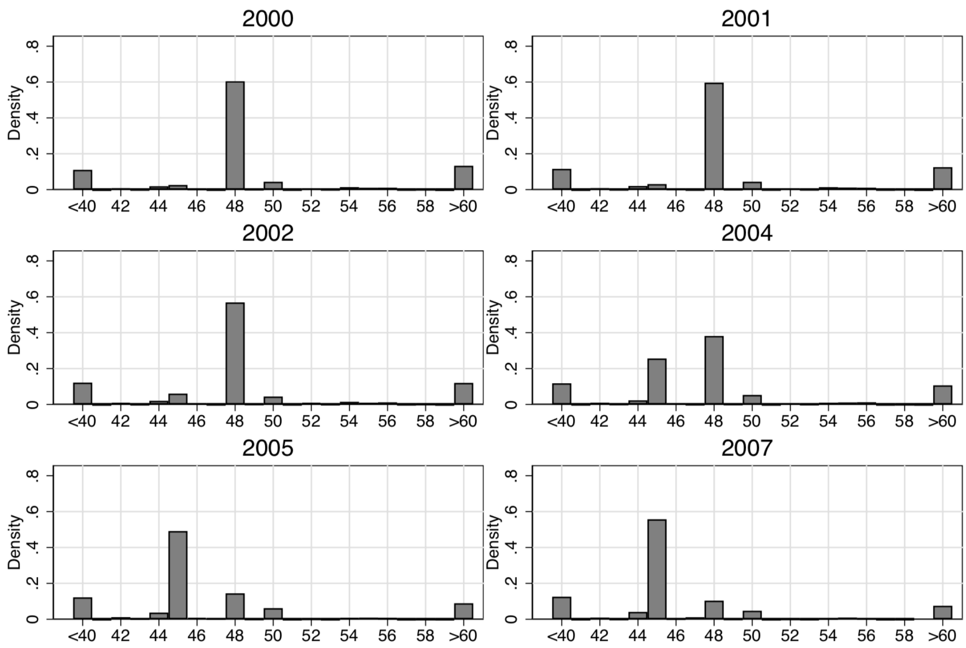

Figure 2.4: Distribution of usual working hours

Notes: The figure shows the distribution of usual hours reported by private employees working in the occupation categories reported in Table 2.2 for June of each year. All available monthly information is used to improve precision of estimates. Sample sizes are n_{2000}=7137; n_{2001}=7118 ; n_{2002}= 6849 ; n_{2004}= 6246; n_{2005}=5502; and n_{2007}=5063.

Figure 2.5: Evolution of usual working hours

Notes: The figure shows the usual workweek hours mean and mode in the private sector for each quarter between 2000 and 2007. It uses all monthly information reported in the Social Protection Survey by workers in the private sector from January of 2000 to December of 2007. The figure is based on 8651 workers in the Social Protection Survey who reported working hours between 2000 and 2007.

In Figure 2.6, I show official estimates made by the Chilean National Institute of Statistics about the evolution of participation rates, employment rates, the Nominal Wage Index (NWI) and the Nominal Labour Cost Index (NLCI) between January 2000 and January 2008. The NWI measures the monthly evolution of hourly wages paid to hired workers during standard workweek hours, while the NLCI captures expenses incurred by firms in maintaining their workers, including overtime payments.[23] Naturally, both the participation and employment rates follow seasonal patterns; however, little change can be seen in the evolution of the participation and employment rates before and after the announcement of the compulsory reduction in the standard workweek, i.e. in December 2001. From 2002 until late 2004, neither figure provides any evidence of anticipation behaviours in wages and labour

[23]The cost of labour is calculated as wages plus employer costs for extraordinary compensation, reimbursement of worker expenses, employer contributions, staff welfare services, training and improvement, and other costs of labour. It excludes reparations and non-monthly payments.

costs. Similarly, there is no evidence that nominal wages or nominal labour costs changed before January 2005. If anything, there is a small change in the growth rate of both trends after the reduction in the workweek became compulsory.

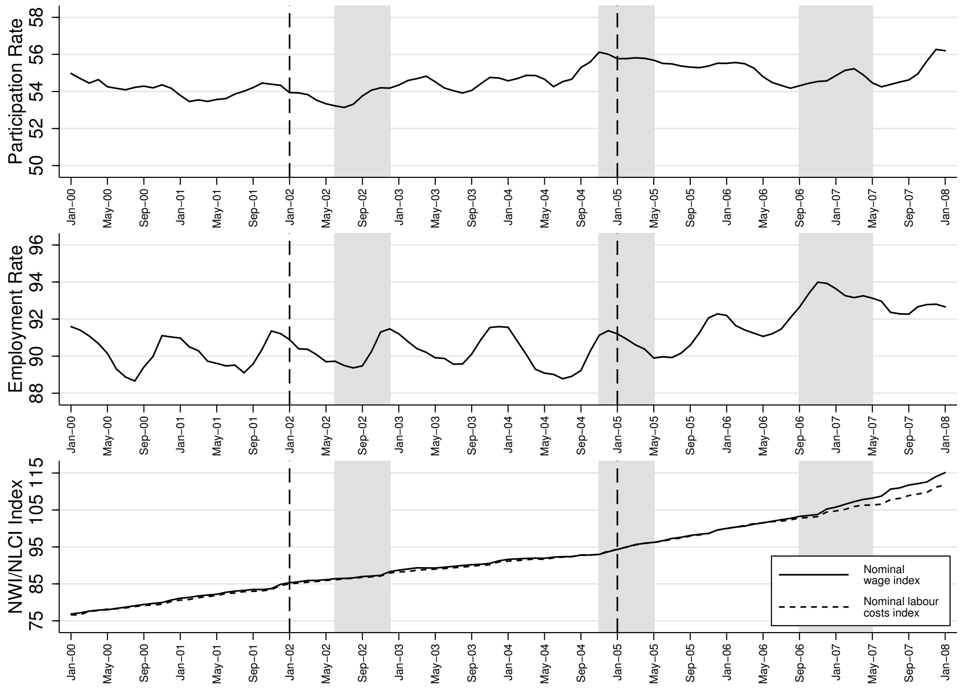

Figure 2.6: Evolution of participation/employment rates and nominal wage and labour cost indexes

Notes: The figure shows the participation rate, employment rate, the Nominal Wage Index (NWI) and the Nominal Labour Cost Index (NLCI) between January 2000 and January 2008. The participation and employment rate were computed using the 3-month moving average estimates provided by the Instituto Nacional de Estadisticas (INE). The NWI and NLCI have base 100 in January 2006 and are published by the INE.

The data provide no evidence that adjustments in usual hours, participation rates, employment rates or nominal wages occurred during 2002, implying that it is plausible to use this period as a pre-reform period. The data show that if there were voluntary adjustments between workers and employers, it is likely they were implemented between mid-2003 and late 2004. Based on this, the difference-in-difference strategy described in the next section considers the first survey as if it was collected before the reform was implemented and uses the third survey as data collected once the reform had been fully implemented. As Figure 2.3 shows, the fieldwork of the second survey occurred at the same time as the reduction in the standard workweek became compulsory, complicating the use of health outcomes collected in this survey, mainly because the date of the interview is unavailable.

2.5 Empirical methodology

In this section, I describe the matching difference-in-difference method I use to identify the effect of the workweek reduction on health outcomes. First, I describe the potential outcome model and the implementation of the identification strategy. Second, I describe the definition of treatment and control groups. Third, I show results of the matching algorithm. Finally, and before moving to the regression analysis, I show preliminary descriptive evidence of the main outcomes in the period before and after the reduction in workweek hours.

2.5.1 Identification of the Average Treatment Effect on the Treated (ATT) under Difference-in-Difference with Matching

Several challenges have been identified in the literature to identifying a causal effect of working hours on health-related outcomes. First, unobserved factors may affect both working hours and health outcomes. Second, reverse causality could also be present, with health affecting causally working hours. Third, reducing working hours could have a direct effect on labour income, which in itself could independently cause changes in health behaviours, and separating these two effects may be challenging even if working hours are randomly allocated to individuals. To overcome these challenges, I exploit the quasi-experiment generated by the compulsory reduction in working hours and identify the ATT using a difference-in-difference method combined with matching (Heckman et al., 1997).

To discuss the identification assumptions of the parameter of interest in this study, I use the following potential outcome framework. Let's define Y_{it}^{1} the health outcome for worker i in the period t. Define t_0 as the period before the implementation of the compulsory reduction in working hours mandated in the labour reform and t_1 as the period afterwards. The conterfactual scenario for the same individual i is defined as Y_{it}^{0}. Following the exposition of Blundell and Costa Dias (2009), the linear potential outcome model can be written as

$$Y_{it}^{1} = \beta + u(X_i) + \alpha(X_i) + [(u_{it} - u(X_i)) + (\alpha_i - \alpha(X_i))] \quad (2.1)$$

$$Y_{it}^{0} = \beta + u(X_i) + (u_{it} - u(X_i)) \quad (2.2)$$

Where X_i are observables and u_{it} is the residual term defined as $u_{it} = (n_i + m_t + o_{it})$. The residual term is composed by n_i, an individual fixed effect, m_t, an aggregate macro shock, and o_{it}, an idiosyncratic transitory shock. $u(X_i)$ is the predictable part of Y_{it}^{0}. The term $(u_i - u(X_i))$ is what is left in the residual term after conditioning on X_i. The term α_i is the effect of treatment specific to individual i, the term $(\alpha_i - \alpha(X_i))$ represents the unobservable heterogeneity, and $\alpha(X)$ is the Average Treatment Effect (ATE) over individuals with observable characteristics X. The parameter of interest, i.e. ATT, is defined as $E(Y_{it}^{1} - Y_{it}^{0} | T = 1)$, where T denotes individuals affected by the labour reform.

In this model, the ATT is identified under the following two assumptions. First, once we control for observable characteristics, the evolution of the Y_{it}^{0} is independent of the treatment status. In other words, this means that changes in workers' health that were affected by the reform would have been the same as in the non-affected workers in the absence of the policy. This assumption is formalised as:

$$\begin{aligned} & E(Y_{it}^{1}|T=1, t=t_1) - E(Y_{it}^{1}|T=1, t=t_0) \\ = & E(Y_{it}^{0}|T=0, t=t_1) - E(Y_{it}^{0}|T=0, t=t_0) \end{aligned}$$

Second, the common support assumption in the matching method requires that the characteristic X is represented among both treated and control workers.

$$P[d_{it_1}|X, t] < 1$$

In other words, the probability that a worker observed at time t with characteristics X_i would belong to the treatment group in the period after the reform implementation (t_1) is below one. When these two assumptions hold, the ATT can be estimated over the common support of X using the following matching estimator.

$$\widehat{ATT} = \hat{\delta} = \sum_{i \in T} \left\{ [y_{it_1} - y_{it_0}] - \sum_{j \in C} \widetilde{w}_{ij} [y_{it_1} - y_{it_0}] \right\} w_i \tag{2.3}$$

Where $\widetilde{w}_{ij}$ is the weight associated with the comparison worker j for the treated individual i and w_i reweight and reconstruct the outcome distribution for the treated individuals (Blundell and Costa Dias, 2009).

To assess whether the common trend assumption holds, we should ask what sort of measured and unmeasured factors are likely to explain the variation in health outcomes (such as tobacco use, frequency of exercise and SAH) across treated and control workers and over time. A primary concern that could potentially bias the estimates is any time-invariant factor (n_i), such as attitudes towards smoking or practising exercise that could also be associated with working hours. However, I use a within-individual specification that eliminates any time-invariant factor, providing an estimate free from this bias. On the other hand, time-variant factors (o_{it}), such as unobserved personal shocks can potentially bias the estimates if the shock induces changes in both hours and health-related behaviours. An example of such a shock is a traumatic experience that may simultaneously affect motivation towards work and changes in healthy behaviours. Although I cannot account for this in my empirical strategy, I match workers based on a large number of covariates and restrict the analyses to workers in the common support, which mitigates this issue.

Even though in the two-group two-periods difference-in-difference model the parallel trend assumption is not testable, it is sometimes possible to use external information to show that, on average, trends in health outcomes by treatment status are stable in the pre-treatment period. Unfortunately, to the best of my knowledge no periodically and consistent information regarding standard workweek hours and health outcomes was collected in a national survey in Chile between 2000 and 2007. However, without collecting working hours, tobacco use among adults was measured from 2000 to 2008 by the Chilean National Study of Drugs in the General

Population, which allows me to present some aggregated evidence of the pre-reform trends for this outcome. In Figure 2.7, I show that between 2001 and 2002, the proportion of people smoking did not see any significant change, which may suggest that the announcement of the reform did not change smoking behaviours. Interestingly, a small reduction can be observed after 2005 across all measurements of tobacco use. In the next section, after defining the control and treatment groups in detail, I provide evidence of parallel trends in usual workweek hours and job-characteristics linked to workers' health.

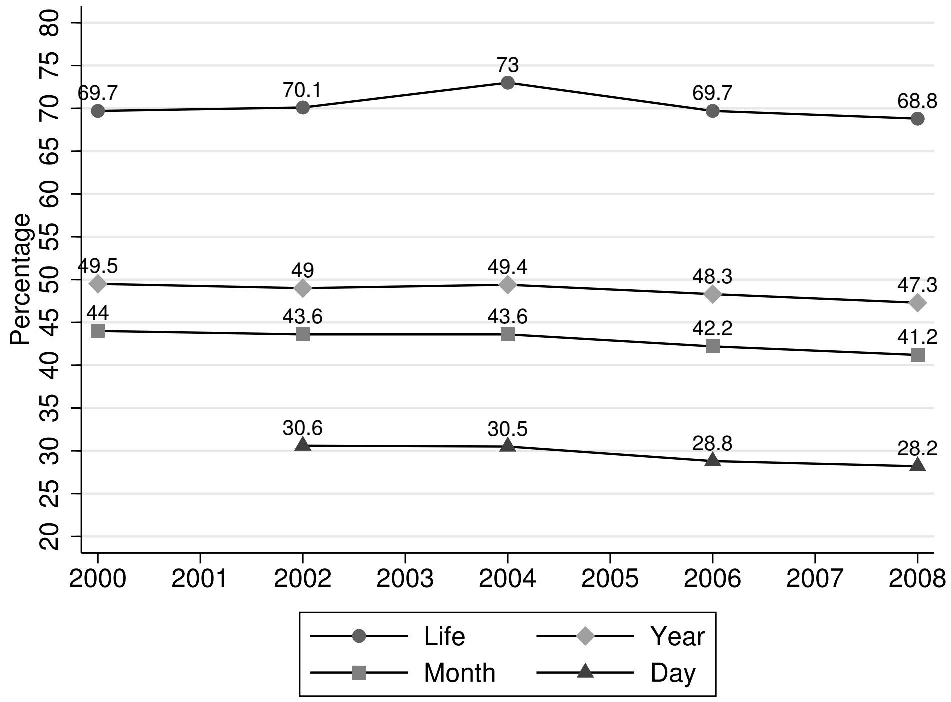

Figure 2.7: Prevalence of tobacco use

Notes: The figure shows the prevalence of tobacco use from 2000 to 2008 using different measure of use: if you have ever consumed in life (life), in the last year (year), in the last month (month), and daily use (day). Source: National study of drugs in the general population of Chile.

2.5.2 Implementation

Assuming linearity in the potential outcome model, I estimate the ATT by first taking the within-individual difference in health outcomes ($y_{it_1} - y_{it_0}$), and then matching the treated and controls based on the covariates in Table 2.2. In my preferred specification, I use Nearest Neighbour Propensity Score Matching (NN-PSM) based on a single neighbour. I also provide results based NN-PSM with five neighbours, Nearest Neighbour Matching (NNM) with a single and five neighbours (Abadie and Imbens, 2006, 2011), and Kernel Propensity Score Matching (K-PSM) (Heckman et al., 1997). I show results using different matching methods since this helps to ensure that the results are not driven by the matching algorithm, especially in small samples (Heckman et al., 1997). The matching algorithms were chosen since there is a trade-off between bias and variance among them. Conditional on a matching algorithm, choosing a single neighbour achieves less bias but higher variance when compared with multiple neighbours. Similarly, K-PSM methods, when compared with NN-PSM methods, should obtain lower variance and larger bias. NNM is not based on the propensity score but, instead, it weights the imputed potential outcome for each worker based on the similarity of a weighted function of the covariates. In the former case, I report bias-corrected estimates, which are consistent when the matching algorithm uses continuous covariates (Abadie and Imbens, 2006, 2011). I strengthen the feasibility of the common support assumption by restricting the estimation of ATT to treated workers whose propensity score is larger than the maximum and smaller than the minimum in the control group, and the same restriction is applied to workers in the control group. For the NN-PSM and NNM estimates, I report confidence intervals and robust standard errors derived by (Abadie and Imbens, 2006, 2008, 2011), which take into account the estimation of the propensity score. For K-PSM matching, I report bootstrapped standard errors based on 250 replications.

Table 2.2: Comparison of characteristics across matched and unmatched samples

	Unmatched Sample				Matched Sample			
Variable	Treated	Control	Difference	p-value	Treated	Control	Difference	p-value
Male	0.743	0.498	0.244	0.000	0.740	0.734	0.006	0.917
Age	39.147	41.084	-1.937	0.001	39.241	39.012	0.229	0.821
Education								
No education or pre school	0.005	0.016	-0.011	0.143	0.005	0.076	-0.071	0.220
First level or Differential level	0.294	0.084	0.210	0.000	0.284	0.158	0.125	0.017
Second level: Scientific-Humanist	0.323	0.233	0.090	0.001	0.328	0.304	0.024	0.689
Second level: Technical-Professional	0.179	0.104	0.075	0.000	0.182	0.185	-0.003	0.956
Third level: Technical-Professional Institute	0.132	0.159	-0.027	0.229	0.134	0.213	-0.079	0.155
Third level: College or Postgraduate	0.067	0.405	-0.338	0.000	0.068	0.065	0.003	0.859
Children ages 0-18 in household	1.144	1.042	0.102	0.139	1.126	1.029	0.097	0.549
Marital Status								
Single	0.202	0.220	-0.018	0.477	0.203	0.143	0.061	0.135
Regions								
Metropolitan Region	0.435	0.417	0.017	0.572	0.437	0.511	-0.074	0.297
North	0.111	0.071	0.040	0.014	0.104	0.133	-0.029	0.546
Center	0.341	0.285	0.057	0.043	0.345	0.226	0.119	0.042
South	0.113	0.227	-0.114	0.000	0.115	0.130	-0.016	0.686
Occupation								
Professionals	0.023	0.294	-0.272	0.000	0.023	0.016	0.007	0.333
Technicians and associate professionals	0.071	0.162	-0.091	0.000	0.073	0.114	-0.041	0.232
Clerical support workers	0.162	0.207	-0.045	0.069	0.165	0.173	-0.008	0.849
Service and sales workers	0.144	0.107	0.037	0.054	0.147	0.111	0.035	0.438
Skilled agricultural forestry and fishery workers	0.072	0.006	0.066	0.000	0.071	0.047	0.023	0.507
Craft and related trades workers	0.186	0.065	0.121	0.000	0.188	0.177	0.011	0.833
Plant, machine operators and assemblers	0.139	0.052	0.088	0.000	0.142	0.164	-0.022	0.694
Elementary occupations	0.166	0.094	0.072	0.000	0.156	0.168	-0.013	0.850
Industry								
Agriculture, Hunting, Forestry, Fishing, Mining and Quarrying	0.154	0.019	0.135	0.000	0.140	0.095	0.045	0.317
Manufacturing	0.233	0.071	0.161	0.000	0.237	0.227	0.010	0.868
Construction, Electricity, Gas and Water supply	0.109	0.036	0.074	0.000	0.111	0.133	-0.022	0.724
Commerce, Hotels and Restaurants	0.209	0.058	0.151	0.000	0.212	0.238	-0.026	0.676
Transport and Communications	0.065	0.039	0.027	0.032	0.067	0.097	-0.031	0.478
Financial Intermediation	0.073	0.097	-0.024	0.186	0.075	0.074	0.001	0.980
Public, Social and Personal Services	0.120	0.670	-0.550	0.000	0.122	0.107	0.015	0.516
Months employed between Dec 1997 and Dec 2001	46.415	47.058	-0.643	0.116	46.505	46.458	0.047	0.962
Unionized	0.116	0.288	-0.172	0.000	0.118	0.099	0.020	0.577
Attended the doctor for an emergency consultation	0.161	0.162	-0.001	0.982	0.164	0.121	0.044	0.233
Attended the doctor for hospitalization	0.087	0.110	-0.023	0.232	0.088	0.103	-0.014	0.744
Observations	1,866	309			1,835	309		
Mean absolute standardized bias		29.329				8.826		
Median absolute standardized bias		20.210				6.518		
Pseudo R2		0.352				0.058		

Notes: The table shows descriptive statistics of individual characteristics measured at baseline. All variables, with the exception of occupation, industry, and union status, are recorded at the 2002 interview. The variables occupation, industry, and union status are measured in January 2001. Columns 1 and 2 show the mean of the control and treatment groups. Column 3 shows difference between the mean of Treated and Control groups and column 4 refer to two-sided p-value.

2.5.3 Definition of treatment group

I define the treatment group using the eligibility status of workers at the beginning of the pre-reform period using the rules indicated in the law. The pre-reform period could be considered as immediately after the announcement of the reform, i.e. in January 2002 because non-anticipatory behaviour was observed until mid-2003. The treatment group includes all individuals working between 46-48 hours per week in the private sector in January 2002. Since working overtime hours has also been associated with health deterioration, I also present results when the treatment group includes individuals working 46-60 hours per week. In the above definition, I cap the hours worked per week at 60, because – including overtime – this is the maximum legal number of working hours established by Chilean Law.

Additionally, depending on job type, some employees working in the private sector were explicitly excluded from the compulsory reduction in working hours. In particular, self-employed workers, such as managers, administrators, and those who work without immediate superior control, were not affected by the workweek reduction. Moreover, the armed forces, workers who provide services to different employers, those who work in a place freely chosen by them, and those who do not exercise their functions on the premises of the firm[24] [25] were also not affected by the reduction in hours, and were therefore excluded from the treatment group. To implement the exclusion of individuals working in the private sector, I use the main occupation reported by workers in January 2002, as defined by the International Standard Classification of Occupations (ISCO). Specifically, I exclude workers in the private sector who were classified as managers or armed forces.

2.5.4 Definition of control group

The construction of an appropriate control group is essential for the credibility of the evaluation of the reform. Using a control group that resembles as closely as possible the characteristics of the treatment group should strengthen the common trend assumption because it is expected that the controls will respond to shocks in similar ways to the treated workers. For this reason, the control group is defined as individuals who worked 43 or 45 hours per week in January 2002 in the same occupations and industries as the treated workers and who worked in both private and public organizations. Employees in the public sector were included in the control group because their standard weekly working hours cannot exceed 44 hours,[26]

[24] Such as commission agents and insurance agents, travelling salesmen and collectors, among others.

[25] Other workers that have not been affected by the reform are individuals on board fishing vessels, professional sportsmen, and staff who work in hotels, restaurants or clubs (except administrative, laundry, lingerie and kitchen staff). Additionally, a change included by the reform was to exempt from the maximum working hours workers who provide services through long distance technologies.

[26] While in Chile, the Labour Code governs labour relationships in the private sector, the Administrative Statute regulates the labour relationships of people working in the public sector. Article N59 of the Administrative Statute (Law 18,834) indicates that standard weekly working hours cannot exceed 44 hours, distributed from Monday to Friday, and cannot exceed nine hours a day.

and they were not affected by the compulsory reduction in hours. In section 2.7.2, I provide evidence that the definition of the control group does not drive the results.

2.5.5 Additional sample restrictions

The empirical analysis focuses only on workers aged 25-65 at the moment of the first survey, excluding individuals aged 18-24, who are more likely to be attending tertiary education. I also restrict the analysis to people who were working positive hours during the third survey, specifically in January 2007. Additionally, it is vital that the treatment and control workers, who are defined as such based on their usual working hours in January 2002, continued working the same number of hours when the baseline health information was collected. Given that the fieldwork of the first survey occurred over a period of seven months starting in May 2002, it may still be possible that individuals who worked, for example, 48 hours in January 2002, were working 45 hours when the health outcomes were collected. To avoid this potential mismatch, I restrict the sample to ensure that the treated and control workers continued working 46-48, and 43-44 hours respectively, at the moment of the first interview. In practice, although important, the misclassification is small and occurs only in 2.2% of the sample. Finally, I exclude individuals with missing observations in health outcomes or the covariates used in the matching method.

2.5.6 Comparation between unmatched and matched samples

In the final sample, the control group includes 309 workers, while the sample size in the treatment group depends on the range of hours used in the treatment definition. When the treatment is defined using the range 46-48 hours, the treatment group includes 1,866 workers, and when overtime hours are considered, i.e. 46-60 hours, it consists of 2,435 workers. I exclude 31 and 41 workers from the 46-48 and 46-60 hours treatment groups, respectively, to ensure that the common support assumption holds. In Tables 2.2 and 2.12, I show differences in characteristics between the treatment and control groups before and after the matching. At the baseline, several differences can be observed between the unmatched treatment and control groups; however, the characteristics of the matched treatment and control samples are more similar, indicating that the matching procedure does a good job in balancing the characteristics between groups. In both tables, I also report the mean and median standardised bias across covariates, and the Pseudo-R^2 of the logistic model used to compute the propensity score. These statistics show a reduction in both the mean and median of over 200% and a large decrease in the Pseudo-R^2. Similar evidence is provided for both treatment definitions in Figures 2.8 and 2.10, which show the distribution of the standardised percentage bias across covariates; and in Figures 2.9 and 2.11, which show kernel density estimates of the propensity score, before and after the matching.

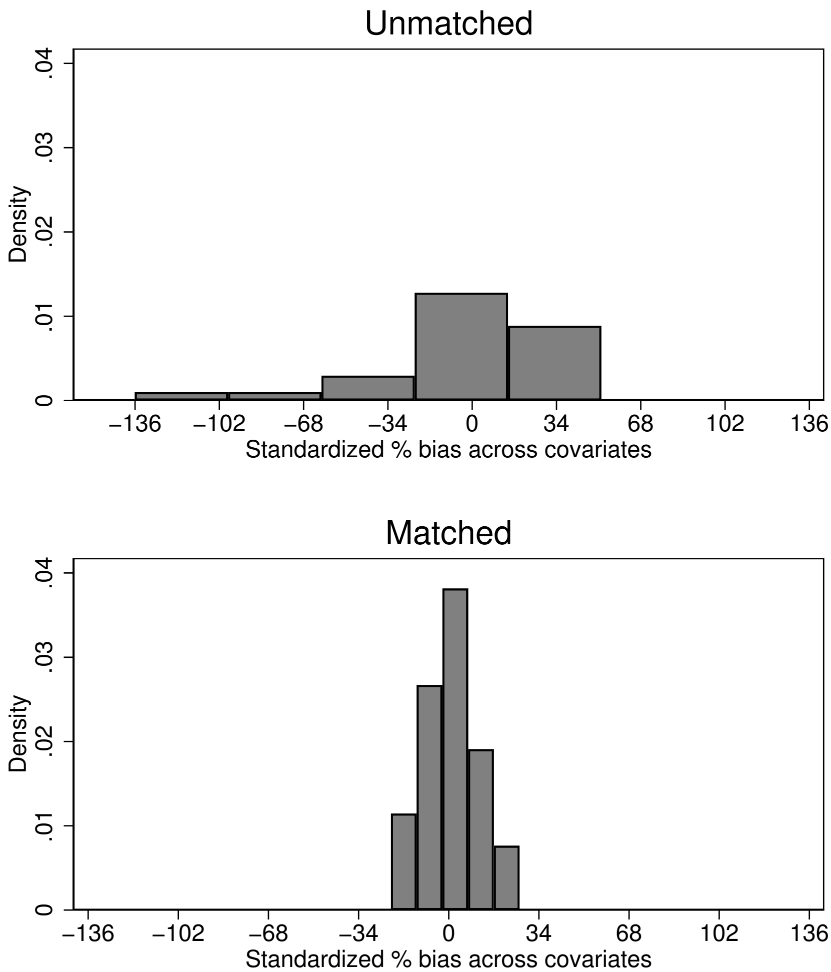

Figure 2.8: Standardised Percentage Bias Across Covariates. Treatment 46-48

Notes: The figure show the distribution of the standardised percentage bias across covariates before and after matching.

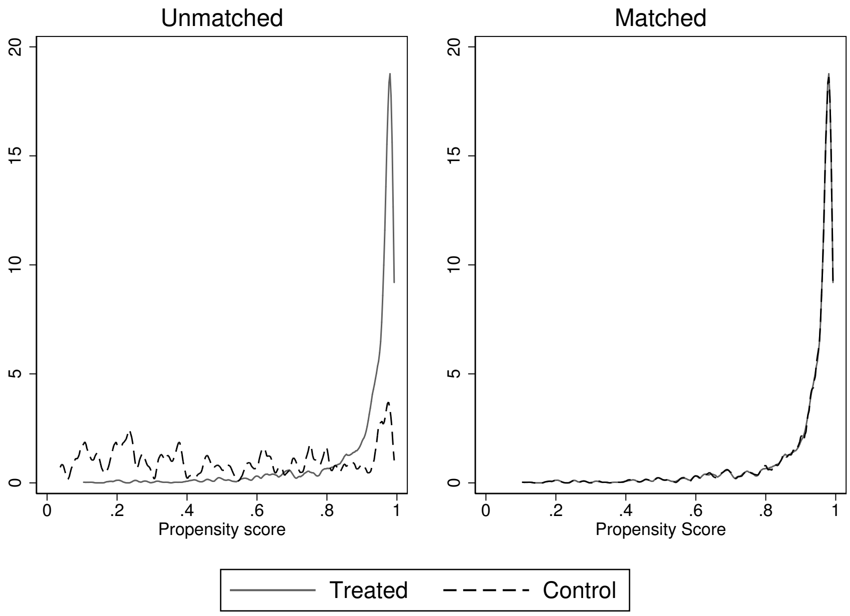

Figure 2.9: Kernel Density Estimates of the Propensity Score. Treatment 46-48

Notes: The figure shows kernel density estimates of the propensity score before and after matching.

2.5.7 Working hours, labour income, and health outcomes in treatment and control groups

Before moving on to the regression analysis, I provide simple descriptive evidence of the reform's effect on usual weekly hours, labour income, and health outcomes. Regarding usual working hours, in Figures 2.1 and 2.5, I show the average usual weekly hours worked on the main job during the relevant period using OECD and SPS data, respectively. Both figures show a decreasing trend in usual hours worked in Chile and a sharp drop after January 2005, which can be explained mainly by the implementation of the labour reform. Similarly, in Table 2.3, which uses the 46-48 hours treatment definition, I show trends of the usual workweek duration over the analysed period by treatment status. A clear drop in the usual weekly hours is observed in the treatment group at the third survey, while workers not affected by the new law remain relatively constant over time. Naturally, a more significant reduction in hours in the treatment group is observed in Table 2.10, which uses the 46-60 hours range. Additionally, in Table 2.4, I provide evidence in favour of the parallel trend assumption for job characteristics that are considered to be associated with workers' health. Column 1 shows the estimates when the outcome is the percentage of workers who are economically active, providing evidence about transitions from and to inactivity. Columns 2 and 3 show the percentage of workers participating in industries where they are more likely to work in risky activities- such as construction or agriculture. I find no significant effect in the interacted coefficient between year and treatment status before 2004, which indicates that the composition of these characteristics among the treatment and control groups evolved similarly before the compulsory cut in working hours became effective.

Table 2.5 shows the mean of usual working hours, labour income, and health outcomes by treatment status before and after the reform. Regarding labour income, as mentioned previously, in September 2004, the Ministry of Labour made effective a regulation indicating that regardless of the remuneration scheme, the employer must maintain the same remuneration of its workers as that prior to the reform. While this may be true for workers who remained in the same job after the reform, it is not necessarily true for workers who changed jobs. Therefore, empirically, it is crucial to provide evidence that the effect of the reform on health outcomes is not driven by differential changes in remunerations between the treated and controls. The results in Table 2.5 show that for both the treatment and controls there is an increase in the log of labour income after the compulsory cut was implemented, which explains the non-significant effect shown in the next section when estimating the ATT.

Table 2.3: Usual working hours per week

	Worked 43-45 h, SPS 1 (2002)					Worked 46-48 h, SPS 1 (2002)							
	Mean	SD	25^{th}	50^{th}	70^{th}	Mean	SD	25^{th}	50^{th}	70^{th}	Diff.	Std. Error	Obs.
1998	44.17	4.47	44	44	45	48.40	4.37	48	48	48	-4.237***	0.277	2075
2000	44.46	3.49	44	44	45	48.16	2.86	48	48	48	-3.706***	0.184	2128
2002 - SPS 1	44.98	3.32	44	44	46	47.99	3.53	47	48	48	-3.017***	0.215	2175
2005 - SPS 2	44.28	9.08	44	44	45	46.18	7.65	45	45	48	-1.898***	0.488	2133
2007 - SPS 3	44.66	7.32	44	45	45	46.21	7.35	45	45	47	-1.547***	0.451	2175

Notes: The table shows summary statistics of the usual working hours per week by treatment status. *** indicates statistical significance at the 1% level.

Table 2.4: Test for parallel trends

		Industry	
	Economically Active	Agriculture, Hunting, Forestry, Fishing, Mining and Quarrying	Construction
	(1)	(2)	(3)
2000	1.203*	-0.246	-0.405
	(0.683)	(0.257)	(0.319)
2001	2.942***	-0.243	-0.728
	(1.007)	(0.257)	(0.467)
2002	2.996***	0.162	-0.270
	(1.065)	(0.546)	(0.737)
2003	2.403**	0.566	-0.593
	(1.200)	(0.991)	(1.241)
2004	2.484**	0.647	-0.647
	(1.172)	(0.998)	(1.302)
2005	2.403**	1.402	0.189
	(1.192)	(1.059)	(1.334)
2006	2.376**	1.214	0.512
	(1.174)	(1.042)	(1.259)
2007	2.780**	1.294	-0.351
	(1.130)	(0.906)	(1.330)
Treatment × 2000	-0.445	0.056	0.379
	(0.721)	(0.339)	(0.421)
Treatment × 2001	-1.072	0.389	0.620
	(1.059)	(0.413)	(0.622)
Treatment × 2002	-1.173	0.244	0.310
	(1.125)	(0.669)	(0.878)
Treatment × 2003	-1.459	-0.433	0.455
	(1.276)	(1.168)	(1.407)
Treatment × 2004	-1.491	-0.545	0.549
	(1.247)	(1.174)	(1.468)
Treatment × 2005	-0.936	-2.211*	0.142
	(1.260)	(1.246)	(1.486)
Treatment × 2006	-0.972	-2.022	-0.262
	(1.244)	(1.234)	(1.424)
Treatment × 2007	-1.804	-1.741	1.907
	(1.206)	(1.107)	(1.491)
Workers	2175	2175	2175
Observations	19562	19562	19562

Notes: The table estimates of individual fixed effects regression to test parallel trends for outcomes that are associated with worker's health. Robust standard error are shown in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level.

Concerning health outcomes, workers in the treatment and control groups differ in their smoking behaviour but show similar rates of exercise before the reform, as shown in Tables 2.5 and 2.12. In particular, workers in the treatment group are more likely to smoke and report more cigarettes consumption per day before the reform, as compared to workers in the control group. Workers in both the control and treatment groups show a similar level of engagement in physical activities before the reform. This contrasts with what is observed for Self-Assessed Health, which is higher for workers in the control group before the reform. In the post-reform period, workers in the treated group experienced a decrease in tobacco use while the number of cigarettes smoked per day remains at relatively the same level as before the reform. In control workers smoking behaviours remain similar to before the reform. Regarding sedentary behaviour, I observe that the frequency of exercise increases by more among the treated workers than among the control workers after the reform. In terms of Self-Assessed Health, in contrast, the increase in both the treated and control groups is similar after the reform. Overall, this evidence is consistent with a beneficial change towards more healthy behaviours being induced by the reform. In the next section, I provide the results of the causal analysis of the effects.

Table 2.5: Estimates of hours, wages and health outcomes in control and treatment groups, before and after the reform

	Before		After	
Variable	Treated	Control	Treated	Control
Panel A. Hours and labour income				
Hours	48.0	44.2	46.3	44.2
Log Labour Income	5.2	5.7	5.5	5.9
Panel B. Smoking and sedentary behaviours				
Smoking behaviours				
Current Smoker (%)	41.3	35.3	35.1	33.9
Smoke >= 5 cigarettes per day (%)	16.9	14.9	14.9	16.3
Number of Cigarettes per day	2.3	1.9	2.2	2.1
Sedentary behaviours				
Some Exercise (%)	38.4	37.9	43.0	38.8
Exercise at least once per week (%)	31.2	28.8	26.2	25.3
Exercise at least 3 times per week (%)	11.7	12.9	12.8	10.9
Panel C. Self Assesed Health				
Very Good (%)	11.2	15.9	20.4	25.1
Very Good or Good (%)	75.9	80.3	76.8	79.2
Observations	1866	309	1866	309

Notes: The table shows statistics before and after the implementation of the reform. The period before refers to the fist survey and the period after refers to the third survey.

2.6 Results

In this section, I first provide evidence that the policy change reduced the usual weekly hours worked without changing labour income. Then, I report the effect of the shorter workweek on healthy behaviours and SAH. Finally, I discuss the impact of the reform on sub-populations that have previously been analysed in the literature. I present estimates by gender, as well as by the level of education. I estimate the ATT separately for each specific sub-population, using the methods described in the previous section. In section 2.7, I provide evidence that the results are robust to different specifications, matching algorithms and the definition of the treatment and control groups.

2.6.1 The effect of the reform on hours and labour income

Table 2.6 displays the direct effect of the shorter workweek on usual working hours and the logarithm of labour income for the different matching methods. As expected, the estimates across specifications show that the reform caused a significant reduction in working hours. In particular, column 1 shows an estimated reduction for treated workers of around four hours. These estimates show that the decrease in hours occurred without substantial changes in labour income, at least within the sample of workers considered in the analysis, in line with the regulation established by the Ministry of Labour that employers had to maintain the remuneration of their workers.

2.6.2 The effect of the reform on health outcomes

Given that the estimates show no effects of the reform on remuneration, it is now possible to analyse the effect of the reduction in working hours on healthy behaviours and SAH, keeping labour income constant. In Table 2.7, I present the estimates of the effect of the reform on smoking behaviours, sedentary behaviours, and Self-Assessed Health. The estimates show that the reduction in working hours induced by the reform decreased the probability of smoking by 7.7 percentage points, as shown in column 1. Furthermore, I find that the decline in tobacco use is also observed in regard to the probability of consuming five or more cigarettes per day, and the number of cigarettes consumed per day. While in the former the impact of the reform is negative and significant, around 10.0 percentage points, in the latter the impact is negative but less precisely estimated, around half cigarettes per day.

Table 2.6: Effects of reform on usual hours and labour income

	PSM		NNM		PSM
	NN=1	NN=5	NN=1	NN=5	Kernel
	(1)	(2)	(3)	(4)	(5)
Hours	-4.052	-3.820	-3.536	-3.648	-3.358
	(0.751)***	(1.062)***	(0.784)***	(0.869)***	(0.940)***
	[-5.524,-2.580]	[-5.902,-1.738]	[-5.072,-2.000]	[-5.351,-1.944]	[-5.227,-1.497]
Log Labour Income	0.144	0.068	-0.000	0.036	0.035
	(0.091)	(0.074)	(0.097)	(0.079)	(0.071)
	[-0.035,0.323]	[-0.077,0.214]	[-0.190,0.190]	[-0.118,0.190]	[-0.108,0.168]
Observations	2,143	2,143	2,143	2,143	2,143

Notes: The table shows the coefficient estimated using a difference-in-difference approach combined with propensity score matching. Common support is imposed by dropping observations whose propensity score is higher than the maximum or less than the minimum propensity score of the control. Columns differ by the matching algorithm used with the difference-in-difference. Columns 1 and 2 show estimates using Propensity Score Matching with one and five neighbours, columns 2 and 3 show estimates using Nearest Neighbors Matching using one and five neighbours, and column 6 show estimates using Kernel Propensity Score Matching. Confident intervals and robust standard errors derived by Abadie and Imbens (2006, 2008, 2011) are shown for NN-PSM and NNM estimates. Bootstrapped standard errors, based on 250 replications are shown for K-PSM estimates. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level. The matching is based on variables listed in Table 2.2.

I evaluate the impact of the reform on physical activity by analysing the effect on the probability of doing some exercise, and how frequently workers exercise per week, i.e. once per week or at least three times per week. Both outcomes help to capture changes in sedentary behaviours, i.e. workers who started exercising, and in the intensive margin, workers who moved towards exercising more frequently. Overall, the estimates indicate a positive but non-significant effect on the probability of doing some exercise. I do not find evidence of an impact on the probability of exercising at least once per week or exercising at least three times per week. The impact of the reform on SAH, which I display in Panel B of Table 2.7, shows that workers affected by the reduction in workweek hours did not experience changes in the evaluation of their health. While the estimates present a decline in the probability of workers assessing their health as “Very Good”, these are non-significant. Similarly, the estimates of the impact on the probability that workers assessed their health as “Good” or “Very Good”, i.e. in the two higher categories of the SAH scale, show non-significant effects.

Table 2.7: Effects of reform on health outcomes

	PSM		NNM		PSM
	NN=1	NN=5	NN=1	NN=5	Kernel
	(1)	(2)	(3)	(4)	(5)
Panel A. Smoking and sedentary behaviours					
Smoking behaviours					
Current Smoker	-0.077	-0.119	-0.085	-0.100	-0.118
	(0.038)**	(0.040)***	(0.041)**	(0.040)**	(0.045)***
	[-0.151,-0.002]	[-0.198,-0.040]	[-0.166,-0.005]	[-0.178,-0.021]	[-0.205,-0.028]
Smoke >= 5 cigarettes per day	-0.099	-0.087	-0.106	-0.105	-0.085
	(0.048)**	(0.042)**	(0.042)**	(0.040)***	(0.045)*
	[-0.193,-0.006]	[-0.169,-0.005]	[-0.189,-0.023]	[-0.184,-0.026]	[-0.165,0.001]
Number of Cigarettes per day	-0.537	-0.667	-0.399	-0.521	-0.734
	(0.415)	(0.358)*	(0.402)	(0.489)	(0.439)*
	[-1.349,0.276]	[-1.368,0.033]	[-1.187,0.390]	[-1.479,0.436]	[-1.486,0.143]
Sedentary behaviours					
Some Exercise	0.054	0.054	0.058	0.032	0.019
	(0.073)	(0.063)	(0.069)	(0.061)	(0.069)
	[-0.088,0.197]	[-0.070,0.178]	[-0.077,0.192]	[-0.088,0.152]	[-0.124,0.139]
Exercise at least once per week	-0.035	0.006	0.009	-0.044	-0.036
	(0.077)	(0.068)	(0.053)	(0.059)	(0.063)
	[-0.186,0.116]	[-0.127,0.138]	[-0.095,0.113]	[-0.160,0.072]	[-0.154,0.078]
Exercise at least 3 times per week	0.038	0.046	0.070	0.028	0.044
	(0.070)	(0.058)	(0.063)	(0.056)	(0.052)
	[-0.099,0.175]	[-0.068,0.161]	[-0.053,0.194]	[-0.082,0.138]	[-0.057,0.135]
Panel B. Self Assesed Health					
Very Good	-0.064	-0.076	-0.034	-0.019	-0.086
	(0.054)	(0.050)	(0.056)	(0.059)	(0.055)
	[-0.170,0.042]	[-0.174,0.022]	[-0.144,0.075]	[-0.136,0.097]	[-0.243,0.006]
Very Good or Good	-0.084	-0.024	0.062	0.053	-0.005
	(0.104)	(0.065)	(0.048)	(0.053)	(0.059)
	[-0.288,0.120]	[-0.151,0.103]	[-0.032,0.156]	[-0.051,0.157]	[-0.144,0.099]
Observations	2,143	2,143	2,143	2,143	2,143

Notes: The table shows the coefficient estimated using a difference-in-difference approach combined with propensity score matching. Common support is imposed by dropping observations whose propensity score is higher than the maximum or less than the minimum propensity score of the control. Columns differ by the matching algorithm used with the difference-in-difference. Columns 1 and 2 show estimates using Propensity Score Matching with one and five neighbours, columns 2 and 3 show estimates using Nearest Neighbors Matching using one and five neighbours, and column 6 show estimates using Kernel Propensity Score Matching. Confident intervals and robust standard errors derived by Abadie and Imbens (2006, 2008, 2011) are shown for NN-PSM and NNM estimates. Bootstrapped standard errors, based on 250 replications are shown for K-PSM estimates. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level. The matching is based on variables listed in Table 2.2.

2.6.3 Impact of the reform on sub-populations: gender and education

In this section, I report the impact of the reform on specific subpopulations following previous literature on the effect of working hours on health outcomes. In particular, I first describe the impact on men and women, and then on workers with and without tertiary education. Tertiary education in Chile is defined as having a degree or spending more than one year in either a technical-professional institute or at university.

Before discussing the effect of the reform on health outcomes, I show estimates of the impact of the reform on hours and labour income. Table 2.9 shows the estimated effects when the treatment is defined as 46-48 hours per week. I show estimates of NN-PSM with one neighbour, which concur with the estimates in column 1 of Table 2.7.

2.6.3.1 Impact on hours and labour income

For a comparison with the main estimates, column 1 of Table 2.8 shows results for all workers. In the same table, columns 2 and 3 show estimates for men and women, while columns 4 and 5 show estimates for low and high educational groups. The results show that the impact of the reform was higher among men and workers without tertiary education. In particular, men working 46-48 hours before the reform reduced their usual workweek duration by around 4.5 hours. Similarly, the estimated impact for workers without tertiary education is just under 6 hours. Interestingly, as shown in column 3, these results are smaller for women, whose usual workweek hours reduced by only under 2 hours. As mentioned previously, besides evaluating the impact of the reform on working hours, it is necessary to analyse its effect on labour income, ensuring that the estimated impacts on health outcomes are not affected by variations in remuneration. Except for workers with tertiary education, I find no effect on the log of labour income. For this reason, in the next sub-section I discuss only estimates by gender and workers without tertiary education.

Table 2.8: Effects of reform on usual hours and labour income by gender and education

		Gender		Education	
	All	Men	Women	Low	High
	(1)	(2)	(3)	(4)	(5)
Hours	-4.052	-4.513	-1.799	-5.696	-0.617
	(0.751)***	(1.920)**	(1.121)	(1.742)***	(1.243)
	[-5.524,-2.580]	[-8.277,-0.749]	[-3.995,0.398]	[-9.110,-2.282]	[-3.054,1.820]
Log Labour Income	0.144	0.139	0.019	0.127	-0.197
	(0.091)	(0.118)	(0.018)	(0.096)	(0.058)***
	[-0.035,0.323]	[-0.092,0.369]	[-0.017,0.055]	[-0.062,0.316]	[-0.311,-0.084]
Observations	2,143	1,479	587	1,620	529

Notes: The table shows the coefficient estimated using a difference-in-difference approach combined with Nearest Neighbour Propensity Score Matching with one neighbour. Common support is imposed by dropping observations whose propensity score is higher than the maximum or less than the minimum propensity score of the control. Column 1 estimates for all workers, similar to column 1 in Table 2.6. Columns 2 and 3 show results for men and women, respectively. Column 4 present refers to workers without tertiary education, and column 5 refers to workers with tertiary education. Confident intervals and robust standard errors derived by Abadie and Imbens (2006, 2008, 2011) are shown. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level. The matching is based on variables listed in Table 2.2.

2.6.3.2 Impact on health outcomes

For men, even though the reform reduced the workweek by just under five hours (column 2 of Table 2.9), the only significant impact found is observed on the probability of tobacco use, which reduced by 11.3 percentage points. In contrast, the estimates of the reduction of the compulsory cut in working hours among women reveal a consistent pattern of objective health improvements. Women workers affected by the policy reduced the probability of tobacco use by 6.2 percentage points and increased the probability of exercising by 13.8 percentage points. Similarly, the reform reduced the probability of smoking five or more cigarettes per day by 23.3 percentage points. And, the reform increased by 17.3 and 19.9 the probability of exercising at least once per week and at least three times per week, respectively.

Table 2.9: Effects of reform on health outcomes by gender and education

		Gender		Education	
	All	Men	Women	Low	High
	(1)	(2)	(3)	(4)	(5)
Panel A. Smoking and sedentary behaviours					
Smoking behaviours					
Current Smoker	-0.077	-0.113	-0.062	-0.259	-0.037
	(0.038)**	(0.043)***	(0.028)**	(0.065)***	(0.044)
	[-0.151,-0.002]	[-0.197,-0.029]	[-0.117,-0.008]	[-0.386,-0.132]	[-0.122,0.049]
Smoke >= 5 cigarettes per day	-0.099	-0.046	-0.233	-0.227	-0.038
	(0.048)**	(0.029)	(0.037)***	(0.065)***	(0.047)
	[-0.193,-0.006]	[-0.103,0.011]	[-0.305,-0.160]	[-0.355,-0.100]	[-0.130,0.054]
Number of Cigarettes per day	-0.537	-0.356	-0.665	-2.462	-0.520
	(0.415)	(0.284)	(0.058)***	(1.050)**	(0.440)
	[-1.349,0.276]	[-0.911,0.200]	[-0.779,-0.551]	[-4.520,-0.405]	[-1.382,0.343]
Sedentary behaviours					
Some Exercise	0.054	-0.036	0.138	0.068	0.009
	(0.073)	(0.099)	(0.056)**	(0.050)	(0.088)
	[-0.088,0.197]	[-0.230,0.158]	[0.029,0.247]	[-0.030,0.167]	[-0.164,0.181]
Exercise at least once per week	-0.035	-0.068	0.173	0.021	-0.010
	(0.077)	(0.082)	(0.046)***	(0.079)	(0.075)
	[-0.186,0.116]	[-0.229,0.092]	[0.082,0.264]	[-0.134,0.176]	[-0.157,0.137]
Exercise at least 3 times per week	0.038	0.064	0.199	0.071	-0.023
	(0.070)	(0.076)	(0.039)***	(0.052)	(0.058)
	[-0.099,0.175]	[-0.085,0.214]	[0.122,0.276]	[-0.031,0.174]	[-0.137,0.091]
Panel B. Self Assesed Health					
Very Good	-0.064	-0.031	0.227	-0.063	0.006
	(0.054)	(0.065)	(0.148)	(0.071)	(0.065)
	[-0.170,0.042]	[-0.159,0.097]	[-0.063,0.517]	[-0.202,0.076]	[-0.122,0.134]
Very Good or Good	-0.084	0.021	-0.097	0.051	-0.096
	(0.104)	(0.090)	(0.149)	(0.097)	(0.045)**
	[-0.288,0.120]	[-0.154,0.197]	[-0.390,0.195]	[-0.139,0.240]	[-0.184,-0.008]
Observations	2,143	1,479	587	1,620	529

Notes: The table shows the coefficient estimated using a difference-in-difference approach combined with Nearest Neighbour Propensity Score Matching with one neighbour. Common support is imposed by dropping observations whose propensity score is higher than the maximum or less than the minimum propensity score of the control. Column 1 estimates for all workers, similar to column 1 in Table 2.7. Columns 2 and 3 show results for men and women, respectively. Column 4 present refers to workers without tertiary education, and column 5 refers to workers with tertiary education. Confident intervals and robust standard errors derived by Abadie and Imbens (2006, 2008, 2011) are shown. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level. The matching is based on variables listed in Table 2.2.

Although the reduction in standard working hours was associated with improvements in health behaviours among women, and to some extent among men, I do not find that the reform had a significant impact on Self-Assessed Health.

Columns 4 and 5 of Table 2.9 show the effects by education level. Overall, the results suggest that the reduction in the standard working hours had positive effects on changing smoking behaviours among low educated workers. In particular, it decreased the probability of smoking by 25.9 percentage points and the probability of smoking five or more cigarettes per week by 22.7 percentage points. Regarding physical activity, the impact of the reform increased the probability of exercising by 6.8 and 9.8 percentage points when the treatment is defined as 46-48 hours and 46-60 hours, respectively. However, only the former is significant (column 4 in Table 2.9). In Panel B of Table 2.16, estimates of the impacts on SAH show that among low educated workers, the reform decreased the probability of assessing your health as "Very Good" by 14.2 percentage points. However, I do not find an effect when the two higher categories of SAH scale are grouped, i.e. "Good" and "Very Good".

2.7 Robustness

To test the sensitivity of my main results, I perform a battery of robustness analyses that change the specification of the propensity score algorithm, the model specification, and the definition of the control and treatment groups. I show that the main ATT estimates remain relatively unchanged across the different specifications.

2.7.1 Matching algorithm

Tables 2.7 and 2.14 show estimates of the effect of the reform using different matching methods. Table 2.7 shows the results when the treatment is defined using the 46-48 hours range, and Table 2.14 shows the results using the 46-60 hours range. Columns 1 and 2 display estimates using NN-PSM with one and five neighbours. Columns 3-4 show estimates that, instead of matching on the propensity score, are based on Nearest Neighbour Matching. Column 5 displays estimates based on Kernel PSM. When compared with column 1, i.e. the preferred specification, the estimates in columns 2-5 provide evidence that the results do not vary when different matching algorithms are used. In particular, negative and significant estimates of the impact of the reform on tobacco use remain unchanged across the specifications, and the policy's impact on sedentary behaviours and SAH remains consistently non-significant.

2.7.2 Definition of treatment and control group

I change the definition of the treatment and control groups by narrowing and widening the range of hours in each group, respectively. First, I redefine the treatment group by including workers who indicated that they worked overtime, i.e. 46-60 hours per week in January 2002. In Table 2.13, I show estimates of the impact of the reform on hours and the logarithm of labour income, and in Table 2.14, I show the results of the impact on health outcomes. As expected, when overtime hours are considered, the reduction in hours is slightly larger than when only standard hours are used in the definition of the treatment group, i.e. 46-48 hours. Importantly, I find no effect on labour income when I use the treatment definition that uses overtime hours.

Regarding the impact of the reform on health outcomes, the magnitude and significance of the estimates, as shown in Table 2.14 vis a vis 2.7, remain relatively unchanged. Similarly, Tables 2.24 and 2.25 show estimates using the definitions of the treatment group as previously described but changing the definition of the control group considering individuals who worked between 41-45 hours in January 2002.[27] The estimates of the impact of the reform on health behaviours and SAH are similar to those when the control group is defined using the 44-45 hours range, which provides evidence that the main effect on smoking behaviours is not driven by the definitions of the control and treatment groups.

2.7.3 Model specification

In Table 2.17, I show estimates of ATT that do not use propensity score matching, but instead use linear and non-linear difference-in-difference models. Columns 1-3 show estimates when the treatment is defined using the 46-48 hours range,

[27] The main impacts remain similar when the control group is defined using individuals who worked between 40-45 hours in January 2002.

and columns 4-6 show estimates when it is defined using the 46-60 hours range. Columns 1 and 4 show estimates based on a fixed effects (FE) regression, columns 2 and 5 show estimates based on a OLS regression controlling for the variables listed in Table 2.2, and columns 3 and 6 show estimates based on a Probit difference-in-difference as defined by Athey and Imbens (2006) and Puhani (2012).[28] In all of the specifications, I restrict the sample to workers who remained in the common support as defined in the previous sections. Similarly, I estimate the ATT for the sub-populations included in the analysis, i.e. men and women, and workers with and without tertiary education. For both definitions of the treatment, the FE, OLS and Probit estimates are shown, respectively, in Tables 2.18-2.19, Tables 2.20-2.21, and Tables 2.22-2.23. Overall, the results are similar to the estimates based on matching methods. The reform had a negative and significant impact on tobacco use; however, the point estimates of smoking behaviours are lower than the estimates based on matching methods. Across the different specifications, the reduction in smoking behaviours is mainly observed among women and workers without tertiary education, and I do not find an impact on SAH.

2.8 Conclusion

Most of the economics literature and policy debates have been focused on the effect of a reduction in working hours on employment creation and productivity; however, little emphasis has been placed on its impact on individuals' health. The overwhelming correlational evidence that long working hours are associated with cardiovascular disease and stroke, together with the fact that smoking and sedentary behaviours are relevant mediators of this association, contrast with the lack of causal evidence in this area. Quasi-experimental research designs in the past years have provided evidence regarding the detrimental effect of working prolonged hours on workers' health. However, this literature has focused only on industrialized countries, which have more robust labour markets and improved underlying population health than the rest of the world. In this context, studying the Chilean case is par-

[28] For more details see equation (10) in Puhani (2012).

ticularly interesting due to its high prevalence of tobacco use (33,4%), sedentary lifestyle (86,7%), and deaths attributable to cardiovascular diseases (27.5%). Additionally, the Chilean labour reform allows for isolating the reduction in working hours from other policy changes, such as changes in remuneration.

In this study, I evaluate the impact of the reduction — from 48 to 45 hours— in the standard workweek in Chile on smoking behaviours, physical activity, and the Self-Assessed Health of workers. I find that the reform reduced the probability of smoking by 7.7 percentage points, which implies a reduction in tobacco use among workers from 40% to approximately 32%. Furthermore, I find evidence that the policy decreased the probability of smoking five or more cigarettes per day by around 9.9 percentage points. In contrast, I find that the reform did not affect the frequency with which workers exercise. A similar null result is observed regarding the impact of the reform on Self-Assessed Health. Overall, these results are consistent across changes in the matching algorithm, as well as model specifications and the definition of the treatment and control groups.

The impact of the three hours reduction in working hours on specific subpopulations provides evidence of changes towards more healthy behaviours, specifically among working women and workers without tertiary education. For women, the reform reduced the probability of smoking by 6.2 percentage points, while at the same time increasing the probability of exercising by 13.8 percentage points. In the analysis of smoking and physical activity at the intensive margin, I find that the reform reduced the probability of smoking five or more cigarettes per day by 23.3 percentage points and increased the probability of exercising at least three times per week by 19.9 percentage points. The effects on smoking behaviours among workers without tertiary education were considerable too. The probability of tobacco use was around 25.9 percentage points lower after the reform. I find similar results for this group of workers when I evaluate the effects on the probability of smoking five or more cigarettes per day and the number of cigarettes per day, where I find a reduction of 22.7 percentage points and 2.2 cigarettes. Among women and workers without tertiary education, I find null effects for Self-Assessed Health. Overall, these results point to the relevance of evaluating the broader impacts of labour reforms on outcomes and sub-populations that are not directly targeted. Furthermore, my research suggests that public programmes that help to reduce the time-constraints within the household, such as universal childcare programmes, or that reduce the perceived cost of exercising among women, have the potential to improve health in the long run.

2.9 Appendix of chapter 2

2.9.1 Additional figures and tables of chapter 2

Table 2.10: Average usual time at work per week. Treatment 46-60 hours

	Worked 43-45 h, SPS 1 (2002)					Worked 46-60 h, SPS 1 (2002)							
	Mean	SD	25^{th}	50^{th}	70^{th}	Mean	SD	25^{th}	50^{th}	70^{th}	Diff.	Std. Error	Obs.
1998	44.17	4.47	44	44	45	48.40	4.37	48	48	48	-4.237***	0.277	2075
2000	44.46	3.49	44	44	45	48.16	2.86	48	48	48	-3.706***	0.184	2128
2002 - SPS 1	44.98	3.32	44	44	46	47.99	3.53	47	48	48	-3.017***	0.215	2175
2005 - SPS 2	44.28	9.08	44	44	45	46.18	7.65	45	45	48	-1.898***	0.488	2133
2007 - SPS 3	44.66	7.32	44	45	45	46.21	7.35	45	45	47	-1.547***	0.451	2175

Notes: The table shows summary statistics of the usual working hours per week by treatment status. *** indicates statistical significance at the 1% level.

Table 2.11: Comparison of characteristics across matched and unmatched samples. Treatment 46-60 hours

Variable	Unmatched Sample Treated	Control	Difference	p-value	Matched Sample Treated	Control	Difference	p-value
Male	0.751	0.498	0.252	0.000	0.748	0.733	0.015	0.784
Age	39.096	41.084	-1.988	0.001	39.189	39.687	-0.498	0.651
Education								
No education or pre school	0.005	0.016	-0.012	0.111	0.004	0.055	-0.051	0.117
First level or Differential level	0.286	0.084	0.202	0.000	0.275	0.208	0.067	0.334
Second level: Scientific-Humanist	0.326	0.233	0.093	0.000	0.331	0.309	0.022	0.704
Second level: Technical-Professional	0.174	0.104	0.071	0.000	0.177	0.216	-0.039	0.510
Third level: Technical-Professional Institute	0.137	0.159	-0.022	0.320	0.139	0.133	0.006	0.864
Third level: College or Postgraduate	0.072	0.405	-0.332	0.000	0.074	0.079	-0.005	0.840
Children ages 0-18 in household	1.173	1.042	0.131	0.052	1.156	1.087	0.069	0.676
Marital Status								
Single	0.202	0.220	-0.018	0.460	0.202	0.146	0.056	0.155
Regions								
Metropolitan Region	0.456	0.417	0.038	0.198	0.457	0.451	0.006	0.930
North	0.105	0.071	0.034	0.033	0.100	0.113	-0.013	0.775
Center	0.331	0.285	0.046	0.092	0.333	0.289	0.045	0.516
South	0.108	0.227	-0.119	0.000	0.110	0.147	-0.038	0.405
Occupation								
Professionals	0.027	0.294	-0.268	0.000	0.027	0.023	0.005	0.623
Technicians and associate professionals	0.075	0.162	-0.087	0.000	0.076	0.089	-0.013	0.653
Clerical support workers	0.150	0.207	-0.057	0.018	0.152	0.153	-0.000	0.991
Service and sales workers	0.146	0.107	0.039	0.038	0.149	0.130	0.019	0.631
Skilled agricultural forestry and fishery workers	0.064	0.006	0.058	0.000	0.061	0.102	-0.040	0.559
Craft and related trades workers	0.197	0.065	0.132	0.000	0.198	0.196	0.002	0.974
Plant, machine operators and assemblers	0.149	0.052	0.097	0.000	0.151	0.123	0.028	0.507
Elementary occupations	0.156	0.094	0.063	0.001	0.148	0.165	-0.017	0.744
Industry								
Agriculture, Hunting, Forestry, Fishing, Mining and Quarrying	0.138	0.019	0.118	0.000	0.124	0.132	-0.008	0.904
Manufacturing	0.232	0.071	0.161	0.000	0.236	0.256	-0.020	0.728
Construction, Electricity, Gas and Water supply	0.115	0.036	0.079	0.000	0.116	0.126	-0.010	0.828
Commerce, Hotels and Restaurants	0.208	0.058	0.150	0.000	0.211	0.238	-0.027	0.644
Transport and Communications	0.079	0.039	0.040	0.001	0.080	0.048	0.032	0.109
Financial Intermediation	0.074	0.097	-0.023	0.198	0.076	0.048	0.027	0.058
Public, Social and Personal Services	0.118	0.670	-0.552	0.000	0.120	0.132	-0.012	0.672
Months employed between Dec 1997 and Dec 2001	46.389	47.058	-0.669	0.096	46.463	46.209	0.254	0.775
Unionized	0.111	0.288	-0.177	0.000	0.113	0.109	0.005	0.896
Attended the doctor for an emergency consultation	0.162	0.162	-0.000	1.000	0.165	0.174	-0.010	0.841
Attended the doctor for hospitalization	0.083	0.110	-0.027	0.141	0.084	0.057	0.027	0.248
Observations	2,435	309			2,394	309		
Mean absolute standardized bias			29.552				6.336	
Median absolute standardized bias			20.499				7.307	
Pseudo R2			0.343				0.036	

Notes: The table shows descriptive statistics of individual characteristics in the sample. All variables, with the exception of occupation, industry, and union status, are recorded at the 2002 interview. The variables occupation, industry, and union status are measured in January 2001. Columns 1 and 2 show the mean of the control and treatment groups. Column 3 shows difference between means of Treated and Control groups and column 4 refer to two-sided p-value.

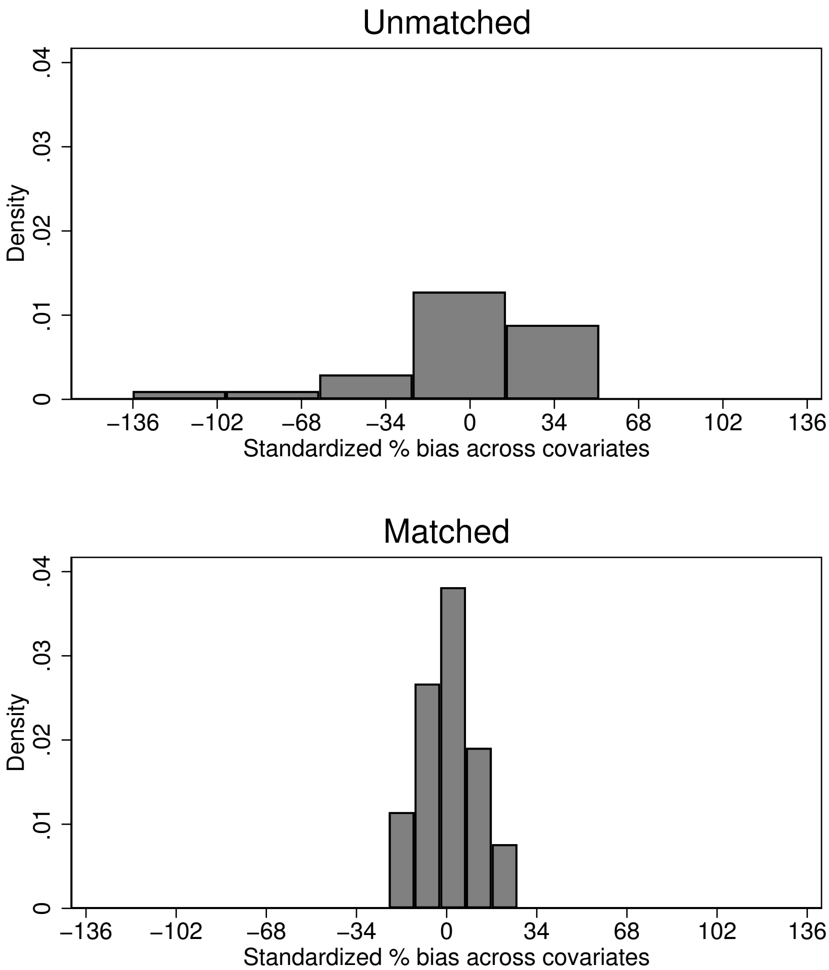

Figure 2.10: Standardised Percentage Bias Across Covariates. Treatment 46-60 hours

Notes: The figure shows the distribution of the standardised percentage bias across covariates before and after matching.

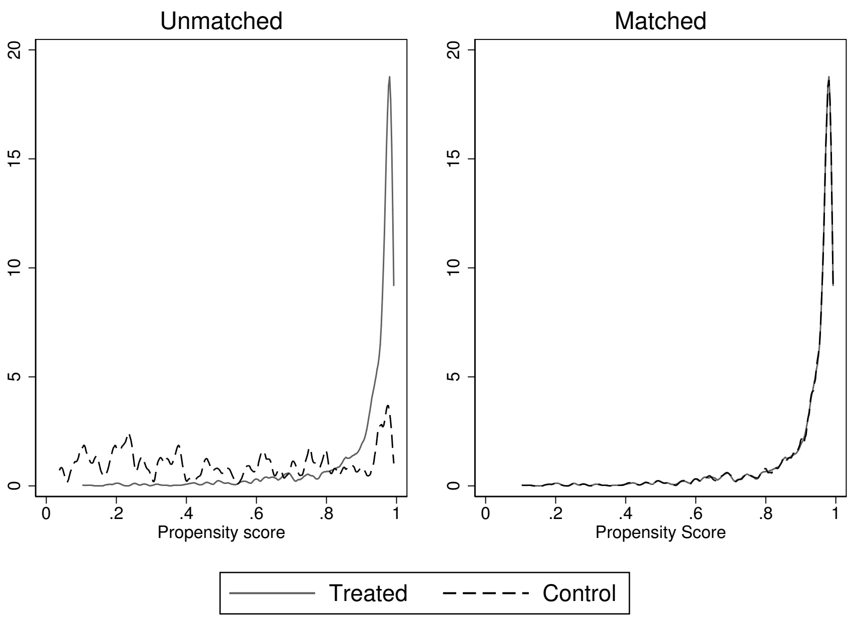

Figure 2.11: Kernel Density Estimates of the Propensity Score. Treatment 46-60

Notes: The figure shows kernel density estimates of the propensity score before and after matching.

Table 2.12: Estimates of hours, wages and health outcomes in control and treatment groups, before and after the reform. Treatment 46-60 hours

	Before		After	
Variable	Treated	Control	Treated	Control
Panel A. Hours and labour income				
Hours	49.5	44.2	46.7	44.2
Log Labour Income	5.3	5.7	5.5	5.9
Panel B. Smoking and sedentary behaviours				
Smoking behaviours				
Current Smoker (%)	42.2	35.3	37.1	33.9
Smoke >= 5 cigarettes per day (%)	17.9	14.9	16.6	16.3
Number of Cigarettes per day	2.4	1.9	2.3	2.1
Sedentary behaviours				
Some Exercise (%)	38.4	37.9	42.9	38.8
Exercise at least once per week (%)	31.4	28.8	25.9	25.3
Exercise at least 3 times per week (%)	11.3	12.9	12.0	10.9
Panel C. Self Assesed Health				
Very Good (%)	12.0	15.9	20.1	25.1
Very Good or Good (%)	75.4	80.3	76.8	79.2
Observations	2435	309	2435	309

Notes: The table shows statistics before and after the implementation of the reform. The period before refers to the fist survey and the period after refers to the third survey.

Table 2.13: Effects of reform on usual hours and labour income. Treatment 46-60 hours

	PSM		NNM		PSM
	NN=1	NN=5	NN=1	NN=5	Kernel
	(1)	(2)	(3)	(4)	(5)
Hours	-4.344	-4.852	-4.879	-4.855	-4.389
	(1.271)***	(1.410)***	(0.821)***	(0.889)***	(0.934)***
	[-6.835,-1.853]	[-7.616,-2.088]	[-6.488,-3.271]	[-6.598,-3.112]	[-6.467,-2.481]
Log Labour Income	0.030	0.054	0.009	0.041	0.026
	(0.102)	(0.079)	(0.101)	(0.081)	(0.070)
	[-0.170,0.229]	[-0.101,0.209]	[-0.188,0.206]	[-0.119,0.200]	[-0.107,0.169]
Observations	2,703	2,703	2,703	2,703	2,703

Notes: The table shows the coefficient estimated using a difference-in-difference approach combined with propensity score matching. Common support is imposed by dropping observations whose propensity score is higher than the maximum or less than the minimum propensity score of the control. Columns differ by the matching algorithm used with the difference-in-difference. Columns 1 and 2 show estimates using Propensity Score Matching with one and five neighbours, columns 2 and 3 show estimates using Nearest Neighbors Matching using one and five neighbours, and column 6 show estimates using Kernel Propensity Score Matching. Confident intervals and robust standard errors derived by Abadie and Imbens (2006, 2008, 2011) are shown for NN-PSM and NNM estimates. Bootstrapped standard errors, based on 250 replications are shown for K-PSM estimates. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level. The matching is based on variables listed in Table 2.2.

Table 2.14: Effects of reform on health outcomes. Treatment 46-60 hours

	PSM		NNM		PSM
	NN=1	NN=5	NN=1	NN=5	Kernel
	(1)	(2)	(3)	(4)	(5)
Panel A. Smoking and sedentary behaviours					
Smoking behaviours					
Current Smoker	-0.122	-0.109	-0.079	-0.091	-0.105
	(0.045)***	(0.044)**	(0.042)*	(0.041)**	(0.046)**
	[-0.209,-0.035]	[-0.196,-0.023]	[-0.162,0.003]	[-0.172,-0.011]	[-0.193,-0.024]
Smoke >= 5 cigarettes per day	-0.101	-0.088	-0.105	-0.100	-0.078
	(0.035)***	(0.042)**	(0.044)**	(0.042)**	(0.044)*
	[-0.169,-0.032]	[-0.170,-0.006]	[-0.191,-0.019]	[-0.182,-0.019]	[-0.160,0.015]
Number of Cigarettes per day	-0.973	-0.701	-0.462	-0.528	-0.709
	(0.440)**	(0.328)**	(0.415)	(0.494)	(0.437)
	[-1.835,-0.111]	[-1.345,-0.058]	[-1.276,0.352]	[-1.497,0.440]	[-1.599,0.261]
Sedentary behaviours					
Some Exercise	0.078	0.065	0.045	0.028	0.024
	(0.069)	(0.072)	(0.069)	(0.061)	(0.068)
	[-0.058,0.214]	[-0.076,0.207]	[-0.090,0.180]	[-0.091,0.147]	[-0.119,0.135]
Exercise at least once per week	-0.022	-0.006	0.003	-0.059	-0.038
	(0.070)	(0.067)	(0.059)	(0.059)	(0.063)
	[-0.160,0.116]	[-0.138,0.126]	[-0.112,0.118]	[-0.174,0.056]	[-0.162,0.094]
Exercise at least 3 times per week	-0.011	0.046	0.066	0.012	0.037
	(0.065)	(0.061)	(0.063)	(0.056)	(0.051)
	[-0.138,0.117]	[-0.073,0.165]	[-0.058,0.190]	[-0.097,0.121]	[-0.075,0.137]
Panel B. Self Assesed Health					
Very Good	-0.095	-0.060	-0.054	-0.030	-0.101
	(0.038)**	(0.046)	(0.061)	(0.061)	(0.055)*
	[-0.169,-0.020]	[-0.151,0.031]	[-0.173,0.064]	[-0.149,0.089]	[-0.213,-0.015]
Very Good or Good	0.052	-0.002	0.061	0.041	0.002
	(0.069)	(0.071)	(0.047)	(0.053)	(0.055)
	[-0.084,0.188]	[-0.141,0.137]	[-0.031,0.154]	[-0.064,0.145]	[-0.122,0.106]
Observations	2,703	2,703	2,703	2,703	2,703

Notes: The table shows the coefficient estimated using a difference-in-difference approach combined with propensity score matching. Common support is imposed by dropping observations whose propensity score is higher than the maximum or less than the minimum propensity score of the control. Columns differ by the matching algorithm used with the difference-in-difference. Columns 1 and 2 show estimates using Propensity Score Matching with one and five neighbours, columns 2 and 3 show estimates using Nearest Neighbors Matching using one and five neighbours, and column 6 show estimates using Kernel Propensity Score Matching. Confident intervals and robust standard errors derived by Abadie and Imbens (2006, 2008, 2011) are shown for NN-PSM and NNM estimates. Bootstrapped standard errors, based on 250 replications are shown for K-PSM estimates. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level. The matching is based on variables listed in Table 2.2.

Table 2.15: Effects of reform on usual hours and labour income by gender and education. Treatment 46-60 hours

		Gender		Education	
	All	Men	Women	Low	High
	(1)	(2)	(3)	(4)	(5)
Hours	-4.344	-4.513	-1.799	-5.696	-0.617
	(1.271)***	(1.920)**	(1.121)	(1.742)***	(1.243)
	[-6.835,-1.853]	[-8.277,-0.749]	[-3.995,0.398]	[-9.110,-2.282]	[-3.054,1.820]
Log Labour Income	0.030	0.139	0.019	0.127	-0.197
	(0.102)	(0.118)	(0.018)	(0.096)	(0.058)***
	[-0.170,0.229]	[-0.092,0.369]	[-0.017,0.055]	[-0.062,0.316]	[-0.311,-0.084]
Observations	2,703	1,479	587	1,620	529

Notes: The table shows the coefficient estimated using a difference-in-difference approach combined with Nearest Neighbour Propensity Score Matching with one neighbour. Common support is imposed by dropping observations whose propensity score is higher than the maximum or less than the minimum propensity score of the control. Column 1 estimates for all workers, similar to column 1 in Table 2.13. Columns 2 and 3 show results for men and women, respectively. Column 4 present refers to workers without tertiary education, and column 5 refers to workers with tertiary education. Confident intervals and robust standard errors derived by Abadie and Imbens (2006, 2008, 2011) are shown. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level. The matching is based on variables listed in Table 2.11.

Table 2.16: Effects of reform on health outcomes by gender and education. Treatment 46-60 hours

		Gender		Education	
	All	Men	Women	Low	High
	(1)	(2)	(3)	(4)	(5)
Panel A. Smoking and sedentary behaviours					
Smoking behaviours					
Current Smoker	-0.122	-0.113	-0.062	-0.259	-0.037
	(0.045)***	(0.043)***	(0.028)**	(0.065)***	(0.044)
	[-0.209,-0.035]	[-0.197,-0.029]	[-0.117,-0.008]	[-0.386,-0.132]	[-0.122,0.049]
Smoke >= 5 cigarettes per day	-0.101	-0.046	-0.233	-0.227	-0.038
	(0.035)***	(0.029)	(0.037)***	(0.065)***	(0.047)
	[-0.169,-0.032]	[-0.103,0.011]	[-0.305,-0.160]	[-0.355,-0.100]	[-0.130,0.054]
Number of Cigarettes per day	-0.973	-0.356	-0.665	-2.462	-0.520
	(0.440)**	(0.284)	(0.058)***	(1.050)**	(0.440)
	[-1.835,-0.111]	[-0.911,0.200]	[-0.779,-0.551]	[-4.520,-0.405]	[-1.382,0.343]
Sedentary behaviours					
Some Exercise	0.078	-0.036	0.138	0.068	0.009
	(0.069)	(0.099)	(0.056)**	(0.050)	(0.088)
	[-0.058,0.214]	[-0.230,0.158]	[0.029,0.247]	[-0.030,0.167]	[-0.164,0.181]
Exercise at least once per week	-0.022	-0.068	0.173	0.021	-0.010
	(0.070)	(0.082)	(0.046)***	(0.079)	(0.075)
	[-0.160,0.116]	[-0.229,0.092]	[0.082,0.264]	[-0.134,0.176]	[-0.157,0.137]
Exercise at least 3 times per week	-0.011	0.064	0.199	0.071	-0.023
	(0.065)	(0.076)	(0.039)***	(0.052)	(0.058)
	[-0.138,0.117]	[-0.085,0.214]	[0.122,0.276]	[-0.031,0.174]	[-0.137,0.091]
Panel B. Self Assesed Health					
Very Good	-0.095	-0.031	0.227	-0.063	0.006
	(0.038)**	(0.065)	(0.148)	(0.071)	(0.065)
	[-0.169,-0.020]	[-0.159,0.097]	[-0.063,0.517]	[-0.202,0.076]	[-0.122,0.134]
Very Good or Good	0.052	0.021	-0.097	0.051	-0.096
	(0.069)	(0.090)	(0.149)	(0.097)	(0.045)**
	[-0.084,0.188]	[-0.154,0.197]	[-0.390,0.195]	[-0.139,0.240]	[-0.184,-0.008]
Observations	2,703	1,479	587	1,620	529

Notes: The table shows the coefficient estimated using a difference-in-difference approach combined with Nearest Neighbour Propensity Score Matching with one neighbour. Common support is imposed by dropping observations whose propensity score is higher than the maximum or less than the minimum propensity score of the control. Column 1 estimates for all workers, similar to column 1 in Table 2.14. Columns 2 and 3 show results for men and women, respectively. Column 4 present refers to workers without tertiary education, and column 5 refers to workers with tertiary education. Confident intervals and robust standard errors derived by Abadie and Imbens (2006, 2008, 2011) are shown. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level. The matching is based on variables listed in Table 2.11.

Table 2.17: Effects of reform on health outcomes, Robustness Analysis

	Treatment 46-48 h			Treatment 46-60 h		
	FE	OLS	Probit	FE	OLS	Probit
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Smoking and sedentary behaviours						
Current Smoker	-0.049**	-0.049**	-0.048**	-0.038	-0.038	-0.036
	(0.024)	(0.024)	(0.024)	(0.023)	(0.023)	(0.024)
Smoke 5 or more cigarettes per day	-0.040*	-0.041*	-0.042*	-0.033	-0.034	-0.035
	(0.022)	(0.022)	(0.024)	(0.022)	(0.022)	(0.025)
Some Exercise	0.037	0.036	0.038	0.035	0.034	0.036
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Exercise at least once per week	-0.017	-0.017	-0.013	-0.022	-0.022	-0.017
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
Exercise at least 3 times per week	0.031	0.031	0.030	0.027	0.027	0.025
	(0.026)	(0.026)	(0.022)	(0.025)	(0.025)	(0.021)
Panel B. Self Assessed Health						
Very Good	0.001	-0.001	0.017	-0.009	-0.011	0.004
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
Very Good or Good	0.016	0.012	0.012	0.021	0.018	0.019
	(0.030)	(0.030)	(0.032)	(0.030)	(0.029)	(0.033)
Observations	4266	4266	4266	5380	5380	5380

Notes: In this table, columns 1,2 and 3, as well as columns 4,5, and 6, show the coefficient estimated using, respectively, an fixed effects difference-in-difference regression, OLS controlling on variables listed in Table 2.2, and non-linear difference-in-difference as described in Puhani (2012). In parenthesis, columns 1, 2, 4, and 5 show cluster standard errors at individual level, and columns 3 and 6 show standard errors calculated with delta method. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level.

Table 2.18: Effects of reform on health outcomes by gender and education. Treatment 46-48. Fixed Effects

		Gender		Education	
	All	Men	Women	Low	High
	(1)	(2)	(3)	(4)	(5)
Panel A. Smoking and sedentary behaviours					
Current Smoker	-0.049**	-0.025	-0.079**	-0.094***	-0.024
	(0.024)	(0.033)	(0.036)	(0.034)	(0.036)
Smoke 5 or more cigarettes per day	-0.040*	-0.022	-0.065**	-0.106***	0.018
	(0.022)	(0.031)	(0.032)	(0.033)	(0.032)
Number of cigarettes per day	-0.369	-0.262	-0.545*	-0.691*	-0.076
	(0.237)	(0.345)	(0.325)	(0.365)	(0.348)
Some Exercise	0.037	-0.003	0.107**	0.083*	0.068
	(0.036)	(0.053)	(0.052)	(0.050)	(0.056)
Exercise at least once per week	-0.017	-0.060	0.068	0.009	-0.011
	(0.032)	(0.048)	(0.045)	(0.043)	(0.052)
Exercise at least 3 times per week	0.031	0.004	0.067**	0.080**	-0.035
	(0.026)	(0.040)	(0.034)	(0.037)	(0.039)
Panel B. Self Assessed Health					
Very Good	0.001	-0.026	0.011	-0.009	0.021
	(0.032)	(0.047)	(0.046)	(0.041)	(0.052)
Very Good or Good	0.016	0.054	-0.038	0.040	-0.009
	(0.030)	(0.039)	(0.047)	(0.049)	(0.039)
Observations	4266	2944	1168	3228	1052

Notes: The table shows coefficients estimated using a difference-in-difference implemented by estimating an OLS regression with individual fixed effects. Cluster standard errors at individual level are shown in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level.

Table 2.19: Effects of reform on health outcomes by gender and education. Treatment 46-60. Fixed Effects

		Gender		Education	
	All	Men	Women	Low	High
	(1)	(2)	(3)	(4)	(5)
Panel A. Smoking and sedentary behaviours					
Current Smoker	-0.038	-0.017	-0.069**	-0.082**	-0.015
	(0.023)	(0.033)	(0.034)	(0.034)	(0.034)
Smoke 5 or more cigarettes per day	-0.033	-0.019	-0.045	-0.097***	0.014
	(0.022)	(0.031)	(0.032)	(0.033)	(0.030)
Number of cigarettes per day	-0.350	-0.282	-0.432	-0.621*	-0.248
	(0.234)	(0.340)	(0.324)	(0.362)	(0.333)
Some Exercise	0.035	-0.004	0.114**	0.086*	0.048
	(0.036)	(0.052)	(0.050)	(0.049)	(0.054)
Exercise at least once per week	-0.022	-0.064	0.075*	0.006	-0.024
	(0.032)	(0.048)	(0.043)	(0.042)	(0.049)
Exercise at least 3 times per week	0.027	0.005	0.060*	0.077**	-0.040
	(0.025)	(0.040)	(0.032)	(0.036)	(0.037)
Panel B. Self Assessed Health					
Very Good	-0.009	-0.040	0.013	-0.014	-0.001
	(0.032)	(0.046)	(0.045)	(0.041)	(0.050)
Very Good or Good	0.021	0.057	-0.019	0.041	0.011
	(0.030)	(0.039)	(0.046)	(0.049)	(0.038)
Observations	5380	3750	1452	4076	1302

Notes: The table shows coefficients estimated using a difference-in-difference implemented by estimating an OLS regression with individual fixed effects. Cluster standard errors at individual level are shown in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level.

Table 2.20: Effects of reform on health outcomes by gender and education. Treatment 46-48. OLS controling for individual characteristics

		Gender		Education	
	All	Men	Women	Low	High
	(1)	(2)	(3)	(4)	(5)
Panel A. Smoking and sedentary behaviours					
Current Smoker	-0.049**	-0.024	-0.079**	-0.094***	-0.024
	(0.024)	(0.034)	(0.036)	(0.034)	(0.037)
Smoke 5 or more cigarettes per day	-0.041*	-0.021	-0.066**	-0.106***	0.017
	(0.022)	(0.032)	(0.032)	(0.034)	(0.033)
Number of cigarettes per day	-0.372	-0.255	-0.555*	-0.691*	-0.083
	(0.238)	(0.349)	(0.329)	(0.366)	(0.351)
Some Exercise	0.036	0.001	0.106**	0.083*	0.069
	(0.036)	(0.052)	(0.053)	(0.049)	(0.057)
Exercise at least once per week	-0.017	-0.058	0.069	0.009	-0.010
	(0.032)	(0.048)	(0.045)	(0.043)	(0.052)
Exercise at least 3 times per week	0.031	0.005	0.069**	0.081**	-0.035
	(0.026)	(0.040)	(0.034)	(0.037)	(0.040)
Panel B. Self Assessed Health					
Very Good	-0.001	-0.023	0.004	-0.009	0.017
	(0.032)	(0.047)	(0.047)	(0.041)	(0.053)
Very Good or Good	0.012	0.059	-0.050	0.040	-0.015
	(0.030)	(0.040)	(0.047)	(0.049)	(0.039)
Observations	4266	2944	1168	3228	1052

Notes: The table shows coefficients estimated using a difference-in-difference implemented by estimating an OLS regression and controlling on variables listed in Table 2.2. Cluster standard errors at individual level are shown in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level.

Table 2.21: Effects of reform on health outcomes by gender and education. Treatment 46-60. OLS for individual characteristics

		Gender		Education	
	All	Men	Women	Low	High
	(1)	(2)	(3)	(4)	(5)
Panel A. Smoking and sedentary behaviours					
Current Smoker	-0.038	-0.016	-0.068**	-0.083**	-0.014
	(0.023)	(0.033)	(0.034)	(0.034)	(0.034)
Smoke 5 or more cigarettes per day	-0.034	-0.018	-0.045	-0.097***	0.015
	(0.022)	(0.031)	(0.032)	(0.033)	(0.031)
Number of cigarettes per day	-0.353	-0.272	-0.427	-0.622*	-0.240
	(0.235)	(0.344)	(0.327)	(0.364)	(0.336)
Some Exercise	0.034	-0.001	0.113**	0.085*	0.047
	(0.036)	(0.051)	(0.051)	(0.049)	(0.054)
Exercise at least once per week	-0.022	-0.062	0.075*	0.006	-0.024
	(0.032)	(0.048)	(0.043)	(0.042)	(0.050)
Exercise at least 3 times per week	0.027	0.005	0.062*	0.077**	-0.040
	(0.025)	(0.040)	(0.032)	(0.037)	(0.037)
Panel B. Self Assessed Health					
Very Good	-0.011	-0.037	0.008	-0.014	-0.005
	(0.032)	(0.047)	(0.045)	(0.041)	(0.051)
Very Good or Good	0.018	0.063	-0.030	0.042	0.004
	(0.029)	(0.039)	(0.046)	(0.049)	(0.037)
Observations	5380	3750	1452	4076	1302

Notes: The table shows coefficients estimated using a difference-in-difference implemented by estimating an OLS regression and controlling on variables listed in Table 2.11. Cluster standard errors at individual level are shown in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level.

Table 2.22: Effects of reform on health outcomes by gender and education. Treatment 46-48. Probit DiD

		Gender		Education	
	All	Men	Women	Low	High
	(1)	(2)	(3)	(4)	(5)
Panel A. Smoking and sedentary behaviours					
Current Smoker	-0.048**	-0.021	-0.078**	-0.096***	-0.021
	(0.024)	(0.035)	(0.035)	(0.036)	(0.036)
Smoke 5 or more cigarettes per day	-0.042*	-0.020	-0.072**	-0.119***	0.016
	(0.024)	(0.033)	(0.036)	(0.043)	(0.028)
Some Exercise	0.038	0.002	0.103**	0.083*	0.068
	(0.036)	(0.051)	(0.046)	(0.047)	(0.056)
Exercise at least once per week	-0.013	-0.057	0.058	0.013	-0.011
	(0.032)	(0.047)	(0.036)	(0.042)	(0.050)
Exercise at least 3 times per week	0.030	0.004	0.061**	0.068***	-0.036
	(0.022)	(0.035)	(0.025)	(0.025)	(0.041)
Panel B. Self Assessed Health					
Very Good	0.017	-0.002	0.016	0.001	0.026
	(0.032)	(0.047)	(0.047)	(0.045)	(0.055)
Very Good or Good	0.012	0.067	-0.046	0.043	-0.017
	(0.032)	(0.051)	(0.041)	(0.051)	(0.034)
Observations	4266	2944	1168	3228	1052

Notes: Notes: The table shows coefficients estimated using a non-linear difference-in-difference implemented as equation (10) in Puhani (2012). It uses a Probit model for binary outcomes and compute the cross difference of the conditional expectation of the observed health outcomes minus the cross difference of the conditional expectation of the conterfactual health outcome. The Probit model include variables in Table 2.2. Standard errors shown in parenthesis are computed by delta method. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level.

Table 2.23: Effects of reform on health outcomes by gender and education. Treatment 46-60. Probit DiD

		Gender		Education	
	All	Men	Women	Low	High
	(1)	(2)	(3)	(4)	(5)
Panel A. Smoking and sedentary behaviours					
Current Smoker	-0.036	-0.013	-0.067*	-0.084**	-0.011
	(0.024)	(0.034)	(0.035)	(0.036)	(0.034)
Smoke 5 or more cigarettes per day	-0.035	-0.016	-0.053	-0.111**	0.016
	(0.025)	(0.034)	(0.037)	(0.044)	(0.028)
Some Exercise	0.036	-0.000	0.110***	0.086*	0.046
	(0.036)	(0.051)	(0.042)	(0.047)	(0.055)
Exercise at least once per week	-0.017	-0.061	0.065*	0.011	-0.021
	(0.032)	(0.047)	(0.033)	(0.041)	(0.049)
Exercise at least 3 times per week	0.025	0.004	0.052**	0.064***	-0.041
	(0.021)	(0.034)	(0.023)	(0.024)	(0.039)
Panel B. Self Assessed Health					
Very Good	0.004	-0.021	0.019	-0.006	-0.000
	(0.032)	(0.048)	(0.045)	(0.046)	(0.054)
Very Good or Good	0.019	0.073	-0.027	0.046	0.003
	(0.033)	(0.052)	(0.042)	(0.051)	(0.035)
Observations	5380	3750	1452	4076	1302

Notes: The table shows coefficients estimated using a non-linear difference-in-difference implemented as equation (10) in Puhani (2012). It uses a Probit model for binary outcomes and compute the cross difference of the conditional expectation of the observed health outcomes minus the cross difference of the conditional expectation of the conterfactual health outcome. The Probit model include variables in Table 2.11. Standard errors shown in parenthesis are computed by delta method. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level.

Table 2.24: Effects of reform on health outcomes. Treatment 46-48 h, Controls 41-45 h

	PSM		NNM		PSM
	NN=1	NN=5	NN=1	NN=5	Kernel
	(1)	(2)	(3)	(4)	(5)
Panel A. Smoking and sedentary behaviours					
Smoking behaviours					
Current Smoker	-0.150	-0.113	-0.068	-0.090	-0.096
	(0.036)***	(0.040)***	(0.038)*	(0.038)**	(0.048)**
	[-0.221,-0.080]	[-0.192,-0.034]	[-0.142,0.006]	[-0.164,-0.015]	[-0.120,-0.052]
Smoke >= 5 cigarettes per day	-0.162	-0.100	-0.091	-0.096	-0.080
	(0.048)***	(0.041)**	(0.039)**	(0.038)**	(0.041)**
	[-0.257,-0.068]	[-0.180,-0.020]	[-0.167,-0.015]	[-0.171,-0.020]	[-0.106,-0.049]
Number of Cigarettes per day	-1.509	-0.825	-0.262	-0.457	-0.643
	(0.533)***	(0.370)**	(0.383)	(0.487)	(0.064)***
	[-2.553,-0.464]	[-1.551,-0.100]	[-1.012,0.488]	[-1.412,0.498]	[,,]
Sedentary behaviours					
Some Exercise	0.064	0.016	0.034	0.031	0.013
	(0.087)	(0.056)	(0.063)	(0.058)	(0.026)
	[-0.107,0.234]	[-0.095,0.126]	[-0.090,0.157]	[-0.083,0.144]	[-0.011,0.025]
Exercise at least once per week	0.042	0.016	0.019	-0.012	0.006
	(0.092)	(0.057)	(0.064)	(0.063)	(0.039)
	[-0.138,0.222]	[-0.095,0.128]	[-0.107,0.145]	[-0.136,0.112]	[-0.036,0.019]
Exercise at least 3 times per week	0.051	0.077	0.067	0.038	0.069
	(0.069)	(0.052)	(0.058)	(0.053)	(0.042)
	[-0.084,0.187]	[-0.026,0.180]	[-0.047,0.181]	[-0.065,0.141]	[0.041,0.100]
Panel B. Self Assesed Health					
Very Good	-0.039	-0.056	-0.032	-0.009	-0.070
	(0.064)	(0.052)	(0.056)	(0.056)	(0.051)
	[-0.164,0.086]	[-0.158,0.046]	[-0.142,0.078]	[-0.118,0.100]	[-0.128,-0.055]
Very Good or Good	0.066	0.022	0.058	0.068	0.009
	(0.051)	(0.064)	(0.046)	(0.052)	(0.040)
	[-0.034,0.165]	[-0.104,0.148]	[-0.033,0.149]	[-0.034,0.171]	[-0.037,0.020]
Observations	2,168	2,168	2,168	2,168	2,168

Notes: The table shows coefficients estimated using a difference-in-difference approach combined with propensity score matching. Common support is imposed by dropping observations whose propensity score is higher than the maximum or less than the minimum propensity score of the control. Columns differ by the matching algorithm used with the difference-in-difference. Columns 1 and 2 show estimates using Propensity Score Matching with one and five neighbours, columns 2 and 3 show estimates using Nearest Neighbors Matching using one and five neighbours, and column 6 show estimates using Kernel Propensity Score Matching. Confident intervals and robust standard errors derived by Abadie and Imbens (2006, 2008, 2011) are shown for NN-PSM and NNM estimates. Bootstrapped standard errors, based on 250 replications are shown for K-PSM estimates. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level. The matching is based on variables listed in Table 2.2.

Table 2.25: Effects of reform on health outcomes. Treatment 46-60 h, Controls 41-45 h

	PSM		NNM		PSM
	NN=1	NN=5	NN=1	NN=5	Kernel
	(1)	(2)	(3)	(4)	(5)
Panel A. Smoking and sedentary behaviours					
Smoking behaviours					
Current Smoker	-0.088	-0.086	-0.061	-0.081	-0.085
	(0.047)*	(0.039)**	(0.038)	(0.038)**	(0.044)*
	[-0.179,0.004]	[-0.163,-0.009]	[-0.135,0.014]	[-0.155,-0.007]	[-0.128,-0.065]
Smoke >= 5 cigarettes per day	-0.049	-0.071	-0.087	-0.091	-0.068
	(0.070)	(0.038)*	(0.040)**	(0.039)**	(0.052)
	[-0.186,0.087]	[-0.146,0.005]	[-0.165,-0.010]	[-0.167,-0.015]	[-0.137,-0.063]
Number of Cigarettes per day	-0.438	-0.550	-0.297	-0.473	-0.589
	(0.587)	(0.324)*	(0.381)	(0.483)	(0.589)
	[-1.589,0.713]	[-1.186,0.085]	[-1.044,0.450]	[-1.419,0.474]	[-0.981,-0.149]
Sedentary behaviours					
Some Exercise	-0.013	-0.001	0.022	0.029	0.019
	(0.068)	(0.060)	(0.063)	(0.057)	(0.012)
	[-0.147,0.120]	[-0.117,0.116]	[-0.101,0.145]	[-0.082,0.140]	[.,.]
Exercise at least once per week	0.023	0.014	0.015	-0.022	0.004
	(0.091)	(0.065)	(0.064)	(0.062)	(0.017)
	[-0.156,0.202]	[-0.114,0.142]	[-0.111,0.141]	[-0.145,0.100]	[.,.]
Exercise at least 3 times per week	0.076	0.062	0.072	0.023	0.061
	(0.084)	(0.051)	(0.057)	(0.051)	(0.035)*
	[-0.089,0.241]	[-0.038,0.162]	[-0.040,0.183]	[-0.077,0.124]	[0.055,0.105]
Panel B. Self Assesed Health					
Very Good	-0.075	-0.059	-0.050	-0.018	-0.081
	(0.051)	(0.050)	(0.058)	(0.056)	(0.018)***
	[-0.175,0.025]	[-0.157,0.039]	[-0.163,0.063]	[-0.128,0.093]	[-0.096,-0.070]
Very Good or Good	-0.026	-0.023	0.053	0.056	0.015
	(0.063)	(0.052)	(0.046)	(0.052)	(0.005)***
	[-0.149,0.097]	[-0.125,0.079]	[-0.037,0.143]	[-0.045,0.158]	[0.010,0.017]
Observations	2,689	2,689	2,689	2,689	2,689

Notes: The table shows coefficients estimated using a difference-in-difference approach combined with propensity score matching. Common support is imposed by dropping observations whose propensity score is higher than the maximum or less than the minimum propensity score of the control. Columns differ by the matching algorithm used with the difference-in-difference. Columns 1 and 2 show estimates using Propensity Score Matching with one and five neighbours, columns 2 and 3 show estimates using Nearest Neighbors Matching using one and five neighbours, and column 6 show estimates using Kernel Propensity Score Matching. Confident intervals and robust standard errors derived by Abadie and Imbens (2006, 2008, 2011) are shown for NN-PSM and NNM estimates. Bootstrapped standard errors, based on 250 replications are shown for K-PSM estimates. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level. The matching is based on variables listed in Table 2.11.

2.9.2 The Social Protection Survey and Sample

The Social Protection Survey (EPS) is the largest and oldest longitudinal survey in Chile, with a representative sample of the respondents distributed in all regions of the country. It includes detailed information in topics such as education, health, social security, job training, assets, family history and information about the home. To date, there have been five rounds, in the years 2002, 2004, 2006, 2009, 2012 and 2015.

The target population of the first wave (2002) are individuals who were affiliated in an AFP[29] or the INP[30] since January 1981 until August 2001, and who were also available in the system in August of 2001. The second wave (2004) a new sample of non-members of the pension system pensions was incorporated together with an update of affiliates to the AFP system. Thus, starting from 2004, the EPS has national representativeness (excluding the armed forces and the police who have their own pension system). Consecutively, the 2006 wave, interviewed individuals present, at least once, in the 2002 or 2004 wave. The SPS Chilean Data is publicly available in the official webpage of the Ministry of Labour.[31] All data files contain a unique ID that I use to merge information at the individual level. I create a monthly panel data of employment status (employed, unemployed, looking for a job for the first time or inactive) using the retrospective information asked in each wave. Attrition between 2002-2006 waves for the main analytical sample is 6.0%. In my main empirical specification, I do not use the sampling weight provided by the Ministry.

2.9.3 Description of the Chilean Labour Reform

Among the objectives of the Chilean labour reform were the improvement of regulations for workers' organizations and protection against anti-union practices, to enable labour relations in a globalized world and, at the same time, improve the rights of workers. In regard to the latter, the reform incorporated mechanisms to prevent discrimination in employment and to provide means that would discourage labour dumpling. The reform also included tools to improve the job training regime, particularly among younger workers. New hiring modalities were introduced to allow work to be carried out from places other than the business premises through technological means, to promote youth employment and to allow greater labour flexibility. Finally, the reform aimed to provide greater protection to seasonal workers, who represent an important fraction of the Chilean labour market.

The reform changed the Chilean Labour Code, which is the code that regulates

[29]AFP stands for Administradora de Fondos de Pensiones (Private pension management funds).
[30]INP stands for Instituto Nacional de Prevision (National Institute of Pensions).
[31]https://www.previsionsocial.gob.cl/sps/biblioteca/encuesta-de-proteccion-social/bases-de-datos-eps/

labour relations in Chile, in two main areas.[32]

1. **Individual contract of work and job training**

2. **Trade union organizations and staff delegates, and collective negotiation**

Below, I briefly describe the changes to each of these areas.

1. **Individual contract of work and job training**

Working Day

The working day was reduced from 48 to 45 hours per week. Details about this change are described in the main text.

Exceptions

The working day in Chile applies to all workers in the private sector, excluding workers who provide services to different employers; managers, administrators, and all those who work without immediate superior control; those hired to provide services in their own home or in a place freely chosen by them; or other workers who do not perform their duties on the premises of the firm. Likewise, workers who work onboard fishing vessels, and professional athletes and technical staff of sports entities are excluded from the limitation to working hours.

The reform added the following groups to the list of workers excluded from the maximum limit for working hours:

- Workers hired to provide their services preferably outside the place or site of operation of the company, through the use of computers or telecommunications means.

- Staff who work in hotels, restaurants or clubs –except for administrative, laundry, lingerie and kitchen staff–, when, in all these cases, daily movement is notoriously low, and workers must be constantly available to the public. For this group, a maximum of 12 hours per day was included, distributable across a maximum of 5 days a week.

[32]More details about this changes can be found in Sánchez (2013)

Extraordinary hours

The reform did not change the overtime premium of 50% of the hourly wage; however, it added new rules regarding the type of agreement that could be made. Before the reform, overtime hours –agreed between employers and employees– had to be explicitly specified in a document or contract, without restrictions about the time or situation. The reform established that overtime hours could only be agreed to meet the needs or temporary situations of the company. The said agreements, which have the option to be renewed upon agreement by the parties, must be in writing and have a temporary validity of no more than three months.

Weekly shift and leisure hours

The reform defined new rules for the establishment of exceptional systems for the distribution of work and leisure hours, which are common in the construction and mining sectors. Before the reform, companies could request the Undersecretaries of Labour to approve extraordinary hours, which were evaluated on a case-by-case basis. The reform established that this resolution would be valid for a maximum of four years, in order to limit the period for which companies are authorized to use exceptional systems for the distribution of work and leisure hours.

Part-time jobs

The reduction of working hours from 48 to 45 also affected the maximum hours that can be worked in part-time jobs, which are defined as 2/3 of full time. In particular, part-time hours were reduced from 32 to 30 hours.

Termination of the employment contract and job stability

In Chile, a company can fire a worker without paying severance on three grounds: if the contract is terminated due to economic reasons (e.g. economic recession), or due to causes not attributable to the employee (e.g. death of the employee), or due to causes attributable to the employee (e.g. sexual harassment). The reform incorporated new causes attributable to the employee for which the employer can dismiss the worker without compensation, but it also increased the fines that judges can apply to companies in the event that companies terminate the employment relationship illegally. The fines increased between 30% and 150% depending on the cause of dismissal. Additionally, the reform added that the indemnities have to be paid at once when the contract ends, or they can be paid in instalments, which are adjustable by interest.

Occupational training

The reform incorporated a mechanism so that companies can deduct from the severance pay the hours of training provided by the company to workers under 24 years of age who have previously been accredited by the National Training and Employment Service.

2. **Trade union organizations and staff delegates, and collective negotiation**

Trade unions

The reform sought to facilitate the creation of unions, along with giving greater labour protections to workers who participate in the creation of a union. In particular, it gave workers who help with the creation of a union labour protection from the ten days prior to the holding of the respective constitutive assembly, up to thirty days after it has been held, to a maximum of 40 days.

It also clarified what the administrative statutes of the unions must contemplate, the rules related to the union directories, and the rules regarding the minimum number of workers necessary to form a union, which varies depending on the size of the company.

Unfair or anti-union practices and their sanction

The reform increased the fines to companies that disguise or alter their organization or assets with the aim of evading compliance with labour and social security obligations. The reform added a fine of 5 to 100 UTM[33] for employers who simulate the hiring of workers through third parties. And it included a fine of between 10 and 150 UTM for each affected worker for companies that establish multiple legal identities or that divide the company with the objective of reducing or losing individual or collective labour rights for their workers, such as the loss of bonuses, or severance pay for years of service, or the right to organize, or to bargain collectively.

[33]UTM stand for Unidades Tributarias Mensuales or Monthly Tax Units. The UTM is indexed by inflation and its value in January 2020 was 50,978 Chilean pesos, around 50 pounds. Exchange rate: Chilean pesos to GBP 0.001, 2^{nd} January 2021.

In addition, the reform increased fines from 1-10 UTM to 1-20 UTM for all companies, and increased fines to 2-40 UTM if the firm have 50 or more workers, and to 3-60 UTM if the firm have 200 or more workers.

Strike

Before the reform, companies could replace striking workers from the first day of the strike if the company's last offer kept the current benefits and contract time adjusted for price variations. If the last offer did not meet these conditions, the company could replace the workers after a 15-day strike. The reform added a new restriction for companies, which had to pay a bonus of 4 UF[34] per worker replaced.

[34]UF stand for Unidades de Fomento. The UF is indexed by inflation and in January 2021 its value was 29,068 Chilean pesos, around 29 pounds. Exchange rate: Chilean pesos to GBP 0.001, 2nd January 2021.

Chapter 3

Air Quality, Child Health, and Cognitive Performance

In this chapter, I estimate the causal effect of air quality on early childhood cognitive performance and infant health using high-quality child-level longitudinal data. Whilst there is a growing body of literature that looks at the implications of air pollution for either cognitive outcomes or health outcomes (Almond et al., 2018; Bharadwaj et al., 2017a; Currie and Neidell, 2005; Currie et al., 2009, 2014; Ebenstein et al., 2016; Marcotte, 2017; Stafford, 2015), this is one of the first studies to use the same survey population to evaluate both issues together. Furthermore, it adds new evidence to the few empirical studies that exploit quasi-experimental variation in urban air pollution. The lack of quasi-experimental evidence in the literature is mainly due to the fact that it is difficult to credibly identify exogenous variation in air pollution levels throughout life or across geographic areas. Endogenous responses to air quality, such as changes of residence or parental compensatory/reinforcing investment in children, could bias estimates of the causal effect of air pollution on children's outcomes (Bharadwaj et al., 2017a; Graff Zivin and Neidell, 2013).

Using the Chilean Early Childhood Longitudinal Survey (ECLS), I contribute to this literature by providing instrumental variable evidence that exploits the known association between thermal inversions and air pollution. Thermal inversions occur when a layer of warmer air overlies a layer of cold air at the surface, reducing the vertical ventilation of air and resulting in higher concentrations of air pollution at ground level. To implement the empirical strategy, I combine data on daily air pollution from seven monitors throughout Santiago collected by the Chilean National Air Quality Information System (SINCA), daily temperature profile data from the Modern-Era Retrospective analysis for Research version 2 (MERRA-2) collected by the National Aeronautics and Space Administration (NASA), and data on daily weather conditions collected by the Chilean Meteorological Agency (CMA). I link these data with the ECLS data to create measures of lifetime air pollution exposure.

The ECLS study includes rich information about socio-demographic characteristics, health conditions at birth, and cognitive performance. Among the battery of instruments applied in the ECLS, the Peabody Picture Vocabulary Test (PPVT), which measures receptive vocabulary, was applied longitudinally to cohort members between 3 and 5 years old in the first survey. I use the date and location on which the ECLS cohort members were tested to link air pollution exposure to cohort members. Similarly, the ECLS collected birth date and the estimated date of conception of cohort members, which I use to link air pollution exposure during pregnancy.

In the research design for early childhood cognitive performance, because I have child-level panel data, I exploit within-child exposure to air pollution. Since children in my sample were born in two years, and the cognitive evaluations were administered on different dates throughout the fieldwork period, I exploit the variation in both the week of conception and the week in which the test was administered. To further strengthen the identification assumptions in fixed effects models I control for proxy measurements of avoidance behaviours and parental investment, and I provide instrumental variable evidence that exploits the variation in thermal inversions in the Santiago basin.

I find that exposure to poor air quality during pregnancy is connected with poor health outcomes at birth. In particular, fixed effects and instrumental variable estimates show a clear picture of the negative effect of air pollution on health outcomes at birth, indicating that higher levels of particulate matter less than 10 microns in diameter and under (PM10) pollution during pregnancy decrease birth weight, increase the probability of low birth weight, shorten gestation, and increase the probability of having a premature child. A similar pattern is observed when I use the Air Quality Index (AQI), an index used by environmental agencies to rank the health risk of air pollution. Regarding PPVT scores, I find that lifetime exposure to poor air quality during childhood is negatively associated with cognitive performance. I find that a 10% increase in PM10 pollution reduces the PPVT scores by around 12-30% of a standard deviation. Furthermore, I provide evidence that the impact of poor air quality on cognitive performance is around 7% larger among cohort members with respiratory problems, with an estimate of around 18-32% of a standard deviation. When compared with the fixed effects estimates, the instrumental variables estimates are larger in absolute value, which is consistent with attenuation bias.

The results in this chapter provide new evidence in the context of Chile, a middle-income country that during the last decades has consistently reduced its levels of urban air pollution. They fill a gap in the existing research, which has many problems in representing developing countries, raising questions about the external validity of published results.

The remainder of this study is structured as follows. First, I describe the emerging literature in economics that connects air pollution with health and human capital outcomes throughout life. Then, I describe the conceptual framework and the empirical strategy I use to identify the impact of air pollution on cohort member's outcomes. In section 3.3, I describe the data and the empirical variation used in the fixed effects instrumental variable design. Finally, I present the main results in section 3.7 and conclude in section 3.8.

3.1 Background

An increasing body of evidence suggests that early childhood exposure to air pollution influences health and human capital outcomes later in life (Almond et al., 2018; Currie et al., 2014). Outdoor air pollution has been negatively linked with infant mortality (Arceo et al., 2015; Chay and Greenstone, 2003), respiratory and cardiovascular problems (Brunekreef and Holgate, 2002; Cohen et al., 2005; Shah et al., 2013), child health (Beatty and Shimshack, 2014; Currie et al., 2014; Jans et al., 2018), subjective well-being (Zhang et al., 2017b), mental health (Bishop et al., 2018), and labour market outcomes (Chang et al., 2016, 2019; Hanna and Oliva, 2015); however, less is known about the effect of accumulated air pollution on cognitive performance, particularly in developing countries, where the average levels of exposure are higher than in developed countries.

In studying the effect of air pollution on cognitive performance, scholars have focused mainly on academic performance using standardised test scores. Some studies focus on the effect of air pollution in-utero exposure on later academic performance, while others evaluate the negative effects of transitory exposure to air pollution across the lifetime. For instance, Sanders (2012) and Bharadwaj et al. (2017a) study the detrimental effect of in-utero exposure on 10^{th} grade (15 to 16 years of age) and 4th grade (8 to 9 years of age) test scores, respectively. Sanders (2012) use the exogenous shock caused by the industrial recession of the 1980s in Texas, which induced county-level variation in total suspended particulate (TSP) exposure, to study the effect of a reduction in TSP at birth on academic maths performance. Using an instrumental variable strategy, he finds that a one standard deviation reduction in TSP was associated with an increase of almost 6 per cent of a standard deviation in test scores. Bharadwaj et al. (2017a), using a sibling fixed effects strategy, find a negative association between in-utero CO exposure and maths and language test scores in Santiago, Chile.

Studies that focus their analysis on the transitory effect of air pollution on cognitive performance provide similar evidence. Ham et al. (2014) use grade-school fixed effects methods to study the effect of changes in air pollution on the maths and language standardised test scores of students from 2^{nd} through to 6^{th} grade in California (7 to 12 years of age). The authors find a negative association between air pollution (ozone and particulate matter) and academic performance. Ebenstein et al. (2016) use individual fixed effects methods to provide evidence of the adverse effects of air quality on high-stakes exams. They show that Israeli high school students who experienced a lower performance in the exams due to transitory air pollution exposure are also more likely to have lower postsecondary educational attainment and earnings. Similar results are provided by studies that evaluate the impact of transitory indoor air quality on cognitive performance. Stafford (2015) find that renovation projects specifically designed to improve school air quality in Texas are positively linked with a performance improvement among students in their standardised maths and reading test scores.

Most of the studies described above rely on administrative educational data. Although these studies allow the researchers to have larger samples sizes, usually they do not have detailed individual information to control for confounders relevant to this literature. To improve on this, scholars have started to use longitudinal survey data, which allow for controlling by individual fixed effects and time-variant confounders. Marcotte (2017) use the Early Childhood Longitudinal Survey – Kindergarten (ECLS-K) to study the effect of pollen and particulate matter on maths and reading test scores in the US. The author uses six individual measures of maths and reading scores between Kindergarten and 2^{nd} grade (5 to 8 years of age) to estimate individual fixed effects models. While the author find a negative effect of short term fine airborne particulate matter exposure on math and reading test scores, they do not find that lifetime air pollution exposure –measured from birth to the week the test was taken– impair test performance. Following a similar strategy, but focusing on Chinese adults, Zhang et al. (2018) study the effect of both cumulative and transitory exposure to air pollution. They use two waves of the China Family Panel Study, a nationally representative survey of Chinese families and individuals, and find evidence that the damage cause to cognitive performance by cumulative air pollution exposure is relatively more severe than the effect of transitory air pollution exposure. As far as I know, these are the only two studies that have used high-quality longitudinal data together with quasi-experimental research designs to provide causal evidence of the transitory and cumulative impact of air quality on cognitive performance.

Transitory and cumulative air pollution exposure could affect cognitive performance at early ages through several mechanisms. First, exposure to Carbon Monoxide (CO) is typically studied as a potential mechanism since exposure to it in-utero reduces the body's ability to transport oxygen to the foetus and mother's organs (Brunekreef and Holgate, 2002). Furthermore, CO that crosses the placenta has the additional effect of lowering the foetus' oxygen level during sensitive periods, affecting the immature foetal cardiovascular and respiratory systems (Guxens et al., 2018; Neidell, 2004). In-utero detrimental effects caused by air pollution are therefore associated with health at birth (Chay and Greenstone, 2003; Currie and Neidell, 2005; Currie et al., 2009, 2014). For example, Currie et al. (2009) find that, even at low levels of CO exposure, a one-unit increase in CO during the third trimester of pregnancy increases the risk of a low birth weight by 8% in New Jersey. Currie and Walker (2011) use the opening of E-Z Pass toll plaza conversions, which allow equipped vehicles to drive through toll lanes without stopping to pay a toll, to evaluate the impact of a reduction in ambient air pollution on child health. They find that the new payment system resulted in a significant reduction in the risk of prematurity and low birth weight. Similar studies that have relied on quasi-experimental research designs have found a positive association between air pollution, infant mortality (Chay and Greenstone, 2003) and respiratory problems (Beatty and Shimshack, 2014; Guarnieri and Balmes, 2014; Moretti and Neidell, 2011; Neidell, 2004; Schlenker and Walker, 2016).

Second, medical studies provide evidence that outdoor air pollution can affect cognitive performance after birth through its detrimental effect on brain development. Oxygen deficiency, which is associated with CO poisoning, impairs cognitive performance by preventing the body from releasing adequate oxygen to vital organs, in particular the brain (Brani et al., 2005). Indeed, air pollution produces observable changes in the brain and respiratory systems. Children exposed to air pollution are more likely to have white-matter lesions (Caldern-Garcidueas et al., 2008), experience neuroinflammation and neuropathology (Block and Caldern-Garcidueas, 2009), and present chronic inflammation of the respiratory tract (Caldern-Garcidueas et al., 2011). Furthermore, higher air pollution exposure in-utero is associated with white-matter abnormalities in children (Peterson et al., 2015) and a thinner cortex in several brain regions (Guxens et al., 2018; Pujol et al., 2016).

Disentangling the causal effect of accumulated air pollution on child outcomes from observational studies has been a challenge for most empirical papers in the economic literature. Instrumental variables, natural experiments and within individual and area fixed effects research designs have been used to deal with endogenous exposure to outdoor air pollution. Among the instrumental variable approaches, an increasingly accepted source of exogenous variation is the atmospheric phenomenon known as thermal inversion. A thermal inversion occurs when the typical gradient between temperature and altitude (i.e. temperature decreases with altitude) is reversed, impeding the vertical ventilation of air, which then results in higher concentrations of air pollution. Previous papers that have used thermal inversions as an exogenous variation have studied the transitory effects of air pollution on infant and adult mortality (Arceo et al., 2015; Hicks et al., 2016; Miller and Ruiz-Tagle, 2018), child health (Jans et al., 2018), labour productivity (Fu et al., 2017; He et al., 2018), crime (Bondy et al., 2018), road safety (Sager, 2019), and school absenteeism (Chen et al., 2018). For example, Jans et al. (2018) used data from NASA to create vertical temperature profiles across Sweden and show that a 25 per cent increase in PM10 levels, induced by transitory thermal inversions, are associated with a 5.5 per cent increase in children's respiratory problems. Arceo et al. (2015) use the weekly variation in thermal inversion, which is measured from an aerostatic balloon in Mexico City, to find that a 1 μg/m^3 increase in PM10 over the week leads to 0.23 deaths per 100,000 births. One exception to the literature that focuses on temporary effects of thermal inversions is Chen et al. (2017), who exploit the five-year variation in the average strength of thermal inversions within counties in China to study the medium-run effect of air pollution on migration.

In this study, I provide new evidence to add to this emerging literature by evaluating the impact of air pollution on health and cognitive performance for the same sample of children, in the context of a developing country. It also expands the previous literature by using a research design that exploits within cohort member air pollution exposure combined with an instrumental variable research design.

3.2 Conceptual framework and empirical strategy

In this section, I describe the conceptual framework and the empirical strategy used in this study.

3.2.1 Conceptual framework

Canonical human capital models of child health, cognition and air pollution recognize how children's cognitive performance could be affected through transitory and prolonged exposure to poor air quality, and also how parental avoidance behaviour and investment could mitigate the detrimental effects of air pollution (Almond et al., 2018; Bharadwaj et al., 2017a; Currie et al., 2014; Graff Zivin and Neidell, 2013; Marcotte, 2017).

To provide a more clear description of the mechanisms through which air pollution impacts cognition performance and child health, I consider a simple three-period model of human capital accumulation.

Period t=1: From conception to birth

$$H_1 = f_1\left(P_1, A_1, W_1, X\right)$$

Period t=2: From birth to early childhood (2-4 years of age)

$$\begin{aligned} H_2 = &\quad f_2\left(H_1, P_2, A_2, I_2, W_2, X\right) \\ C_2 = &\qquad g_2\left(H_2, I_2, X\right) \end{aligned}$$

Period t=3: School age (5-7 years of age)

$$\begin{aligned} H_3 = &\quad f_3\left(H_2, P_3, A_3, I_3, W_3, X\right) \\ C_3 = &\qquad g_3\left(C_2, H_2, I_3, X\right) \end{aligned}$$

H_t and C_t are health and cognitive measurements at the period t. P_t indicates exposure to air pollution. W_t are weather conditions (e.g. rainfall, temperature, etc.). A_t refers to parental avoidance behaviours to prevent the detrimental effects of poor air quality. I_t indicates time-varying parental investment, and X is a vector of invariant family characteristics. The aim of this chapter is to study the impact of air pollution on health at birth and on cognitive performance during childhood. Total differentiating[1] H_1 and C_3 helps to conceptualise the mechanisms that should be considered in the empirical strategy described in the next section. By differentiating H_1 we obtain:

$$dH_1 = \frac{\partial H_1}{\partial P_1} dP_1 + \frac{\partial H_1}{\partial A_1} dA_1 \tag{3.1}$$

And by differentiating C_3 we obtain:

$$\begin{aligned} dC_3 =& \Delta_{C_3,H_2} \underbrace{\left\{ \frac{\partial H_2}{\partial H_1} \frac{\partial H_1}{\partial P_1} dP_1 + \frac{\partial H_2}{\partial P_2} dP_2 \right\}}_{\text{Effect on Health}} \\ &+ \Delta_{C_3,H_2} \underbrace{\left\{ \frac{\partial H_2}{\partial H_1} \frac{\partial H_1}{\partial A_1} dA_1 + \frac{\partial H_2}{\partial A_2} dA_2 \right\}}_{\text{Parental and Children Avoidance Behaviours}} \\ &+ \underbrace{\left\{ \Delta_{C_3,H_2} \frac{\partial H_2}{\partial H_1} + \frac{\partial C_3}{\partial C_2} \frac{\partial C_2}{\partial I_2} \right\} dI_2 + \frac{\partial C_3}{\partial I_3} dI_3}_{\text{Parental Investments}} \end{aligned} \tag{3.2}$$

where

$$\Delta_{C_3,H_2} = \left(\frac{\partial C_3}{\partial C_2} \frac{\partial C_2}{\partial H_2} + \frac{\partial C_3}{\partial H_2} \right)$$

Equation (3.1) emphasises that health at birth (H_1) could be affected by air pollution contemporaneously through maternal health during pregnancy, but that this could also be alleviated by maternal avoidance behaviours. After birth, air quality may influence cognitive performance through two channels (equation (3.2)): first,

[1]In the total differentiation I do not consider W_t to facilitate the exposition of the arguments. However, I include it in the empirical analysis.

through its direct effect on contemporaneous child health, and second, by worsening cognitive performance, which is affected by the negative effect on health in the early periods. Impaired cognitive performance at early ages may have a detrimental effect on future cognitive performance. In this framework, to evaluate the impact of air pollution, it is important to control for how parents engage in avoidance behaviours and compensatory investment (Bharadwaj et al., 2017a; Graff Zivin and Neidell, 2013).

3.2.2 Empirical strategy

Based on the conceptual framework described above, this study estimates the effect of air pollution on health at birth and cognitive performance during childhood using a fixed effects method combined with an instrumental variable strategy. The air pollutants used in the analysis are particulate matter with a diameter of 10 micrometres and under (PM10) and Monoxide Carbone (CO). Additionally, to provide a sense of aggregate pollution, I use the Air Quality Index (AQI), which is used by environmental agencies to rank the health risks associated with air pollution. As described in more detail in section 3.3, the cognitive and health outcomes come from the Chilean Early Childhood Longitudinal Survey (ECLS).

I use the first two waves of the ECLS study to estimate two different models, one for health outcomes at birth and the other for cognitive performance during childhood. When I focus on cognitive performance, the instrumental variable model takes the following form:

$$C_{iat} = \beta P_{iat} + X_{it}\Phi + W_{iat}\Gamma + \theta_i + \delta_t + \lambda_a + \varepsilon_{iat} \tag{3.3}$$

$$P_{iat} = Z_{iat}\gamma + X_{it}\Phi + W_{iat}\Gamma + \theta_i + \delta_t + \lambda_a + \nu_{iat} \tag{3.4}$$

Equation (3.3) corresponds to the second stage regression of the instrumental variable model. C_{iat} is the cognitive test of children i in area a at time t. P_{iat} is the average air pollution exposure that is measured in two different periods, from conception to the first interview, and between the first and second interviews. X_{it} is a vector that includes time-varying characteristics and W_{iat} measures weather conditions, such as temperature, relative humidity, and wind speed. θ_i is a cohort member fixed effect, δ_t is a time fixed effect, λ_a is an air quality monitoring station fixed effect.[2]

Only using equation (3.3) to estimate the causal effect of air pollution on children's outcomes is challenging because air pollution exposure is unlikely to be randomly assigned across locations or throughout the life course. Avoidance behaviour, measurement error, and parental investment are the three main challenges to identification that have been analysed previously in the literature.

First, when parental avoidance behaviours, such as spending less time outside on polluted days or residential sorting, are not considered in the model, the estimated parameter will only capture the realized exposure to pollution, which differs from the causal parameter (Currie et al., 2014). Similarly, if mothers engage in more avoidance as a response to higher levels of pollution, then more avoidance may lead to better health and higher cognitive scores (Bharadwaj et al., 2017a). Thus, not controlling for avoidance behaviour can introduce a downward bias on least square estimates. To overcome this potential bias, I control for individual time-varying avoidance behaviour following Bharadwaj et al. (2017b) and include a vector of individual exposure to air quality public daily alerts in Santiago. If some mothers systematically change their behaviour due to air quality alerts,[3] controlling by the number of alerts experienced by each mother during the relevant period should reduce omitted variable bias.

Second, relying on air pollution monitoring stations to aggregate exposure across life in fixed effects models may lead to significant attenuation bias due to measurement error (Griliches and Hausman, 1986). Measurement error is likely to arise when estimating the effect of air quality on health and cognitive outcomes, mainly when attributing air pollution from monitors to the locations of children. However, this might not be as problematic in the context of this paper for three rea-

[2]Monitoring station fixed effects indicate the closest monitor to the cohort member's household.
[3]Air quality alerts in Santiago are made available daily by the government agency.

sons. First, I control for monitoring station and child fixed effects, which can help to limit this threat. Second, the instrumental variable approach is relatively robust to classical measurement error. Third, I focus on a period of life where it is less likely that families will move. Furthermore, by using the exact household location, together with the date of the test, I create a more precise air pollution exposure variable than previous empirical research, which has typically used the centroid of a geographic area[4] or the year and month of the interview. Additionally, in theory, attenuation bias from measurement error would result in a lower bound of the estimates.

An additional challenge to identification comes from the large body of literature that argues that parents make an investment to overcome cognitive deficiencies. Not controlling for such an unobservable investment could obscure the causal estimate of air pollution on child outcomes. However, recent evidence indicates that this may not be an issue in the ECLS study. Abufhele et al. (2017) use an oversample of 2,000 twins from the ECLS cohort to test whether parents invest more in better-endowed children (reinforcement behaviour) or whether they invest more in less-endowed children (compensatory behaviour). Consistent with the previous evidence of parental preference within twins, they find evidence of neutral parental behaviour and no significant preference difference between families with less and more educated mothers. Still, I control for time-variant parental investment including the within-sample standardised Home Observation for Measurement of the Environment (HOME) inventory (Bustos et al., 2001; Totsika and Sylva, 2004), which could mitigate the bias due to this omitted variable.

As described in more detail in the next section, daily PM10, CO, and AQI are negatively correlated with daily Ozone concentrations. To avoid the potential downwards bias, in all regressions I control for Ozone concentration.[5]

Equation (3.4) is the first stage regression, where Z_{iat} is an instrumental vari-

[4]An exception is Marcotte (2017), who create a transitory and cumulative air pollution exposure using the exact location of students; however, their data does not allow them to know the exact day on which the maths and reading exams were taken. Instead, the author creates the week of the exam by using days of the month categorized into four groups.

[5]The results are not sensitive to the inclusion of Ozone as a control.

able that captures the frequency of exposure and the intensity of thermal inversion throughout children's lives. It is defined as the percentage of children's lives with thermal inversion events times the average thermal inversion intensity of those events. In the next section, I provide a more detailed definition of, and descriptive evidence about this atmospheric phenomenon in Santiago.

It should be noted that within areas defined by the location of the monitoring stations, exposure to air pollution and thermal inversions varies at the individual level. Provided that the ECLS includes children born over two years, once I condition on age, differences in the individual variation of air pollution are entirely driven by geographical location, the date of conception and the day on which the cognitive test was taken. Under the assumption that these two dates are as good as random, estimating β from equation (3.3) should provide a good approximation of a causal parameter. However, as mentioned before, measurement error and unobserved time-varying differences across individuals may still bias the results.[6]

Besides evaluating the impact of air pollution on cognitive tests, I estimate fixed effects models for health outcomes at birth, for which I use the following empirical specification.

$$H_{iat} = \beta P_{ia} + X_i\Phi + W_{ia}\Gamma + \delta_t + \lambda_a + M_i\Pi + \varepsilon_{iat} \tag{3.5}$$

$$P_{iat} = Z_{ia}\gamma + X_i\Phi + W_{ia}\Gamma + \delta_t + \lambda_a + M_i\Pi + \nu_{iat} \tag{3.6}$$

where H_{iat} indicates the outcome of child i at birth, located in area a, born in year t. Child fixed effects are not included in this specification since the outcomes are measured only once. In this specification, δ_t includes the year of birth fixed effects. The identifying assumption when estimating only equation (3.5) is that, after controlling for observable parental characteristics, individual avoidance behaviour,

[6]Another reason why a fixed effects strategy may not recover a causal estimate is unobserved heterogeneity on fertility behaviours since it challenges the assumption that the birth date can be thought of as a random date (Marcotte, 2017).

weather controls, birth year, and station monitors fixed effects, exposure to air pollution is uncorrelated with ε_{iat}. On the other hand, the instrumental variable approach requires that maternal exposure to thermal inversion events during pregnancy significantly affects exposure to air pollution (relevance assumption) and affects children's outcomes only through air pollution exposure (exclusion assumption). If the two previous assumptions hold, and if thermal inversions do not systematically lead to lower levels of pollution (monotonicity), under constant treatment effects conditional on covariates, the IV estimate identifies the local average treatment effect. In the following sections, I provide evidence about these assumptions.

3.3 Data and descriptive evidence

In this section, I describe the ECLS data as well as the air pollution and weather data used in the empirical analysis.

3.3.1 Early Childhood Longitudinal Survey (ECLS)

The primary data source used in this study is the Chilean Early Childhood Longitudinal Survey (ECLS) (Behrman et al., 2010).[7] It is a representative national longitudinal cohort study that collects a rich set of information about children who were born between 1^{st} January 2006 and 31^{st} August 2009. The first wave was in 2010 and the second wave was in 2012. In each wave, the primary carer of the ECLS cohort member was interviewed twice in separate household visits. In the first visit, socio-demographic, parental and health characteristics were collected using a household questionnaire. This includes detailed information about household characteristics, parental education, family structure, household income, maternal health and risky behaviours during pregnancy. The HOME inventory (Bustos et al., 2001; Totsika and Sylva, 2004), which assesses the quality of parental stimulation and support given to the child, was included too. In the second visit, cognitive, socio-emotional and anthropometric measures were collected by a trained nurse using a battery of standardised tests.

[7] Or in Spanish, Encuesta Longitudinal de La Primera Infancia (ELPI)

I use the Peabody Picture Vocabulary Test[8] (PPVT) as the cognitive measure in the empirical analysis. The PPVT measures receptive vocabulary by relating words with illustrations (Dunn et al., 1986), and can be used to measure how well children comprehend the Spanish language, a measure of cognitive process. I use the PPVT since it is the only cognitive test that was consistently collected in both waves.

Regarding health outcomes, the ECLS data allows for characterising traditional self-reported measurements of health at birth. In particular, I evaluate the effect of air pollution on birth weight and height, low birth weight (measured as $<$2.500 grams), weeks of pregnancy, whether the child was premature (calculated as $<$37 weeks), whether the child was in an incubator, and the number of days in an incubator.

3.4 Air pollutants

Air pollution data in Chile is collected by the Ministry of Environment using the Automatic Monitoring Network of Atmospheric Pollutants (MACAM2),[9] which is part of the National Air Quality Information System (SINCA).[10] I use seven monitoring stations from this network with systematic daily records of particulate matter less than 10 microns in diameter (PM10), ozone (O3), and carbon monoxide (CO).[11] Using only monitoring stations that systematically gathered information during the analysed period is critical since new monitor placement could arise endogenously from political and bureaucratic processes (Auffhammer and Kellogg, 2011; Bharadwaj et al., 2017a). Additionally, I exclude the Las Condes station since it is located around 695 metres above sea level where inversion episodes are not as useful to characterise the air pollution concentration at ground levels. The geographic location of the monitoring stations used in the analysis is shown in Figures 3.1 and 3.2.

[8]The ECLS used the Test de Vocabulario en Imnes Peabody, Hispanic America adaptation (TVIP) Language skills (for children 30-84 months), which is the Spanish version of the Peabody Picture Vocabulary Test (PPVT).

[9]Or in Spanish called 'Red de Monitoreo Automca de Contaminantes Atmosfcos'.

[10]Or in Spanish called 'Sistema de Informacion Nacional de Calidad del Aire'.

[11]The seven monitoring stations used are located in the following municipalities: Independencia, Santiago, Pudahuel, El Bosque, La Florida, Cerrillos, and Cerro Navia.

Daily PM10 is measured as a 24-hours moving average, CO is measured as an 8-hours moving average, and O3 is measured hourly. Using these three air pollutants, I compute a daily AQI using the algorithm developed by the US Environmental Protection Agency. The AQI is a composite measure of CO, PM10 and O3 created to hierarchize air quality based on its corresponding health risks. It is constructed by taking the maximum over piecewise-linear transformations of daily readings for all individual pollutants (EPA, 2006).

In both ECLS waves, I link each cohort member's household residence to all stations within an eight-kilometre radius. In Figure 3.2, I show the geographical distribution of the air quality monitoring stations. I use the geodetic distance[12] between the cohort member's residence and the monitoring stations to construct a daily exposure measure by taking the inverse-distance weighted average over the corresponding monitors. Using the individual daily air pollution exposure combined with the estimated date of conception and the interview dates from both survey waves, I compute the average exposure throughout the cohort member's life. In particular, in the longitudinal sample, I use two periods to compute the average exposure: from the estimated week of conception to the week of the cognitive evaluation in the first survey, and from the week after the evaluation in the first survey to the cognitive evaluation week in the second survey. In the birth sample, I compute air pollution exposure using the period from the estimated week of conception to the birth week.

3.5 Thermal inversions and weather

A thermal inversion is defined as a reversal of the typical gradient between temperature and altitude, in which temperature decreases with altitude. This atmospheric event, in which a layer of warmer air overlies a layer of cold air at the surface, reduces the vertical ventilation of air, resulting in higher concentrations of air pol-

[12]Geodetic distance is defined the length of the shortest curve along the surface of a mathematical model of the earth. I use the ?geodist? Stata command to calculate the geodetic distances (Robert Picard, 2010). The coordinates reference used is WGS 1984 datum (the same as that used by Google Earth/Map and GPS devices) and 'geodist' calculates ellipsoidal distances using Vincenty's (1975) equations.

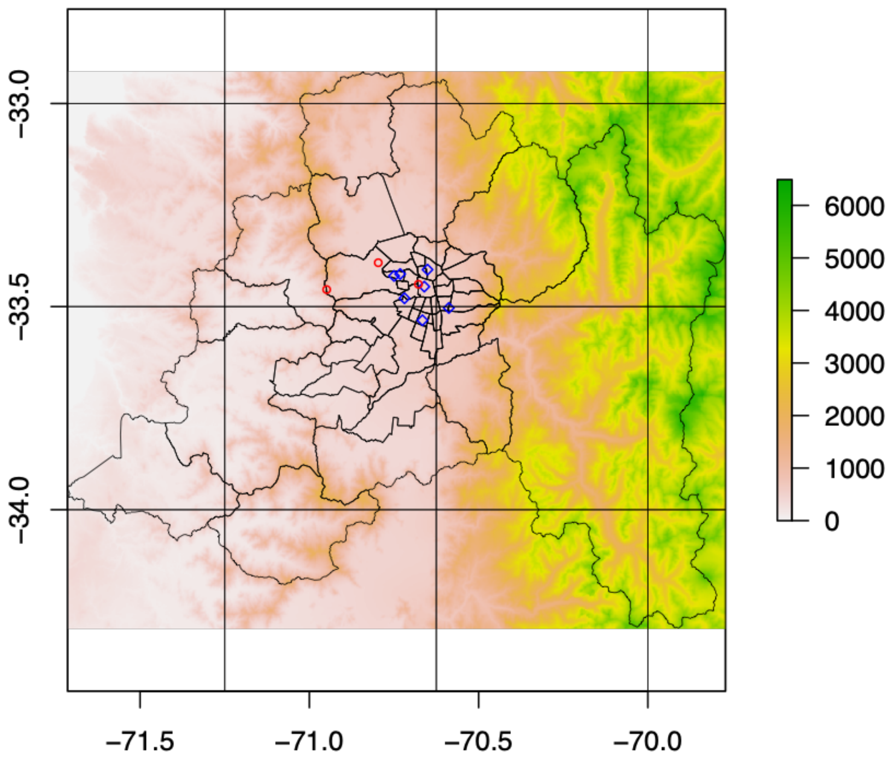

Figure 3.1: Location of air and meteorological monitors, Metropolitan region, Chile

Notes: This figure shows the location of the air (blue circles) and meteorological monitors (red circles) in Santiago. It also includes the topography of the Metropolitan Region, where the different colours indicate the altitude in meters above sea level.

lution at ground level. The main restriction to measuring thermal inversions is the lack of temperature profile data at different altitude levels. Usually, aerostatic balloons are used to measure thermal inversion; however, such data is rarely available for long periods and across wider geographical areas.[13] Therefore, I create daily inversion episodes and the daily intensity of thermal inversion episodes in Santiago using daily ground-level temperature data combined with temperature profile data from the Modern-Era Retrospective analysis for Research and Applications version

[13]An exception is Arceo et al. (2015); Miller and Ruiz-Tagle (2018). When this type of information is not available, using reanalysed atmospheric data seems to be a promising strategy (Chen et al., 2018; Jans et al., 2018; Sager, 2019; Zhang et al., 2017a,b)

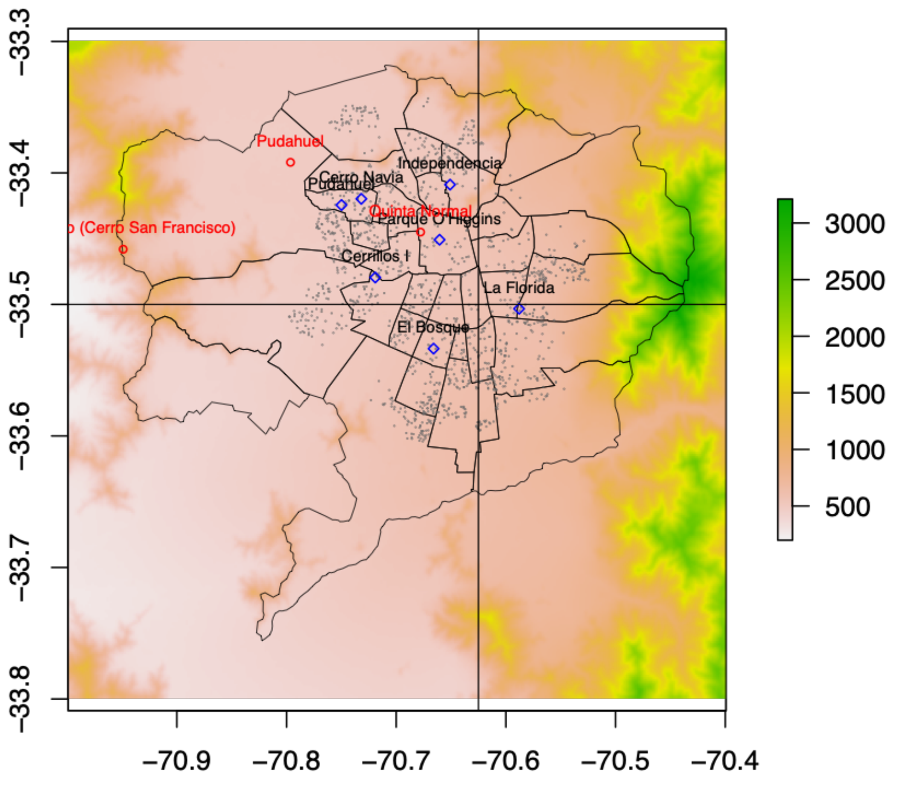

Figure 3.2: Location of children's household, air and meteorological monitors, Santiago, Chile

Notes: This figure shows the location of the analytic sample (black dots), and the air (blue circles) and meteorological monitors (red circles) in Santiago. It also includes the topography of Santiago, where the different colours indicate the altitude in meters above sea level.

2 (MERRA-2). The MERRA-2 data is produced by the National Aeronautics and Space Administration (NASA).

The ground level daily temperature data as well as additional weather data, such as relative humidity, precipitation and wind speed, came from the Pudahuel station located at Comodoro Arturo Merino Benitez International Airport (SCL), which is located 482 metres above the mean sea level (MAMSL). The Pudahuel station belongs to a meteorological network operated by the Chilean Meteorological Agency (DMC).[14] The DMC, which depends on the General Directorate of Civil Aviation (DGAC), is a public body dedicated to studying and forecasting meteorological conditions in Chile.

I retrieve gridded data[15] on air temperatures at higher altitudes from MERRA-2, specifically, from the M2I3NPASM version 5.12.4 product. This data records 3-hour air temperatures at 42 pressure levels. I use the extracted average daily air temperature between 00:00 and 21:00 hours at 925 hPa (ca. 650 MAMSL). I use the grid cell that includes the Pudahuel station to create daily thermal inversion variables,[16] i.e. differences in temperatures at different altitudes but in the same geographical location.

For each day, I calculate the temperature difference using the temperature in the fourth layer (650 meters) minus the temperatures at the Pudahuel station (482 meters). A thermal inversion is observed if the difference is positive, and I measure the strength of the thermal inversion by the difference. Along the same lines that the air pollution measures, I use the estimated dates of conception and birth, and the dates of the cognitive evaluations from both ECLS waves, to compute the frequency of thermal inversions and the average thermal inversion strength experienced by each cohort member.

3.6 Sample restrictions

I restrict the analysis to cohort members born between 1st January 2006 and 31st December 2007 since the PPVT was applied only to cohort members between 30 and 84 months. Additionally, since the instrumental variable strategy is based on the thermal inversions that occur in Santiago, I restrict the sample to cohort members

[14]The US National Oceanic and Atmospheric Administration (NOAA) uses the monitor at Comodoro Arturo Merino Benitez International Airport (SCL) (Longitude=-70.79639, Latitude=-33.39194) to create the 'Summary of the Day' time series used in Bharadwaj et al. (2017a).

[15]The data has a spatial resolution of 0.5°x0.625° grid (around 50x60 km). I downloaded the spatial box (-72.103N, 34.939W, -69.071N,-31.951E) from the following link: `https://disc.gsfc.nasa.gov/datasets/M2I3NPASM_V5.12.4/summary?keywords=merra-2%20inst3_3d_asm_Np`

[16]Figure 3.1 shows the grid, and its extension, of the temperature data retrieved from MERRA-2. As can be seen in the figure, four cells in the grid cover the geographical extension of the data used in this paper. The temperature used to calculate thermal inversion profiles corresponds to the cell that includes the meteorological station 'Pudahuel' (red circle).

who were living in the Chilean capital and in municipalities located below 650 meters above sea level. To reduce the potential measurement error, I further restrict the sample to children who were living within an eight kilometre radius of the selected station monitors located in Santiago (see Figure 3.2).

In the analysis, I show the results for two different samples: the longitudinal sample, which includes all children with longitudinal information on the PPVT scores, and the birth sample, which includes children with non-missing values on health outcomes at birth. I use two different samples to achieve a larger sample size, allowing for higher statistical power in the analysis.

Table 3.1 shows the summary statistics for the longitudinal sample at the first survey and Table 3.2 displays the summary statistics for the birth sample. In both tables, Panel A reports statistics for the control variables, and Panel B reports statistics for the cognitive and health outcomes. While the longitudinal sample is composed of 1,292 cohort members, the birth sample includes 1,747 children. The mothers of children in the longitudinal sample gave birth when they were on average, 27 years old. Around 10% of the mothers reported having smoked and 44% experienced diseases during pregnancy, which is similar to the figures observed in the birth sample. In both samples, around 73% of the mothers reported having secondary education and living on approximately 170 thousand Chilean pesos per capita[17] at the time of the first interview. Around 63% of the sample reported that the cohort member had a history of respiratory problems in both the first and second surveys.

In Panel B of Tables 3.1 and 3.2, I display statistics for the PPVT scores and the health outcomes at birth. Using all children with valid information in the ECLS data, I standardised the PPVT scores with mean 0 and standard deviation 1. The sample means reveal that cohort members in the longitudinal sample have a similar PPVT score than cohort members in the birth sample. Regarding health outcomes at birth, the birth weight and height at birth of children in both samples is around 3.4 kilograms and 50 centimetres on average, leading to a prevalence of low birth weight of approximately 3%. The prevalence of premature pregnancy, defined as

[17]This is around 170 pounds (GBP) or 238 US dollars (USD). Exchange rates: Chilean pesos to GBP 0.001, 2^{nd} January 2021; Chilean pesos to US dollars 0.0014 2^{nd}, January 2021.

children who born at 36 weeks or less of pregnancy, and the prevalence of using an incubator are around 8% and 6%, respectively.

Table 3.1: Descriptive statistics for the longitudinal sample

	(1) Mean	(2) Std. Dev.	(3) Min	(4) Max
Panel A. Control variables				
Cohort member				
Cohort member is female (%)	50.5	50.02	0.0	100.0
Age (months)	41.7	6.81	30.0	58.0
First born (%)	84.7	36.04	0.0	100.0
Second born (%)	14.8	35.51	0.0	100.0
Cohort member had respiratory problems[a] (%)	62.8	48.34	0.0	100.0
Mother				
Mother age (at pregnancy)	27.1	7.13	12.0	46.0
Mother smoked during pregnancy (%)	10.2	30.24	0.0	100.0
Mother had diseases during pregnancy[b] (%)	43.8	49.63	0.0	100.0
Mother had medical conditions during pregnancy[c] (%)	14.7	35.38	0.0	100.0
Maternal education				
Primary education or less (%)	14.1	34.80	0.0	100.0
Secondary education (%)	73.1	44.38	0.0	100.0
Tertiary education (Professional-Technical) (%)	6.4	24.53	0.0	100.0
Tertiary education (University-Postgraduate) (%)	6.4	24.53	0.0	100.0
Household				
Adults living in the household (>18 years)	2.8	1.31	1.0	13.0
Minors living in the household (<=18 years)	1.2	1.03	0.0	7.0
HOME score	-0.0	0.98	-3.2	2.2
Household income per capita	110.0	110.62	0.0	1666.7
Municipality				
Median of household per capita income (2003)[d]	169.3	130.14	68.4	696.2
Avoidance Behaviour				
Number of air quality public daily alerts	105.2	12.57	83.0	129.0
Panel B. Outcome variables				
Cognitive outcomes				
PPVT (first survey)	0.0	1.01	-2.3	3.3
PPVT (second survey)	0.0	0.97	-3.5	2.6
Health outcomes				
Birth weight (kilograms)	3.4	0.48	2.1	5.0
Birth height (centimetres)	49.9	2.04	44.0	55.0
Low birth weight (<2,500 grams,%)	2.6	15.92	0.0	100.0
Pregnancy weeks at birth	38.7	1.96	24.0	42.0
Premature (<37 weeks,%)	8.4	27.72	0.0	100.0
Child was in an incubator (%)	5.9	23.57	0.0	100.0
Days in incubator	0.8	5.52	0.0	113.0
Observations	1292			

Notes: This table shows descriptive statistics for the longitudinal and birth samples used in the analysis. [a] is a binary variable indicating whether the mother indicated that the cohort member had had respiratory problems in the first and second surveys. [b] is defined as a binary variable indicating whether the mother had had at least one of the following list of self-reported diseases: preeclampsia or toxaemia; intrahepatic cholestasis of pregnancy or obstetric cholestasis; urinary infections; haemorrhages; hypertension; placenta previa; gestational diabetes; anaemia; toxoplasmosis; rubella; and syphilis. [c] is defined as a binary variable indicating whether the mother had had at least one of the following self-reported medical conditions: depression; bipolar disorder; anxiety disorder, widespread; obsessive-compulsive disorder; phobia; panic disorder; and posttraumatic stress disorder. [d] The median household per capita income is calculated using the CASEN 2003 survey, which is a Chilean multipurpose national representative survey used by the Chilean Government to measure household, municipality, and regional income distributions.

Table 3.2: Descriptive statistics for the birth sample

	(1) Mean	(2) Std. Dev.	(3) Min	(4) Max
Panel A. Control variables				
Cohort member				
Cohort member is female (%)	49.6	50.01	0.0	100.0
Age (months)	40.8	7.25	27.0	58.0
First born (%)	84.3	36.38	0.0	100.0
Second born (%)	15.1	35.77	0.0	100.0
Cohort member had respiratory problems[a] (%)	63.5	48.16	0.0	100.0
Mother				
Mother age (at pregnancy)	26.8	6.94	12.0	47.0
Mother smoked during pregnancy (%)	11.2	31.57	0.0	100.0
Mother had diseases during pregnancy[b] (%)	41.4	49.28	0.0	100.0
Mother had medical conditions during pregnancy[c] (%)	14.7	35.37	0.0	100.0
Maternal education				
Primary education or less (%)	14.0	34.73	0.0	100.0
Secondary education (%)	72.5	44.68	0.0	100.0
Tertiary education (Professional-Technical) (%)	6.6	24.81	0.0	100.0
Tertiary education (University-Postgraduate) (%)	6.9	25.40	0.0	100.0
Household				
Adults living in the household (>18 years)	2.8	1.28	1.0	13.0
Minors living in the household (<=18 years)	1.2	1.05	0.0	7.0
HOME score	-0.1	0.98	-3.8	2.2
Household income per capita	116.6	123.97	0.0	1666.7
Municipality				
Median of household per capita income (2003)[d]	167.8	131.45	68.4	696.2
Number of Alerts	18.5	10.33	0.0	31.0
Panel B. Outcome variables				
Cognitive outcomes				
PPVT (first survey)	0.0	1.00	-2.0	3.3
PPVT (second survey)	-0.0	1.00	-3.5	2.6
Health outcomes				
Birth weight (kilograms)	3.4	0.49	2.0	5.0
Birth height (centimetres)	49.9	2.01	44.0	55.0
Low birth weight (<2,500 grams,%)	3.0	17.00	0.0	100.0
Pregnancy weeks at birth	38.8	1.70	24.0	42.0
Premature (<37 weeks,%)	6.2	24.19	0.0	100.0
Child was in an incubator (%)	4.2	20.15	0.0	100.0
Days in incubator	0.3	1.88	0.0	36.0
Observations	1747			

Notes: This table shows descriptive statistics for the longitudinal and birth samples used in the analysis. [a] is defined as a binary variable indicating whether the mother indicated that the cohort member had had respiratory problems in the first and second surveys. [b] is defined as a binary variable indicating whether the mother had had at least one of the following list of self-reported diseases: preeclampsia or toxaemia; intrahepatic cholestasis of pregnancy or obstetric cholestasis; urinary infections; haemorrhages; hypertension; placenta previa; gestational diabetes; anaemia; toxoplasmosis; rubella; and syphilis. [c] is defined as a binary variable indicating whether the mother had had at least one of the following self-reported medical conditions: depression; bipolar disorder; anxiety disorder, widespread; obsessive-compulsive disorder; phobia; panic disorder; and posttraumatic stress disorder. [d] is the median household per capita income, calculated using the CASEN 2003 survey, which is a Chilean multipurpose national representative survey used by the Chilean Government to measure household, municipality, and regional income distributions.

3.6.1 Individual-level exposure to air quality and thermal inversions

In Figure 3.3 and 3.4, I display the daily air pollution data I use to create measures of individual exposure to air quality. In particular, Figure 3.3 shows the daily mean of PM10, CO, O3, and AQI from January 2005 to December 2012, illustrating the seasonal variation observed in Santiago. The variation between air quality monitors is shown in Figure 3.4, in which each line shows the 90-day moving average of PM10, CO, O3 and AQI for different monitors. These figures illustrate that although cohort members in Santiago experience a similar seasonal pattern of exposure to air pollution, during winter children who live in Cerro Navia or El Bosque experience 15% higher average PM10 levels than children who live in Independencia or Cerrillos.

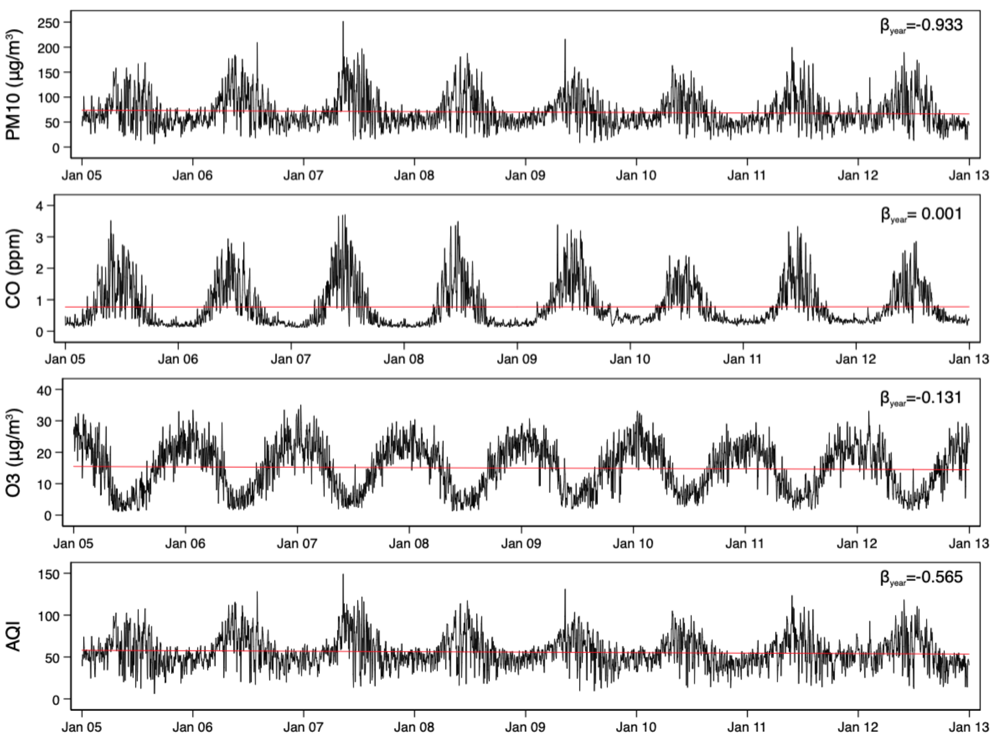

Figure 3.3: Air quality in Santiago, 90-day moving average (PM10, CO, O3, AQI)

Notes: This figure shows the daily mean of PM10, CO, O3 and AQI between January 2005 and December 2012.

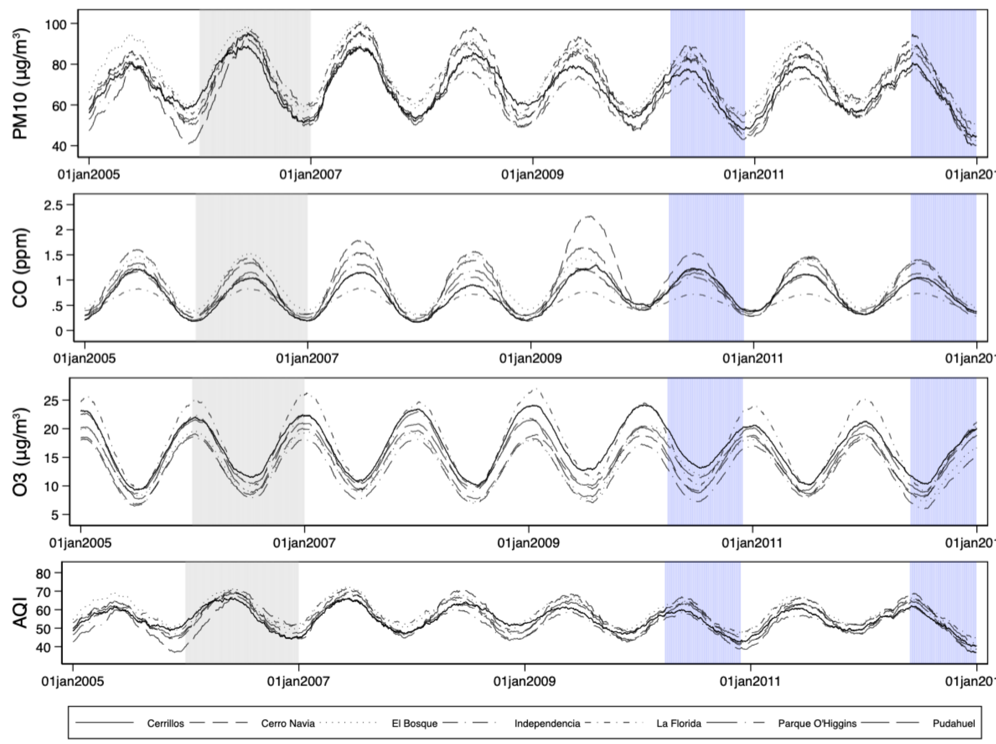

Figure 3.4: Air quality, variation between air monitors, 90-day moving average (PM10, CO, O3, AQI)

Notes: This figure shows the 90-day moving average of PM10, CO, O3 and AQI between January 2005 and December 2012.

The seasonal variation in outdoor air pollution in Santiago's basin is primarily explained by its geography (see topography in Figure 3.1 and 3.2) and changes in ventilation conditions, especially during the winter period. Thermal inversions due to subsidence, which occur when vertical air movements cause the air at higher altitudes to become warmer than at lower altitudes, are known to be associated with reduced ventilation in Santiago (Gerreaud & Retllant, 2006).

In Figures 3.5 and 3.6, I show evidence of the association between thermal inversions and air quality for the period used in the empirical analysis. Figure 3.5 shows that the weekly average PM10 and CO concentrations is higher between May and September, while the O3 concentration shows the opposite pattern.[18] At the

[18]The ozone concentration in urban areas is known to be increasing with increasing temperature and decreasing with increasing relative humidity, leading to lower levels during winter when there are more likely to be cloudy, cool, rainy, or windy days (Camalier et al., 2007; Cox and Chu, 1996). Besides, given that ozone formation is associated with chemical reactions involving air temperature and sunlight, thermal inversions may interfere with O3 formation (Arceo et al., 2015).

same time, it also shows that the weekly percentage of days with thermal inversion episodes follows a similar pattern to the air pollution trends. The same picture is seen in Figure 3.6, in which I show the weekly average intensity of thermal inversions, defined as no negative value of the temperature difference between 650 and 480 MAMSL.

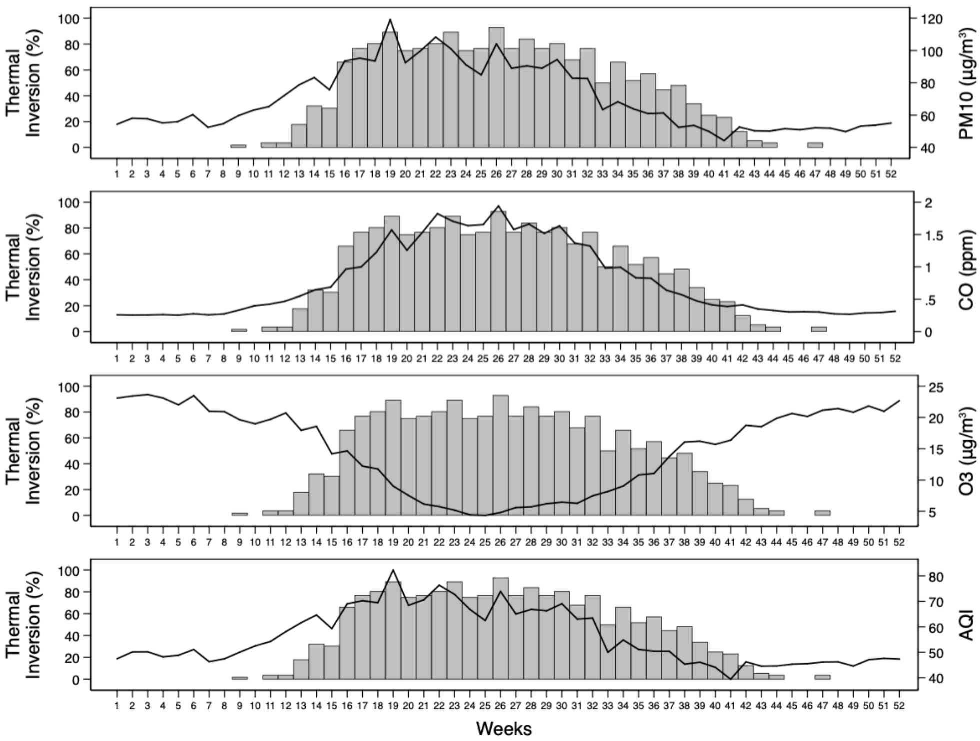

Figure 3.5: Thermal inversions and air quality, by week of the year

Notes: This figure compares the average percentage of days of thermal inversion per week (bars) with the weekly average of PM10, CO, O3, and AQI (lines) in Santiago, Chile. The weekly averages are computed using the seven air monitors used in the empirical analysis and data between January 2005 and December 2012.

In Table 3.3, I present descriptive statistics for the cohort members' exposure to air pollution, weather conditions and thermal inversion episodes for the two periods considered in the longitudinal sample. In Table 3.4, I show the same information for the birth sample. For the longitudinal sample, Panel A in Table 3.3 reports sample means computed from the estimated week of conception to the week of the first ECLS wave, and Panel B reports descriptive statistics from the week after the first ECLS wave to the second ECLS wave. Similarly, in Panel A of Table 3.4, I display statistics computed from the estimated week of conception to the cohort member's

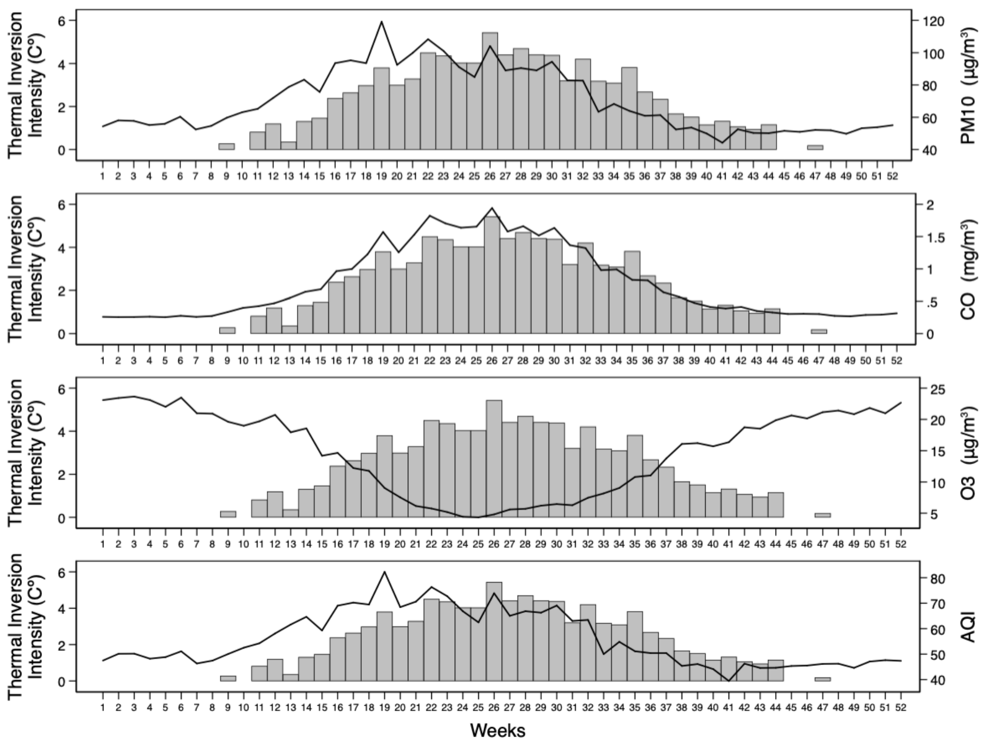

Figure 3.6: Intensity of thermal inversions and air quality, by week of the year

Notes: This figure compares the average intensity of the thermal inversion per week (bars) with the weekly average of PM10, CO, O3, and AQI (lines) in Santiago, Chile. The weekly averages are computed using the seven air monitors used in the empirical analysis and data between January 2005 and December 2012.

birth date.[19] The data shows that, from conception to the week in which the PPVT was evaluated, cohort members experienced an average exposure level of 73 μg/m^3 for PM10, 0.8 ppm for CO and 16 μg/m^3 for O3. Similar average exposure is observed between waves (see Panel B of Table 3.3). Cohort members experienced thermal inversion episodes on 559 days before the first wave, which translates to around 35,9% of children lives at that time. Additionally, during the same period, the average thermal inversion intensity experienced by children was 2.9 °C.

[19]The estimated week of conception is created using each cohort member's birthday and the question "How many weeks pregnant did you have when the child was born?". I impute missing values using the sample mean of pregnancy weeks.

Table 3.3: Descriptive statistics for air pollution, thermal inversion, and weather controls, longitudinal sample

	(1) Mean	(2) Std. Dev.	(3) Min	(4) Max
Panel A. First survey				
Air Quality				
Particulate matter 10	72.5	2.84	65.1	77.8
Carbon monoxide	0.8	0.13	0.5	1.1
Ozone	15.5	1.50	11.9	19.1
Air quality index	57.4	1.75	53.6	60.5
Weather Controls				
Precipitation	0.5	0.04	0.4	0.6
Relative humidity	63.4	0.66	62.0	65.0
Temperature	14.8	0.25	14.1	15.3
Wind speed	5.1	0.09	5.0	5.4
Thermal Inversion				
Thermal inversion events (days)	558.6	85.68	401.0	782.0
% of life with thermal inversion events	35.9	1.82	31.5	40.2
Thermal inversion intensity (° C)	2.9	0.05	2.8	3.0
Thermal inversion - IV	104.7	6.77	89.0	121.5
Panel B. Second survey				
Air Quality				
Particulate matter 10	70.2	3.15	61.6	77.1
Carbon monoxide	0.8	0.11	0.5	1.0
Ozone	14.3	1.31	11.4	18.3
Air quality index	55.7	1.76	51.1	59.4
Weather Controls				
Precipitation	0.4	0.04	0.3	0.5
Relative humidity	61.2	0.91	58.5	62.6
Temperature	14.7	0.42	14.1	15.9
Wind speed	5.8	0.13	5.5	6.1
Thermal Inversion				
Thermal inversion events (days)	295.6	44.32	184.0	377.0
% of life with thermal inversion events	37.2	2.72	29.7	42.0
Thermal inversion intensity (° C)	3.1	0.09	2.7	3.3
Thermal inversion - IV	113.9	10.44	81.9	132.8
Observations	1292			

Notes: This table shows descriptive statistics for air pollutants, thermal inversions and weather controls.

Table 3.4: Descriptive statistics for air pollution, thermal inversion, and weather controls, birth sample

	(1) Mean	(2) Std. Dev.	(3) Min	(4) Max
Panel A. First survey				
Air Quality				
Particulate matter 10	74.3	8.03	54.0	92.0
Carbon monoxide	0.8	0.21	0.3	1.4
Ozone	15.3	2.33	10.7	22.3
Air quality index	58.2	4.58	45.0	67.9
Weather Controls				
Precipitation	0.5	0.23	0.0	1.3
Relative humidity	65.5	2.74	59.7	72.2
Temperature	14.5	1.50	10.2	17.1
Wind speed	4.6	0.45	3.6	5.6
Thermal Inversion				
Thermal inversion events (days)	100.6	28.00	36.0	143.0
% of life with thermal inversion events	36.6	10.12	14.7	61.9
Thermal inversion intensity (° C)	3.0	0.49	1.6	3.7
Thermal inversion - IV	114.5	42.59	23.2	199.7

Notes: This table shows descriptive statistics for air pollutants, thermal inversions and weather controls.

The instrumental variable I use in the empirical strategy is defined as percentage of children's lives with thermal episodes times the average intensity of the thermal inversion episodes. As can be seen in Panels A and B of Table 3.3 the instrumental variable mean in the first and second periods is 105 and 114, respectively.

To clarify the identifying variation in the empirical design, in Figure 3.7, I show the cohort member average exposure to air quality and thermal inversion episodes by months of birth. In Figure 3.8, I show the same results but for the thermal inversion instrumental variable. In particular, I plot the information in Panel A of Table 3.4. The data show that cohort members born in the summer, i.e. from December to February, experience higher air pollution than children born in winter. The differential exposure to air quality due to different birth dates and the date of the PPVT evaluation is the variation exploited in the fixed effects regression in equation 3.3. If the assumption that conditional on age and site fixed effects the timing of the birth has no effect on the PPVT scores holds, then fixed effects estimates should deliver a causal estimate of the impact of air quality on cohort members' outcomes. However, this could not be true, for instance, if fertility behaviours produce seasonal patterns in unobserved parental characteristics (Marcotte, 2017), or, as discussed previously, if parental avoidance behaviours, residential sorting or measurement error are present. Therefore, the instrumental variable strategy based on the frequency and intensity of thermal inversion should further strengthen the identification assumptions.

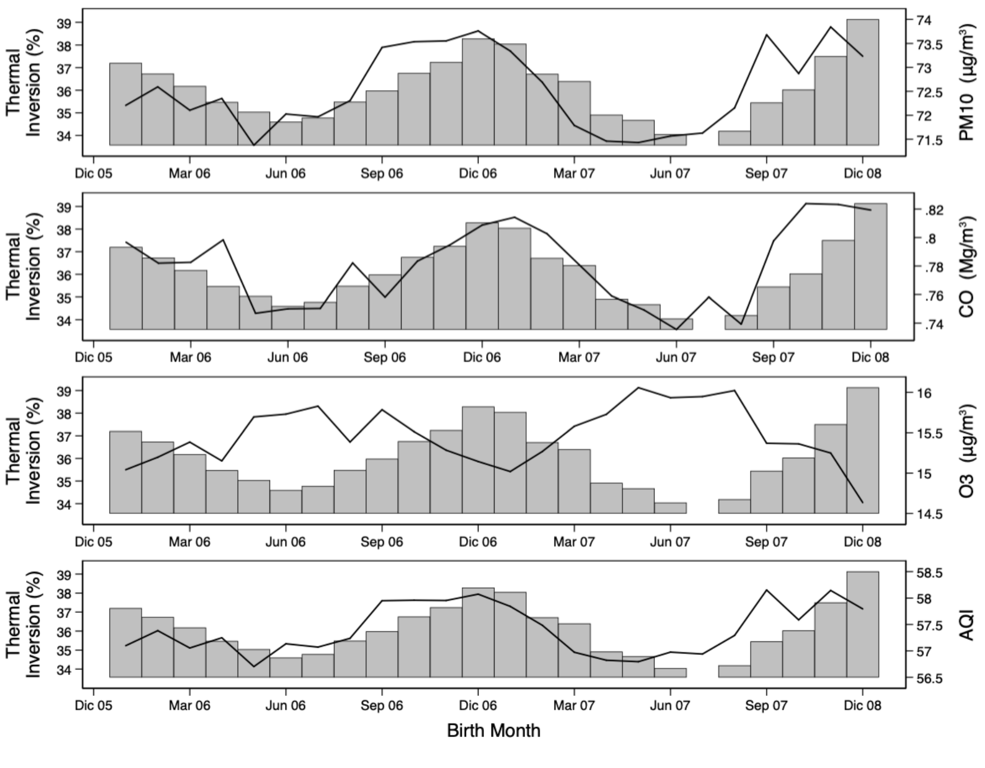

Figure 3.7: Cohort member exposure to thermal inversions and air quality, by month of birth

Notes: This figure compares cohort member exposure to thermal inversions and air quality between the estimated date of conception and the date when the cognitive evaluation in the first wave was taken. In particular, within a month of birth, it compares the average percentage of days of thermal inversions experienced by the child with the average child exposure to PM10, CO, O3, and AQI (lines). The averages are computed using children in the analytic sample.

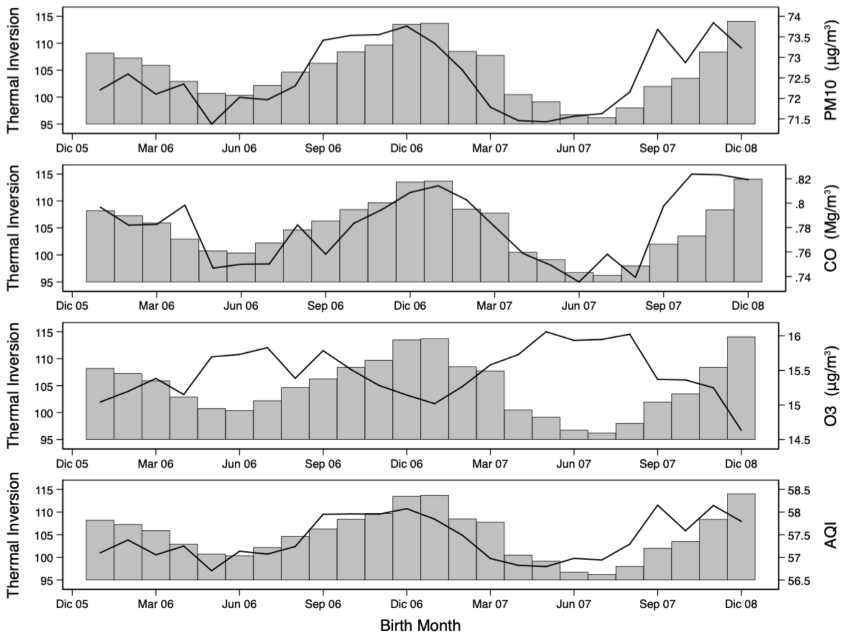

Figure 3.8: Cohort member exposure to thermal inversions weighted by the average intensity and air quality, by month of birth

Notes: This figure compares cohort member exposure to thermal inversions weighted by the average intensity and air quality between the estimated date of conception and the date when the cognitive evaluation in the first wave was taken. In particular, within a month of birth, it compares the average percentage of days of thermal inversions experienced by the child with the average child exposure to PM10, CO, O3, and AQI (lines). The averages are computed using children in the analytic sample.

3.7 Results

In this section, I present fixed effects and instrumental variable estimates using the models described in section 3.2.2. I first describe the results of the impact of air quality on the PPVT scores followed by the results for health outcomes at birth.

3.7.1 Impact of air quality on PPVT scores

Table 3.5 and Panel A of table 3.6 show the estimates of the first and second stage regressions of the instrumental variable strategy. In panel B of Table 3.6 I show the fixed effects estimates. In column 1, I show the baseline specification, in which I control for the following time-varying covariates: cohort member's age in months, four binary variables indicating the highest maternal education achieved, number of adults and minors living in the household, the HOME inventory score, household per capita income, and the number of air quality public daily alerts. This specification also includes weather controls, such as second-degree polynomials of precipitation, relative humidity, temperature, wind speed, and ozone. Additionally, cohort member fixed effects, monitor fixed effects, and year of the survey fixed effects are included. Column 2 excludes individual controls from the model in column 1. Columns 3 and 4, respectively, add to the model in column 1 the quarter in which the PPVT was evaluated, and the same variable interacted with the monitoring stations. Standard errors are clustered at the individual level.

Table 3.5: The effect of thermal inversions on air quality, longitudinal sample (first stage)

	(1)	(2)	(3)	(4)
Panel A: PM10				
Thermal inversion	0.002***	0.003***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Kleibergen-Paap F statistic	375.8	499.2	369.0	366.4
Panel B: CO				
Thermal inversion	0.002***	0.002***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Kleibergen-Paap F statistic	30.0	34.0	50.1	54.6
Panel C: AQI				
Thermal inversion	0.001***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Kleibergen-Paap F statistic	333.8	34.0	338.5	362.1
Dep. var. mean	4.03	-0.26	4.03	4.03
Observations	2584	2584	2584	2584
Weather controls	Yes	Yes	Yes	Yes
Individual controls	Yes	No	Yes	Yes
Monitor FE	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes
Quarter of Test FE	No	No	Yes	No
Monitor X Quarter of Test FE	No	No	No	Yes

Notes: This table shows the estimates of the effect of the percentage of days with thermal inversions episodes (weighted by the average intensity) experienced by children throughout their lives on air pollution concentration. The variables included in each specification are listed at the bottom of Table 3.6. The dependent variables are the logarithms of the air pollutants in Table 3.3. The standard errors (in parenthesis) are clustered at the individual level. Statistical significance is denoted by: ***p< 0.01, **p<0.05, *p<0.10.

I start by analysing the effect of thermal inversion on air quality. Panels A, B, and C in Table 3.5 show the first stage regression for PM10, CO, and AQI, respectively. In the baseline specification, a 10 unit increase in the thermal inversion variable, which is around 1 standard deviation, is associated with an increase of around 2-3% in PM10, CO, and AQI. In all specifications, the coefficients of average exposure to thermal inversion are significant at the one per cent level. Besides, the lowest Kleibergen-Paap F statistic, which tests for a weak instrument, is 30, providing evidence of a strong first stage.

My preferred estimates of the impact of air pollution on cognitive performance are presented in Figure 3.9. This figure shows the estimates in column 1 of Panel A in Table 3.6, in which I show the instrumental variable (IV) estimates. For comparison, in Panel B, I show the fixed effects (FE) estimates. I present the estimated effects of a 1% increase in air pollution on the PPVT scores.

I find that a 1% increase in PM10 leads to a reduction of around 3 per cent of a standard deviation in the PPVT scores. A 1% increase in PM10 pollution translates to an increase of 0.73 μg/m^3 when I use the mean of PM10 pollution at the first survey, of around 72.5 μg/m^3. The data show a similar effect of the CO and AQI on PPVT scores. Respectively, a 1% increase in AQI and CO reduces the PPVT scores by 5 and 3 per cent of a standard deviation.

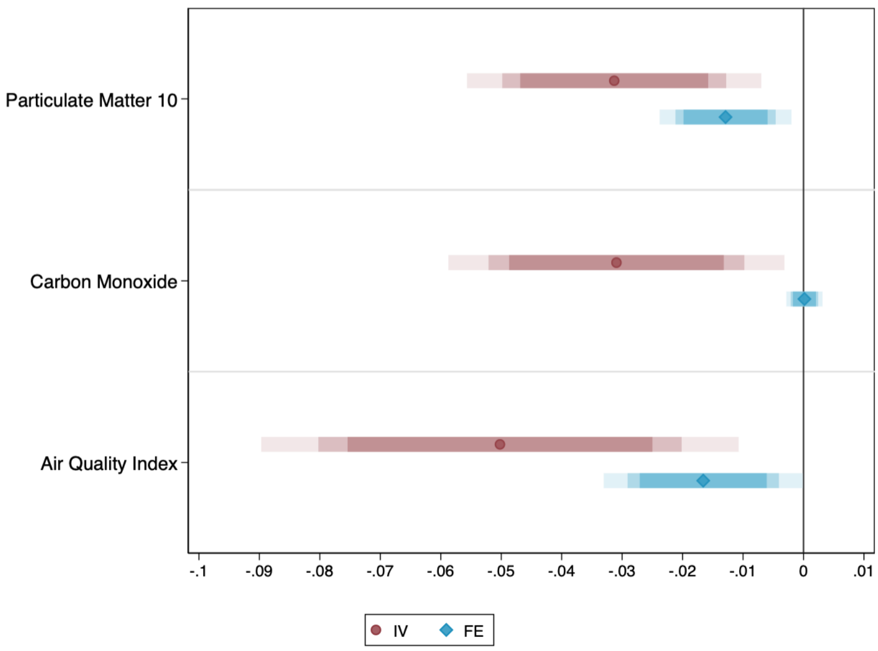

Figure 3.9: Impact of air pollution on cognitive performace

Notes: This figure shows the fixed effects and instrumental variable estimates displayed in column 1 of table 3.6. It also shows the 90, 95, and 99% confidence intervals.

The FE estimates in Panel B suggest a negative and significant association between air pollution and cognitive performance. Although the FE estimates are smaller in absolute value than the IV estimates, consistent with attenuation bias due to measurement error, only for CO I find the difference is statistically significant. In general, it is challenging to identify the direction of the bias due to omitted variables in multivariate settings (Basu, 2020); however, I interpret the IV estimates as suggestive evidence of bias in the FE estimates. For example, based on the conceptual framework described in Section 3.2.1 it is possible that, even after controlling for parental avoidance behaviours and compensatory parental investment, residential sorting would bias the FE estimates. For example, residential sorting negatively associated with the concentration of air pollution levels and positively associated with early childhood cognitive performance, e.g. more wealthy families moving to less polluted neighbourhoods, would lead to negative bias– under-estimating the impacts of air pollution.

The estimates presented in column 2, which do not control for the number of air quality public alerts or HOME inventory scores, or other individual controls, in general have a smaller absolute value than the estimates in column 1, providing evidence of the importance of controlling for avoidance behaviours and proxies of parental compensatory behaviours.

An additional potential concern is that the period when the PPVT was evaluated, e.g. winter or summer, could affect children's performance. For that reason, in columns 3 and 4, I display estimates of models that control for the timing in which the PPVT was evaluated using quarter of PPVT fixed effects and monitoring stations interacted with quarter of the PPVT fixed effects. The impact of air pollution on the test scores is robust to these two specifications, suggesting that the within monitor variation in average exposure to air pollution across life is unrelated to the period of the year in which the PPVT was taken.

I then explore whether the effect of air quality on cognitive performance can be mediated by the presence of respiratory problems. Tables 3.7 and 3.8 show estimates for a sub-sample of cohort members whose parents reported respiratory diseases as one of the most frequent diseases that their children had had since birth,[20]

[20] I restrict the sample to children who reported 'respiratory problems' when their mothers were asked the question "What have been the most frequent diseases that the child has presented since birth?" either in the first or second wave of the ECLS.

Table 3.6: The effect of air pollution on PPVT scores

	(1)	(2)	(3)	(4)
Panel A: Instrumental Variable				
Particulate Matter 10	-0.031***	-0.019**	-0.024***	-0.024**
	(0.009)	(0.008)	(0.009)	(0.009)
Kleibergen-Paap F statistic	375.8	499.2	369.0	366.4
Carbon Monoxide	-0.031***	-0.020**	-0.018**	-0.019**
	(0.011)	(0.009)	(0.008)	(0.008)
Kleibergen-Paap F statistic	30.0	34.0	50.1	54.6
Air Quality Index	-0.050***	-0.030**	-0.038**	-0.037**
	(0.015)	(0.013)	(0.015)	(0.014)
Kleibergen-Paap F statistic	333.8	442.5	338.5	362.1
Panel B: Fixed Effect				
Particulate Matter 10	-0.013***	-0.009**	-0.012***	-0.011**
	(0.004)	(0.004)	(0.004)	(0.004)
Adjusted R-squared	0.05	0.03	0.06	0.09
Carbon Monoxide	0.000	0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R-squared	0.05	0.03	0.06	0.09
Air Quality Index	-0.017***	-0.010*	-0.016**	-0.016**
	(0.006)	(0.006)	(0.006)	(0.007)
Adjusted R-squared	0.05	0.03	0.06	0.09
Dep. var. mean	1.593	1.593	1.593	1.593
Observations	2584	2584	2584	2584
Weather controls	Yes	Yes	Yes	Yes
Individual controls	Yes	No	Yes	Yes
Monitor FE	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes
Quarter of Test FE	No	No	Yes	No
Monitor X Quarter of Test FE	No	No	No	Yes

Notes: This table provides the coefficient estimates of the effect of air pollution on the PPVT scores. The model in column 1 includes the cohort member's age in months, and three binary variables that indicate the highest maternal education achieved at the moment of the interview. In particular, it includes the categories 'Secondary school (any)', 'Higher education (Professional-Technical)', and 'Higher education (University-Postgraduate)', while 'Primary school or less' is used as a baseline category. It also includes the number of adults and minors living in the household, the HOME score, the household per capita income, and the number of air quality public daily alerts. The weather controls included are second-degree polynomials of precipitation, relative humidity, temperature, wind speed, and ozone. It also includes individual fixed effects, monitor fixed effects, and year of the survey fixed effects. Column 2 excludes individual controls. Columns 3 and 4 add to the model in column 1 quarter of the PPVT fixed effects and monitoring stations interacted with the quarter of the PPVT fixed effects, respectively. The standard errors (in parenthesis) are clustered at the individual level. The statistical significance is denoted by: ***p< 0.01, **p<0.05, *p<0.10.

approximately 63% of the Cognitive Sample (see Table 3.1). The FE and IV estimates in Table 3.8 are generally larger than those in Table 3.6, providing evidence that the same level of pollution exposure is more harmful to children with a history of respiratory problems, one of the known channels through which air pollution affects cognitive performance. For instance, the PM10 and AQI instrumental variable estimates for cohort members with respiratory problems are around 10% larger than the estimates for all cohort members.

Table 3.7: The effect of thermal inversions on air quality, the longitudinal sample, and cohort members with respiratory problems (first stage)

	(1)	(2)	(3)	(4)
Panel A: PM10				
Thermal inversion	0.002***	0.003***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Kleibergen-Paap F statistic	216.8	302.9	208.2	204.5
Panel B: CO				
Thermal inversion	0.002***	0.002***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Kleibergen-Paap F statistic	15.9	21.0	29.8	31.1
Panel C: AQI				
Thermal inversion	0.001***	0.002***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Kleibergen-Paap F statistic	203.1	283.6	198.2	204.8
Dep. var. mean	4.04	4.04	4.04	4.04
Observations	1624	1624	1624	1624
Weather controls	Yes	Yes	Yes	Yes
Individual controls	Yes	No	Yes	Yes
Monitor FE	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes
Quarter of Test FE	No	No	Yes	No
Monitor X Quarter of Test FE	No	No	No	Yes

Notes: This table provides the coefficient estimates of the effect of air pollution on the PPVT scores. The variables in each specification are listed at the bottom of Table 3.6. The dependent variables are the logarithms of the air pollutants in Table 3.3. The standard errors (in parenthesis) are clustered at the individual level. The statistical significance is denoted by: ***p< 0.01, **p<0.05, *p<0.10.

3.7.2 Impact of air quality on health at birth

I evaluate the effect of air pollution on the risk of low birth weight, weeks of pregnancy, the probability of being premature, the probability of using an incubator, and the days in the incubator. Table 3.9 presents first stage estimates of the effect of thermal inversions on air pollution during pregnancy. It should be noted that I only report three first-stage estimates in Table 3.9, which are consistent with the specification shown in Table 3.10 and equations (3.5)-(3.6). The first stage estimates of PM10 and AQI, respectively in columns 1 and 3, show that the frequency of thermal inversions and their intensity during pregnancy are relevant and strong instruments;

Table 3.8: The effect of air quality on the PPVT scores, cohort members with respiratory problems

	(1)	(2)	(3)	(4)
Panel A: Instrumental Variable				
Particulate Matter 10	-0.034***	-0.019*	-0.030**	-0.032***
	(0.012)	(0.010)	(0.013)	(0.012)
Kleibergen-Paap F statistic	216.8	302.9	208.2	204.5
Carbon Monoxide	-0.037**	-0.021*	-0.024**	-0.026**
	(0.016)	(0.012)	(0.011)	(0.011)
Kleibergen-Paap F statistic	15.9	21.0	29.8	31.1
Air Quality Index	-0.055***	-0.030*	-0.048**	-0.051**
	(0.020)	(0.016)	(0.020)	(0.020)
Kleibergen-Paap F statistic	203.1	283.6	198.2	204.8
Panel B: Fixed Effect				
Particulate Matter 10	-0.019***	-0.014***	-0.018***	-0.017***
	(0.005)	(0.005)	(0.005)	(0.005)
Adjusted R-squared	0.08	0.04	0.09	0.11
Carbon Monoxide	-0.001	-0.001	-0.002	-0.003*
	(0.002)	(0.002)	(0.002)	(0.002)
Adjusted R-squared	0.07	0.03	0.08	0.10
Air Quality Index	-0.027***	-0.018**	-0.027***	-0.026***
	(0.008)	(0.007)	(0.008)	(0.008)
Adjusted R-squared	0.08	0.04	0.09	0.11
Dep. var. mean	1.598	1.598	1.598	1.598
Observations	1624	1624	1624	1624
Weather controls	Yes	Yes	Yes	Yes
Individual controls	Yes	No	Yes	Yes
Monitor FE	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes
Quarter of Test FE	No	No	Yes	No
Monitor X Quarter of Test FE	No	No	No	Yes

Notes: This table shows the estimates of the effect of the percentage of days with thermal inversions and the average intensity of thermal inversion experienced by children throughout their life on air pollution concentration. The variables in each specification are listed at the bottom of Table 3.6. The standard errors (in parenthesis) are clustered at the individual level. The statistical significance is denoted by: ***p< 0.01, **p<0.05, *p<0.10.

however, this evidence is weaker for CO. For this reason, I focus only on the FE and IV estimates for PM10 and AQI.

Panel A of Table 3.10 shows the IV estimates, while Panel B shows the FE estimates. Within each Panel, the rows indicate the air quality measurements and the columns indicate the health outcomes at birth. I control for a set of variables that are known to be linked to health at birth and have previously been used in the literature. In particular, I control for monitor fixed effects, year of birth fixed effects, weather

Table 3.9: The effect of thermal inversions on air quality, birth sample (first stage)

	PM10 (1)	CO (2)	AQI (3)
Thermal inversion	0.001***	0.001*	0.000***
	(0.000)	(0.000)	(0.000)
Kleibergen-Paap F statistic	15.0	5.9	16.2
Dep. var. mean	4.302	-0.295	4.061
Observations	1747	1747	1747
Weather controls	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes
Monitor FE	Yes	Yes	Yes
Birth year FE	Yes	Yes	Yes

Notes: This table provides the coefficient estimates of the effect of the percentage of days with thermal inversions and the average intensity of thermal inversions. The variables in each specification are listed at the bottom of Table 3.6. The dependent variables are the logarithms of the air pollutants in Table 3.4. The standard errors (in parenthesis) are clustered at the monitor level. The statistical significance is denoted by: ***p<0.01, **p<0.05, *p<0.10.

conditions, and maternal and municipality characteristics. The maternal characteristics include the mother's age at birth, maternal education, whether mother smoked during the pregnancy, the number of diseases during pregnancy,[21] the number of medical conditions during pregnancy,[22] and whether the cohort member was first or second born. I also control for avoidance behaviours during pregnancy and residential sorting at the baseline by including the number of government environmental alerts during pregnancy and the median of the municipality income per capita in 2003. In all models, I also control for ozone exposure during pregnancy. The standard errors are clustered at the monitor level.

I find that, in both the FE and IV models, a worsening exposure to air quality during pregnancy is associated with lower birth weight. For instance, the IV estimates in column 1 of Panel A show that a 1% increase in AQI is associated with an increase in the risk of a low birth weight of around 4.8 percentage points, and a decrease in birth weight of around 220 grams. For PM10, the results are similar,

[21]Defined as the sum of the following list of self-reported diseases: preeclampsia or toxaemia; intrahepatic cholestasis of pregnancy or obstetric cholestasis; urinary infections; haemorrhages; hypertension; placenta previa; gestational diabetes; anaemia; toxoplasmosis; rubella; and syphilis.

[22]Defined as the sum of the following list of self-reported medical conditions: depression; bipolar disorder; anxiety disorder, widespread; obsessive-compulsive disorder; phobia; panic disorder; and post-traumatic stress disorder.

whereby a 1% increase in PM10 exposure during pregnancy reduces birth weight by around 150 grams with respect to a sample mean of 3.4 kilograms, and increases the risk of a low birth weight by 3 percentage points relative to a sample mean of 3%.

Table 3.10: The effect of air pollution on health at birth

	Birth weight (1)	Birth height (2)	Low birth weight (3)	Weeks of pregnancy (4)	Premature (5)	Incubator (6)	Days in Incubator (7)
Panel A: Instrumental Variable							
Particulate Matter 10	-0.152**	-0.653**	0.033**	-1.276***	0.147***	0.039**	0.181
	(0.076)	(0.279)	(0.015)	(0.365)	(0.038)	(0.017)	(0.118)
Kleibergen-Paap F statistic	15.0	15.0	15.0	15.0	15.0	15.0	15.0
Carbon Monoxide	-0.095*	-0.407*	0.020*	-0.796**	0.091***	0.024**	0.113
	(0.054)	(0.209)	(0.011)	(0.324)	(0.034)	(0.012)	(0.077)
Kleibergen-Paap F statistic	5.9	5.9	5.9	5.9	5.9	5.9	5.9
Air Quality Index	-0.222**	-0.954**	0.048**	-1.863***	0.214***	0.056**	0.264
	(0.108)	(0.401)	(0.021)	(0.505)	(0.053)	(0.024)	(0.166)
Kleibergen-Paap F statistic	16.2	16.2	16.2	16.2	16.2	16.2	16.2
Panel B: Fixed Effect							
Particulate Matter 10	-0.013**	-0.032**	0.005***	-0.086***	0.008***	0.002	0.033**
	(0.005)	(0.011)	(0.001)	(0.012)	(0.002)	(0.001)	(0.012)
Adjusted R-squared	0.06	0.07	0.03	0.22	0.20	0.01	0.01
Carbon Monoxide	-0.001	-0.002	0.000	-0.019***	0.002**	-0.000	0.003
	(0.002)	(0.005)	(0.000)	(0.004)	(0.001)	(0.001)	(0.004)
Adjusted R-squared	0.05	0.07	0.02	0.20	0.19	0.01	0.01
Air Quality Index	-0.015**	-0.036**	0.005**	-0.099***	0.009***	0.002	0.039**
	(0.006)	(0.014)	(0.002)	(0.016)	(0.002)	(0.001)	(0.015)
Adjusted R-squared	0.06	0.07	0.02	0.22	0.20	0.01	0.01
Dep. var. mean	3.401	49.867	0.030	38.805	0.062	0.042	0.251
Observations	1747	1747	1747	1747	1747	1747	1747
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monitor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table provides the coefficient estimates of the effect of air pollution on health at birth. All of the models include monitor fixed effects, birth of year fixed effects and three binary variables that indicate the highest maternal education. In particular, maternal education includes the categories 'Secondary school (any)', 'Higher education (Professional-Technical)', and 'Higher education (University-Postgraduate)', while 'Primary school or less' is used as the baseline category. The models also include the mother's age at birth, whether the mother smoked during pregnancy, number of diseases during pregnancy, number of medical conditions during pregnancy, and whether the cohort member was first or second born, the number of government environmental alerts during pregnancy and the median of the municipality income per capita in 2003. The standard errors (in parenthesis) are clustered at the monitor level. The statistical significance is denoted by: ***p< 0.01, **p<0.05, *p<0.10.

Regarding the effects of air quality on cohort member gestation, I find that the average number of pregnancy weeks was reduced by maternal exposure to air pollution during pregnancy. For instance, the IV estimates in columns 4 and 5 show that a 1% increase in AQI shortened gestation by 1.8 weeks and increase the probability of having a premature child by 21.4 percentage points. Similarly, a 1% increase in PM10 increase the probability of having a premature child by 14.7 percentage points and reduce the number of weeks of pregnancy by 1.3 weeks relative to the sample mean of 39 weeks of gestation. The FE models, presented in Panel B, show similar but smaller estimates.

In columns 6 and 7, I show estimates for the probability of being in an incubator after birth and the number of days in an incubator. The IV estimates in Panel A show that exposure to air pollution has a detrimental effect on the probability of being in the incubator, while the FE estimates are non-significant.

3.8 Conclusion

This study evaluates the effect of air pollution on early childhood cognitive performance and health at birth combining data from a rich longitudinal survey, daily air pollution data, and atmospheric climate data collected by NASA. Using a fixed effects instrumental variable strategy that exploits the positive link between thermal inversions and air pollution concentration at ground levels, I provide causal evidence that air pollution worsens both the PPVT scores and several outcomes related to health at birth. These findings relate to the literature in economics that has separately studied the impact of air quality on child health and cognitive performance. In doing so, they contribute to this literature by providing new estimates of both associations for a developing country; these nations have thus far been underrepresented in the international evidence.

Using longitudinal data on cognitive performance, I find a that 1% increase in PM10 pollution leads to a reduction of around 3 per cent of a standard deviation in the PPVT scores. As has been emphasised in the literature, it is challenging to separate the effects of individual pollutants; therefore, I interpret this finding as an aggregate impact of air quality on children's cognitive performance. Evaluating the channels through which air pollution may affect cognitive performance, I find consistent evidence that air pollution during pregnancy affects several health outcomes at birth. Furthermore, the impact of air quality on cognitive performance at early ages is worst among children with respiratory problems.

More research connecting the link between air quality, health and cognitive performance at early ages is needed to understand the interactions between them. In this study, I focus on children from ages 3 to 5 in the first survey, and ages 5 to 7 in the second survey; however, further research using a similar identification strategy could be developed using longitudinal studies that follow children later in life. In particular, there are advantages in using the identification strategy developed in this study in international cohort longitudinal studies, in which a larger battery of cognitive tests is collected longitudinally. The cohort structure of such studies allows for evaluating differential exposure to air pollution, which national standardized academic tests typically do not allow.

Chapter 4

Fast Food and Childhood Obesity: Evidence from the UK

4.1 Introduction

In recent decades, we have witnessed a surge in childhood obesity. Evidence in the UK shows that younger generations are at higher risk of overweight/obesity, with the probability of being overweight or obese 2-3 times higher for children born after the 1980s than before (Johnson et al., 2015). Similar trends have been observed in the US since the 1980s (Flegal and Troiano, 2000). Increasingly, the burden falls disproportionately on those from low-income backgrounds (White et al., 2016) – a reversal from previous generations spanning the 1940s through the 1970s, when lower socioeconomic position tended to be associated with lower weights in the UK (Bann et al., 2018).

The effects of obesity on physical and mental health have been well-documented elsewhere (Bargain and Zeidan, 2019; Djalalinia et al., 2015; Reilly et al., 2003), though only in the fullness of time will we have understand the long-term health effects of the childhood obesity crisis. The societal costs are phenomenal, with the NHS in England estimated to have spent 6.1 billion on overweight and obesity-related ill-health in 2017/18 – more than the Government spent on the police, fire service and judicial system combined. Obesity also has a profound impact on economic development, with its overall cost to the wider society estimated at 27 billion PHE (2017).

Meanwhile, the fast food retail industry in the UK is, by all accounts, booming. Fast food outlets – including chip shops, burger bars and pizza places – are estimated to account for more than a quarter (26%) of all eateries in England. In 2018, the BBC Shared Data Unit reported a 34% increase in fast food outlets from 2010 to 2018 in the UK, and an increase in the average number of fast food outlets per 100,000 people from 47 in 2010 to 61 by 2018 (BBC, 2018). Figures from Public Health England (PHE) reveal England's poorest areas have 5 times more fast food outlets than the most affluent (PHE, 2018). This is consistent with other evidence in the UK (Fraser et al., 2012c, Cummins et al., 2005), the US (Walker et al., 2010) and elsewhere (Helbich et al., 2017; Krian et al., 2015; Shaw, 2012). Furthermore, the number of fast food restaurants and the prevalence of obesity among children born in the 2000s have been rising in the UK. This is evidenced from nationally representative longitudinal data, the Millennium Cohort Study. Figure 4.1 shows the growth of fast food restaurants around study members' residences and schools between 2008 and 2015, together with the trend in cohort members' z-BMI. Alongside this, there is evidence that socioeconomic inequalities in takeaway food outlet density have increased over time (Maguire et al., 2015).

These parallel trends in obesity and fast food availability by socioeconomic status highlight the challenges in understanding the links between fast food outlets and obesity. In particular, observed associations between the two may reflect socioeconomic deprivation rather than the presence of fast food outlets, so associations based on cross-sectional data - which constitute the vast majority of the empirical evidence we have (Fraser et al., 2012a,b; Mason et al., 2018; Snowdon, 2018; Walker et al., 2010; Williams et al., 2013) – must be interpreted cautiously. But media all too often blow them up into sensationalist headlines. Not only that, but the headlines are based on the vast minority of studies finding that living near a fast food outlet increases the risk of childhood obesity – which are outnumbered 4 to 1 by those which find no such association (Snowdon, 2018). We are familiar with headlines such as "Takeaway clampdowns may combat obesity epidemic" (Briggs, 2014) ,

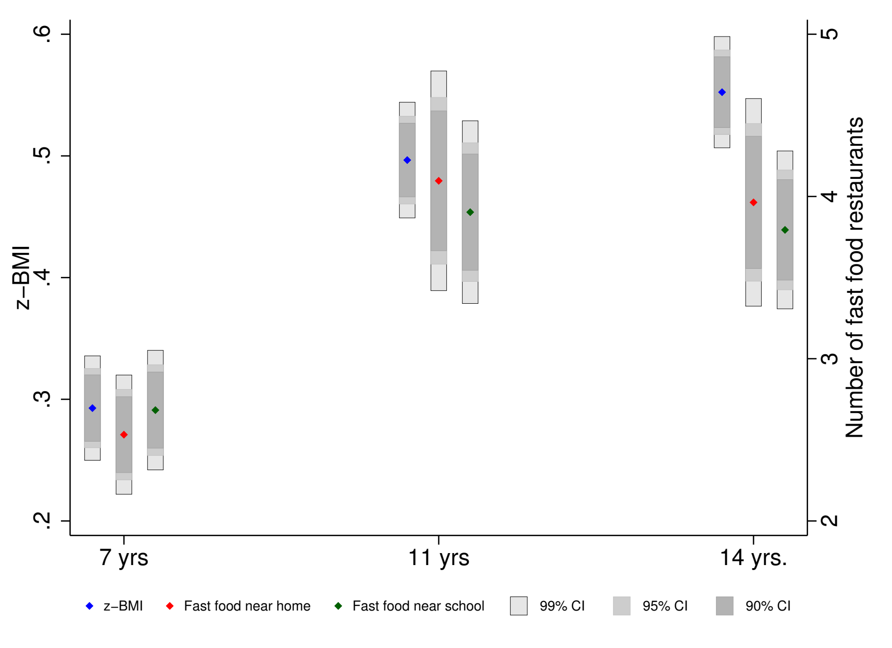

Figure 4.1: Trend in Fast Food restaurants and z-BMI during childhood

Notes: The red (green) dots indicate the average number of fast food restaurant around MCS cohort members' residences (schools) at ages 7, 11 and 14. The figure plots the number of fast food restaurants within 1,600 metres network-based buffers as defined in section II. Blue dots indicate the average z-BMI scores. We standardized cohort members' BMI by age and sex using the 1990 UK Growth Reference (Cole et al., 1995). Grey bars show confidence intervals at 99, 95 and 90 per cent significance levels using MCS survey design and longitudinal weights.

"People who live or work near takeaways twice as likely to be obese" (Cooper, 2014) (both based on Burgoine et al. (2014), a cross-sectional study in only one region of the UK). Newspapers include reports that "Public health experts have warned that heavy exposure of children to fast food outlets and increased consumption of high-fat nutrient-poor food leads to greater risk of childhood obesity, as well as heart disease and stroke in later life" (Duncan and Butler, 2017).

On foot of this, many local authorities across England have taken action to address their food environment: at least 40 areas have developed policies to restrict the growth of new takeaways and fast food outlets, and PHE has helped develop stronger planning guidance to support other areas in doing this (MHCLG, 2014). In November 2017, the Mayor of London, Sadiq Khan, proposed a 'total ban' on new fast food establishments opening within 400 metres walking distance of schools in the city (BBC, 2017).

The disconnect between the evidence and policy is clear. Effective policy relies on high quality, evidence, and whilst there is a large body of public health literature that has grappled with this question, most of the evidence is based on cross-sectional studies (Cobb et al., 2015; Feng et al., 2010; Harrison et al., 2011; Mason et al., 2018; Williams et al., 2013). To our knowledge there are just a few papers that attempt to estimate causal relationships, and these are mostly confined to the US, where the policy/food environment is very different than in the UK. Among the existing evidence, the bulk of it focuses on the availability of fast food restaurants around schools, and far less is concerned with children's homes.

Starting from the important contributions of Davis and Carpenter (2009), Dunn (2010), Currie et al. (2010), and Anderson and Matsa (2011), studies that focus on school exposure to fast food restaurants use different methods and provide mixed results. Currie et al. (2010) and Davis and Carpenter (2009) study how proximity to fast food chains affects school-level obesity rates in California, with both finding a positive but small impact on obesity rates. Davis and Carpenter (2009) use a school-based cross-sectional survey of children from 7^{th} through 11^{th} grade to analyse whether fast foods within a half mile of students' schools has an impact on unhealthy food consumption and obesity rates. They find that students whose schools are near a fast food restaurant are more likely to be obese (0.07 times the odds of being obese) than those whose schools are further from a fast food restaurant, estimating an impact on students' BMI of between 0.08 and 0.14 points. Currie et al. (2010) use fitness assessment data of 9^{th} graders attending public schools to study whether fast food restaurants within 0.1, 0.25 and 0.5 miles of a school increase the prevalence of obese students. They find that fast food restaurants within 0.1 miles of a school increase obesity rates by 5.2 per cent, or 0.81 percentage points; however, no effect was found at larger distances from schools. While both studies analyse a similar period (i.e. 1999-2009) and region, their identification strategies differ. Currie et al. (2010) exploit repeated cross-sectional school data of 9^{th} graders to compare obesity rates of students attending schools that are observationally identical but only differ in how far they are from fast food restaurants. In contrast, Davis and Carpenter (2009) estimate OLS and adjusted logistic models that use repeated cross-sectional individual data. They control for a set of potential individual confounders, including gender, race, frequency of physical activity, among others, and compare obesity rates and BMI from students who experience differences across time and grades in the availability of fast food restaurants.

Anderson and Matsa (2011) and Dunn (2010), based on the fact that travel/time costs affect consumer demand, introduce an instrumental variable approach that exploits the distance between consumers and major highways/roads. Anderson and Matsa (2011) focus on the effect of restaurant consumption and obesity among adults in rural areas in the US, but do not find evidence that adult obesity rates are caused by restaurant availability. Dunn (2010) use an identification strategy that exploits cross-sectional county-level variation in the number of interstate highway exits and finds similar null effects. Subsequent studies focused on children's obesity, based on the early work of Dunn (2010) and Anderson and Anderson and Matsa (2011), use a similar identification strategy. Alviola et al. (2014) and Asirvatham et al. (2019), using data from schools in Arkansas, exploit school proximity to highways as an instrumental variable since fast food chains tend to agglomerate along main roads. Alviola et al. (2014) study the effect of fast food restaurants using a school-level cross-sectional data of public schools during the 2008-09 school year. Focusing on students in kindergarten, and in even numbered grades from 2^{nd} to 10^{th} grade, they find that one additional fast food restaurant within a mile from the school increases school obesity rates by 1.23 percentage points. Asirvatham et al. (2019) use panel data on students in public school during the period 2004-2010. They use student fixed effects with a similar instrumental variable method, i.e. the proximity to interstate and US highways, to account for both unobserved individual confounders and the endogeneity of fast food exposure. They also exploit an exogenous reassignment of public schools created by a court-mandated restructuring. They find a small effect of fast food restaurants on BMI-z scores, with an additional fast food restaurant within a third of a mile, two thirds of a mile, and a mile from the school increasing student's BMI-z scores by 0.024, 0.008 and 0.005 points, respectively. It is difficult to directly compare estimates across studies, as outcomes and contexts differ, but overall the order of magnitudes from cross-sectional studies which rely on instrumental variables are consistently small.

Few studies have provided evidence on the effects of exposure to fast food restaurants near the home, as opposed to schools. Qian et al. (2017) use the same instrumental variable method as the studies mentioned above to assess if fast food restaurants surrounding students' residences have an impact on their BMI z-scores. The authors use same Arkansas' panel data in Asirvatham et al. (2019), but for children from kindergarten to 10^{th} grade who move residence at least once during the 2004-2010 period. Based on an instrumental variable model that exploits within student variation to fast food, they find that an additional fast food restaurant within a half mile and one mile of students' homes increases BMI-z scores by 0.079 and 0.028 points, respectively.

Our paper adds to this body of evidence and provides the first evidence in the UK of the potential casual effect of fast food access on childhood obesity. We contribute to this literature in several ways. First, we provide evidence for the UK when much of the existing literature is focused on the US. Moreover, we use a unique and large, nationally representative longitudinal sample of children born across the UK at the turn of the millennium. This allow us to estimate individual fixed effects and evaluate changes in BMI over time. Second, we consider proximity of fast foods to schools and homes, for the same sample. We can in this way compare effects across both type of exposure. Third, by using three points in childhood at age 7, 11, and 14 we provide evidence for the transition from primary to secondary school. Fourth, we are the first study to provide evidence on body fat alongside BMI, which is particularly important since together present a better picture of adiposity Nuttall (2015). We also use measures of BMI and body fat that were taken by trained personnel, as oppose with self-reported measures used in previous studies. Fifth, we show that fast food availability has a more detrimental effect on children whose mother has lower level of education, further exacerbating socioeconomic inequalities in health.

We find suggestive evidence that an increase in the supply of fast food outlets around children's residences and schools has a relatively small effect, on weight gain. Adding a fast food restaurant within an 800 metres buffer, i.e. around 10 minutes walking, from children's residences increases BMI by 0.06 points and body fat by 0.12 percentage points, a 0.3% and 0.6% increase in the sample mean respectively. We find these effects are smaller in the 1,600 a metre buffer. Our results suggest a similar pattern near children's school. In the 800 metres buffer, we find that an additional fast food outlet increases BMI by 0.07 points and body fat by 0.1 percentage points, an 0.4% increase with respect to the sample mean in both cases. Consistent with psychological and transportation costs faced by consumers, we find that estimates decrease as the buffer size increase, i.e. adding a fast food restaurant located far away from children's residence or schools has a lower effect on obesity. These effects vary by maternal education and children's school period. It is larger and significant among children whose mother had not attained higher education and it is zero among children whose mother had attained higher education, indicating that access to fast food could have a role in further exacerbating disparities in adolescent obesity in the UK. Regarding differences by school period, our estimates around schools are larger during the secondary school period, i.e. between ages 11 and 14, and zero during the primary school period, i.e. between ages 7-11, consistent with changes in children's interaction with fast food as they gain autonomy.

We cannot rule out completely that our results are driven by unobservable changes in demand for fast food, as opposed by changes in the supply of fast food; however, we provide evidence that supports our key identifying assumption. Besides, we strengthen our empirical specification by controlling for a large number of individual time-varying variables, such as children's physical activity, the availability of other food environment outlets, and socioeconomic characteristics, among others. We restrict our analysis to children who did not change residence during the period to provide evidence that estimates are not driven by changes in residence. Additionally, we find that, once we control for individual fixed effects, a large set of time-varying individual-level characteristics are not correlated with fast food availability, presenting evidence in favour of our identifying assumption. Finally, we show evidence in favour of our empirical specification by performing a falsification test that asks whether the increase in the availability of stores that arguably should not be associated with BMI or body fat, e.g. construction services or employment agencies, affect children's obesity.

The paper is organised as follows. In section 4.2, we describe data and present summary statistics. Section 4.3 present out methodology and identification strategy. We present our results in section 4.4 and conclude in section 4.5.

4.2 Data and summary statistics

Our analysis uses rich longitudinal data, a prospective nationally representative birth cohort, the Millennium Cohort Study (MCS), combined with highly granular geographical data from the Ordnance Survey Points of Interest (PoI) and Ordnance Survey Integrated Transport Network (ITN). We combine these data to calculate the number of fast food and other retail food establishments within 400, 800, and 1600 metres network buffer zones around each MCS cohort member's home and school postcodes.

4.2.1 Millennium Cohort Study (MCS)

The MCS is a longitudinal study that follows the lives of a nationally representative sample of 19,244 families with children born between 2000 and early 2002 in the UK (Joshi and Fitzsimons, 2016). Starting when children were 9 months old, and subsequently, at ages 3, 5, 7, 11, 14 and 17 (latter not available at time of writing), the MCS collects extensive information on cohort members' and their families, including parental education; employment and income; housing; family structure; ethnicity; physical and mental health, and health behaviours; cognitive and physical development, among many other characteristics.

We focus our analysis on body mass index (BMI) and percentage of body fat because together provide a more accurate picture of adiposity (Nuttall, 2015). Since age 3, cohort members' weight and height have been measured in the home by trained interviewers, and the percentage of body fat has been measured at ages 7, 11 and 14.[1] BMI is calculated by dividing weight in kilograms by squared height in metres. Height was measured using Leicester height stadiometers[2] and recorded to the nearest completed millimetre. Weight and body fat measurements were taken using Tanita BF-522W scales, which calculate weight to the nearest 0.1kg, and body fat percentage to the nearest 0.1%. The percentage of body fat was calculated measuring the amount of resistance encounter by a weak electrical current as it travels through the body (Chaplin Grey et al., 2010).

4.2.2 Ordnance Survey Point of Interest (PoI)

The PoI dataset contains data on over 4 million commercial and public facilities across Great Britain, available annually from 2005 - 2013, and quarterly from September 2014, with accurate (building centroid) locational information that is updated annually before 2014 and quarterly thereafter reflecting spatial longitudinal changes of commercial facilities (OS, 2015). Data are highly granular: each facility is geocoded and assigned to one of around 600 classes, which in turn are further classified into larger categories and groups.[3] We obtained PoI data using an educational licence and mapped it using ArcGIS 10.4.

As Wilkins et al. (2017) show, PoI has a high level of correspondence with street level audits, which are regarded as the gold standard for spatial data. It is a validated[4] dataset with high spatial and count accuracy, especially post-2010[5], and has been used regularly in UK Retail Food Environment (RFE) research (Burgoine et al., 2017; Cetateanu and Jones, 2014; Fraser et al., 2012a; Harrison et al., 2011; Jennings et al., 2011; Skidmore et al., 2010). We extract data on food outlets from this database, following previous work, to characterize obesogenic environments

[1] In Appendix B we present results using BMI-z scores. We standardized child's BMI by age and sex using the 1990 UK Growth Reference (Cole et al., 1995). Body mass index reference curves for the UK, 1990. Arch Dis Child, 73, 25-9, ibid.

[2] A Leicester height stadiometer is a foldable device with a sliding head plate, a base plate and four connecting rods marked with a measuring scale.

[3] In Appendix C, we show the PoI categories used in this paper.

[4] Using detailed data for the county of Cambridgeshire, UK, Burgoine and Harrison (2013) validate the PoI data, concluding that PoI is a viable alternative to measure obesogenic environments.

[5] Due to a change of supplier in late 2010, which resulted in improved data collection and classification methods, there is some difference in raw category counts in pre- and post-2010 PoI data. For example, Cummins et al. (2005) use the Yellow Pages to identify every listing for McDonald's, finding 942 in January 2005. In the September 2005 PoI dataset, there are 850 McDonald's outlets.

(Cetateanu and Jones, 2014; Jennings et al., 2011; Skidmore et al., 2010) PHE, 2016, PHE, 2017b. We describe this in detail in section 4.2.4 that follows.

4.2.3 Ordnance Survey Integrated Transport Network (ITN)

The ITN dataset is a topologically consistent snapshot of the entire road network of Great Britain, which contains road-routing information, including one-way streets, banned turns, and access restrictions. ITN data are available from 1997 onwards, on an annual or biannual basis.[6] Although most RFE research has used Euclidean distance to construct buffers network-based buffers are considered to be more accurate and generally result in smaller neighbourhood sizes (Bivoltsis et al., 2018; Wilkins et al., 2017). A methodological challenge, identified by Charreire et al. (2010), is to measure travel time to fast food outlets according to different modes of transport (e.g. car, public transport, or on foot). We use the ITN dataset to construct road network-based buffers of different distances around each cohort member's home and school location – specifically, the postcode centroid of the address at interview at each sweep, and the postcode centroid of the school they were attending at each sweep.[7]

4.2.4 Classification of fast food and other outlets

We use PoI data from Septembers of 2008, 2012 and 2015, along with ITN data from October 2008, June 2012, and June 2015. To characterize obesogenic environments across time and locations we count the number of fast food outlets and other food outlets within network-based buffers around MCS cohort members' school and residence.

We use GIS to construct 400, 800, and 1600 metres network-based buffers, enabling us to assess spatial variation without reliance on arbitrary administrative boundaries (Charreire et al., 2010). Although there is still little theoretical or empirical consensus on the appropriate size of neighbourhoods (Boone-Heinonen and

[6] ITN data are available from Edina Digimap on a non-regular basis -i.e. 1 - 3 times per year– from February 2007.

[7] Since schools generally comprise a single unit postcode, this means that school locations are generally located more accurately than homes. Future work aims to use the full residential address, thus reducing this source of distance error.

Gordon-Larsen, 2012), buffer sizes of 400, 800, and 1600 metres are the most prevalent in RFE research, since they equate, respectively, to an average person's 5 minute, 10 minute, and 15 minute walking distance (Wilkins et al., 2019).

One of the most contentious and challenging issues in the economic, epidemiological and geographical literature is the classification of the RFE. The systematic review of Wilkins et al. (2019) found that nearly half of the studies they analysed did not provide a clear definition of how they constructed their RFE categories. This is most likely due to the absence of any standardised food classification schemas (Block et al., 2018). Some researchers have constructed the set of fast-food outlets they analysed based on the biggest/most popular national chains. For example, Currie et al. (2010) used the top ten fast-food chains in the United States, whereas others use industry codes (e.g. Ohri-Vachaspati et al. (2011)). Although it is widely understood that some foods are less healthy than others, as Pinho et al. (2019) note, classifying food retailers according to their healthfulness' is not a straightforward procedure. For example, even though supermarkets are usually considered to be a source of healthy foods (Woodruff et al., 2018), they also offer a wide range of sugar-saturated beverages and snack foods. Correspondingly, many major fast food outlets also offer healthier choices (Mahendra et al., 2017).

As discussed before, there is little consensus regarding which definition of fast food availability is appropriate in studying effects on childhood obesity. While previous studies in the UK have used PoI categories such as 'Fast food and takeaway outlets'' and 'Fast food and delivery services' (Cetateanu and Jones, 2014), studies in the US have used popular fast food chains (Alviola et al., 2014; Currie et al., 2010; Davis and Carpenter, 2009; Dunn, 2010; Dunn et al., 2012; Qian et al., 2017; Zeng et al., 2019). We use the former approach to create a conservative estimate that avoids possible inconsistencies in the classification of fast food outlets between the PoI data versions used in this paper.

Our classification of fast food outlets includes (a) the top fast food outlets in the UK: McDonalds, KFC, Burger King, Wimpy, Subway, Pizza Hut, and Dominos' Pizza. These are identified straightforwardly using the name of the store recorded in the PoI data, (b) fish and chips shops, a common take-away food in the UK, identified using the available category in the PoI data, and (c) kebab and chicken outlets, identified by looking at restaurants that have been classified as food outlets and that contain the words 'Kebab' and/or 'Chicken' in its commercial name. The decision to include fish and chips, and kebab and chicken outlets is largely driven by a combination of context and content: as salient fast food types across the UK, they provide highly calorific and processed meals (Jaworowska et al., 2014). Previous studies have classified fish and chips shops as unhealthy based on their association with diet (Cetateanu and Jones, 2014). In 2006, the UK's Food Standards Agency (FSA) found that 18.5% of doner kebabs constitutes a "significant" threat to public health (FSA, 2006), while in 2009, another study, which sampled 494 kebabs in the UK and classified its nutritional content using the FSA traffic light system for pre packed food, found that 97%, 98% and 96% of kebabs would be "red" for its fat, saturates fat, and salt content, respectively (LACORS, 2009).[8]

Furthermore, when we calculate the number of fast food outlets[9] around 1600 metres from cohort members' residence at age 7 that are in our definition but that are not classified in the PoI fast food categories ('Fast food and takeaway outlets' or 'Fast food and delivery services') we find that 25.9% (619 of 2384) of fast food chains included in our definition were not included in the former PoI categories[10]. This led us to believe that using only PoI categories could produce misleading results.

Additionally, we use other food facilities available in the PoI data in order to control for other food outlets, as the availability of both healthy and unhealthy food has been found to be associated with dietary habits and BMI in cross-sectional analyses (Burgoine et al., 2014; Fraser et al., 2012a,c; Hobbs et al., 2019). Moreover, controlling for other food facilities around children's schools and residences is

[8]The authors found that "the average kebab provides men (women) with 66% (89%) of their Guideline Daily Amount (GDA) of fat, 98% (148%) of their GDA for saturated fats and 98% (98%) of the GDA for salt".

[9]We use the following fast food chains: McDonalds, KFC, Burger King, Wimpy, Subway, Pizza Hut, and Dominos' Pizza, Kebab and Chicken shops, as defined previously.

[10]Notice that in the PoI data at age 7, 83% of 619 restaurants were classified in the PoI categories "Pizza restaurants" or "Restaurant unspecified".

likely a good proxy for neighbourhood characteristics that are correlated with both, factors that contribute obesity and the presence of fast food restaurants (Currie et al., 2010). Our definition of other food facilities includes butchers; confectioners; delicatessens, fishmongers; green and new age goods; grocers, farm shops and pick your own; organic, health; gourmet and kosher foods; convenience stores and independent supermarkets; and supermarket chains.

4.3 Methodology

Our objective is to estimate the causal effect of fast food restaurants availability on cohort members' BMI and percentage of body fat. We estimate the following two empirical specifications:

$$Y_{it} = \alpha_i + \beta F_{it}^{k} + \rho X_{it} + \varepsilon_{it} \tag{4.1}$$

$$Y_{it} = \alpha_i + \gamma_1 F_{it}^{400} + \gamma_2 F_{it}^{800} + \gamma_3 F_{it}^{1600} + \rho X_{it} + \varepsilon_{it} \tag{4.2}$$

where Y_{it} is BMI or percentage of body fat of individual i at ages t=7, 11 and 14. In model (4.1), F_{it}^{k} is the number of fast food outlets within distance k of cohort member' i's location, and we run models separately for home and school locations. We estimate three models, separately for k=400, 800, and 1600 metres. In model (4.2), F_{it}^{400}, F_{it}^{800}, and F_{it}^{1600} denote the number of fast food outlets within a 400 metres buffer of the cohort member's location, between 400 and 800 metres, and between 800 and 1600 metres, respectively. Our key parameters of interest are β, γ_1, γ_2, and γ_3. We also show OLS estimates for comparison.

To allow for the possibility that the availability of food outlets other than fast foods may affect cohort members' weight, the X_{it} vector includes the number of other food outlets as described previously.[11] It is well documented that diet and exercise affect weight gain (Kelly et al., 2016), and so we control for three dummies indicating the frequency of physical activity and a binary variable indicating whether the cohort member skips breakfast at least once a week. With the exception

[11] In Appendix C we describe the definition of X_{it} covariates used in our main specification.

of Davis and Carpenter (2009), previous studies do not control for physical activity or health behaviours. We also control for a range of socioeconomic characteristics of cohort members' families, including six dummies indicating maternal highest educational level at the time of interview, the number of parents in the household, family income, the number of people and siblings living in the household, and two dummies indicating household tenure. We also include dummies for survey wave. ε_{it} is a disturbance error assumed to be independent and identically distributed.

The effect of proximity to fast food restaurants on cohort members' BMI and percentage of body fat is identified under the assumption that, once we control for individual fixed effects, year of survey dummies, and time-varying controls, there are no time-varying unobserved variables systematically correlated both with changes in BMI (or body fat) and changes in the number of fast food outlets. So, the contemporaneous effect of fast food availability on cohort members' BMI is identified by changes in the number of fast food outlets over time. There are two reasons why the number of fast food outlets could change near the cohort members' homes (or schools). The first is through openings and closures of fast food outlets across time. The second is through cohort members moving residence (or school) to or from areas with more or fewer fast food restaurants. Whilst it is unlikely that families are making their residential (or school) decisions on the basis of fast food availability, we nonetheless include a specification restricted to the sample of families who did not change residence during the period, thereby identifying the effect from exogenous opening and closures of fast food outlets, conditional on residence. Additionally, in section 4.5, we test the plausibility of our identification strategy and present falsification tests to provide evidence in favour of our empirical specification.

4.4 Results

In this section we begin by providing summary statistics pertaining to the sample and present our main results. We further provide evidence of heterogeneity in effects, showing estimates for different subsamples, and discuss potential mechanisms. Finally, we present a series of robustness checks, an analysis of the plausibility of our identification strategy, and falsification tests for our main specification.

4.4.1 Summary statistics

We base our analysis on MCS cohort members who were interviewed at ages 7, 11 and 14, including only those with valid measurements of BMI and body fat percentage through this period (the vast majority). We exclude children living in Northern Ireland since PoI data is not available. Our analytic sample includes 8,629 cohort members. Table 4.1 presents the mean and standard deviation of child obesity across time in our analytical sample. We estimate that around 18% of 7 year old cohort members were overweight/obese with an average BMI of 16.5, and with 20.7% of body fat. Four year later, the percentage of cohort members overweight/obese and the percent of body fat increased to 25.7% and 22.0%, respectively. This pattern is also observed at age 14.

Table 4.1: Descriptive statistics

	7 years		11 years		14 years	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Weight in kilograms	25.222	4.746	41.056	9.739	57.96	12.964
Height in centimetres	123.479	5.54	146.167	7.245	164.18	8.131
Body Mass Index	16.45	2.224	19.067	3.543	21.42	4.148
Percentage of Body Fat	20.748	5.218	21.967	7.752	21.7	9.184
Child is obese	0.046	0.211	0.058	0.233	0.073	0.26
Child is overweight-obese	0.18	0.384	0.257	0.437	0.261	0.439
Observations	8268		8268		8268	

Notes: The ‘Overweight/obese’ & ‘Obese’ categories are defined using the International Obesity Task Force (IOTF) cutoffs (Cole et al., 2000) Source: MCS.

Tables 4.2-4.4 show summary statistics at age 7, separately for families who stay in the same residence during the analysed period, changed residence between ages 7 and 11, and changed residence between ages 11 and 14. Cohort members who stay in the same residence constitute 69.8% of our sample, those who changed residence between ages 7 and 11 represent 20.6%, and those who changed residence between ages 11 and 14 represent 15.5%.

Table 4.2: Descriptive statistics by sample of movers and non-movers

	(1) All	(2) Do not move	(3) Move between 7-11	(4) Move between 11-14
Cohort members' Demographics				
Child is male	0.52	0.526	0.498	0.504
Mother's age at wave 1	29.282	30.291	27.164	27.134
Mother is White	0.844	0.839	0.851	0.87
Mother is Mixed	0.033	0.03	0.039	0.045
Mother is Indian	0.023	0.024	0.022	0.015
Mother is Pakistani and Bangladeshi	0.046	0.051	0.038	0.023
Mother is Black or Black British	0.04	0.041	0.037	0.032
Mother is from another Ethnic group	0.014	0.014	0.013	0.015
Mother highest NVQ level is 1 [a,b]	0.081	0.074	0.106	0.087
Mother highest NVQ level is 2 [a]	0.284	0.27	0.314	0.31
Mother highest NVQ level is 3 [a]	0.147	0.143	0.146	0.157
Mother highest NVQ level is 4 [a]	0.282	0.305	0.233	0.237
Mother highest NVQ level is 5 [a]	0.053	0.057	0.041	0.046
Mother has overseas qualification only [a]	0.032	0.032	0.03	0.039
Mother does not have any of these qualification [a]	0.121	0.118	0.129	0.123
Number of Parents/Carers in household				
Two parents/carers [a,b]	0.779	0.828	0.681	0.67
One parent/carer [a]	0.221	0.172	0.319	0.33
OECD equivalised weekly family income [a]	387.501	408.759	338.033	352.264
Number of people in household (not including cohort member) [a]	3.482	3.513	3.488	3.348
Numbers of rooms in the household [a]	6.005	6.237	5.458	5.664
Housing Tenure				
Own - mortgage/loan[a,b]	0.556	0.643	0.359	0.408
Own outright [a]	0.055	0.062	0.041	0.033
Rent or other [a]	0.389	0.295	0.6	0.559

Notes: This table shows descriptive statistics at age 7 by different samples depending if cohort member change residence between ages 7-14. Column 2 includes cohort members who did not change residence. Columns 3 and 4 include cohort members who changed residence between ages 7-11, and 11-14, respectively. [a] Indicates time-varying variables included as controls in equations (4.1) and (4.2). [b] Indicates to the baseline category excluded in the empirical specifications. Source: MCS.

Table 4.3: Descriptive statistics by sample of movers and non-movers (cont.)

	(1) All	(2) Do not move	(3) Move between 7-11	(4) Move between 11-14
Cohort members' Characteristics				
BMI Wave 3	16.231	16.245	16.182	16.247
Some weekly physical activity	0.669	0.7	0.603	0.593
Cohort members' weekly physical activity				
Not at all [a,b]	0.331	0.3	0.397	0.407
1-2 days [a]	0.472	0.483	0.445	0.446
3-4 days [a]	0.17	0.189	0.136	0.125
5 or + days [a]	0.027	0.028	0.023	0.022
Skip breakfast at least one time per week [a]	0.067	0.062	0.08	0.07
Eats unhealthy food between meals (MCS 7y)	0.447	0.452	0.432	0.446
Drinks sweetened (or artificially sweetened) drinks between meals (MCS 7y)	0.37	0.368	0.39	0.349
Drink sweetened drinks (MCS 11y)	0.809	0.809	0.813	0.798
Drink sweetened drinks every week (MCS 11y)	0.594	0.588	0.606	0.604
Never eats at least 2 portions of fruit (MCS 14y)	0.087	0.086	0.096	0.086
Never eats at least 2 portions of vegetables (MCS 14y)	0.074	0.071	0.088	0.073
Never eats at least 2 portions of fruit or vegetables (MCS 14y)	0.129	0.126	0.146	0.121
Eats Fast Food at least 1-2 days a week (MCS 14y)	0.271	0.269	0.273	0.279
Eats Fast Food at least once a month (MCS 14y)	0.722	0.714	0.736	0.741

Notes: This table shows descriptive statistics at age 7 by different samples depending if cohort member change residence between ages 7-14. Column 2 includes cohort members who did not change residence. Columns 3 and 4 include cohort members who changed residence between ages 7-11, and 11-14, respectively. [a] Indicates time-varying variables included as controls in equations (4.1) and (4.2). [b] Indicates to the baseline category excluded in the empirical specifications. Source: MCS.

Tables 4.5- 4.7 display descriptive statistics for the overall analytical sample, and by distance from home (or school) to fast food restaurants. It shows that around 67.8% (71.8%) of individuals have lived (attended school) within 1600 metres, or 1 mile, of fast food restaurants during the analytic period. It also shows that in general, child and family characteristics do not vary significantly by proximity to fast food outlets.

Table 4.4: Descriptive statistics by sample of movers and non-movers (cont.)

	(1) All	(2) Do not move	(3) Move between 7-11	(4) Move between 11-14
2001 Census Demographics of LSOA area				
Share Female	0.514	0.513	0.515	0.516
Mean Age	37.985	38.126	37.636	37.954
Median Age	37.378	37.648	36.741	37.183
Usual resident Pop: 2001 Density (number of people per hectare)	38.925	37.653	42.326	38.728
Share White	0.904	0.904	0.899	0.924
Share Mixed	0.012	0.012	0.013	0.011
Share Asian/British	0.053	0.054	0.057	0.039
Share Black British	0.023	0.023	0.024	0.02
Share Chinese/Other [a]	0.007	0.007	0.007	0.006
Share living in households	0.988	0.988	0.989	0.987
Share living in communal establishments	0.012	0.012	0.011	0.013
Share with owned outright	0.283	0.292	0.262	0.27
Share with owned with a mortgage or loan	0.394	0.403	0.374	0.38
Share with shared ownership	0.006	0.006	0.006	0.006
Share with rented from council (local authority)	0.155	0.145	0.175	0.171
Share with rented from a housing association/registered social landlord	0.059	0.054	0.069	0.066
Share with rented from a private landlord or letting agency	0.073	0.07	0.081	0.075
Share with other tenure [a]	0.031	0.03	0.032	0.032
Share living in a couple: Married	0.513	0.523	0.491	0.498
Share living in a couple: Cohabiting	0.099	0.097	0.104	0.105
Share not living in a couple: Single	0.224	0.22	0.233	0.227
Share not living in a couple: Married	0.01	0.01	0.01	0.009
Share not living in a couple: Separated	0.02	0.019	0.021	0.021
Share not living in a couple: Divorced	0.059	0.057	0.064	0.064
Share not living in a couple: Widowed [a]	0.075	0.074	0.077	0.077
Share households with one person	0.278	0.271	0.293	0.288
Share households with one family only pensioners	0.088	0.09	0.083	0.086
Share households with one family with no children	0.175	0.178	0.167	0.173
Share households with one family with children	0.394	0.396	0.388	0.391
Share households with other type of residents [a]	0.065	0.064	0.068	0.062
Share Part-time Employee	0.122	0.123	0.12	0.123
Share Full-time Employee	0.403	0.406	0.396	0.396
Share Self-employed	0.08	0.082	0.076	0.077
Share Unemployed	0.036	0.034	0.039	0.038
Share Full-time student [a]	0.024	0.024	0.023	0.023
Share Inactive	0.336	0.332	0.346	0.343
Observations	8268	5770	1703	1279

Notes: This table shows 2001 Census Demographics linked with MCS using the cohort member's residence Lower Layer Super Output Areas (LSOA). Lower Layer Super Output Areas small area geographic hierarchy for England and Wales. We show different samples depending if cohort member change residence between ages 7-14. Column 2 includes cohort members who did not change residence. Columns 3 and 4 include cohort members who changed residence between ages 7-11, and 11-14, respectively. [a] Indicates time-varying variables included as controls in equations (4.1) and (4.2). [b] Indicates to the baseline category excluded in the empirical specifications. Source: 2001 Census Demographics.

Table 4.5: Descriptive statistics by availability of fast food restaurants within buffers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		HOME			SCHOOL		
	All	<1600 mts.	<800 mts.	<400 mts.	<1600 mts.	<800 mts.	<400 mts.
Cohort members' Demographics							
Child is male	0.52	0.518	0.517	0.534	0.518	0.519	0.521
Mother's age at wave 1	29.282	28.975	28.799	28.945	29.055	28.797	28.707
Mother is White	0.844	0.797	0.755	0.729	0.805	0.786	0.788
Mother is Mixed	0.033	0.039	0.038	0.036	0.037	0.033	0.039
Mother is Indian	0.023	0.028	0.034	0.031	0.028	0.028	0.029
Mother is Pakistani and Bangladeshi	0.046	0.061	0.086	0.115	0.059	0.07	0.078
Mother is Black or Black British	0.04	0.054	0.068	0.067	0.051	0.062	0.049
Mother is from another Ethnic group	0.014	0.02	0.019	0.023	0.019	0.021	0.017
Mother highest NVQ level is 1 [a,b]	0.081	0.087	0.094	0.109	0.087	0.095	0.119
Mother highest NVQ level is 2 [a]	0.284	0.285	0.29	0.273	0.29	0.271	0.272
Mother highest NVQ level is 3 [a]	0.147	0.144	0.135	0.13	0.146	0.149	0.152
Mother highest NVQ level is 4 [a]	0.282	0.255	0.235	0.234	0.253	0.241	0.242
Mother highest NVQ level is 5 [a]	0.053	0.052	0.051	0.049	0.052	0.049	0.045
Mother has overseas qualification only	0.032	0.035	0.035	0.034	0.036	0.041	0.033
Mother does not have any of these qualification	0.121	0.143	0.16	0.172	0.137	0.155	0.137
Number of Parents/Carers in household							
Two parents/carers [a,b]	0.779	0.761	0.747	0.73	0.763	0.752	0.76
One parent/carer [a]	0.221	0.239	0.253	0.27	0.237	0.248	0.24
OECD equivalised weekly family income [a]	387.501	365.199	342.37	319.731	370.337	357.476	355.1
Number of people in household (not including cohort member)	3.482	3.534	3.594	3.581	3.53	3.586	3.554
Numbers of rooms in the household	6.005	5.81	5.669	5.55	5.858	5.786	5.853
Housing Tenure							
Own - mortgage/loan [a,b]	0.556	0.528	0.502	0.459	0.538	0.518	0.537
Own outright [a]	0.055	0.051	0.051	0.051	0.051	0.052	0.058
Rent or other [a]	0.389	0.421	0.446	0.49	0.41	0.43	0.405

Notes: This table shows descriptive statistics at age 7 of availability of fast food restaurants within 400, 800, 1600 metres buffers. Columns 2 & 5; 3 & 6; and 4 & 7 include cohort members with one or more fast food restaurants within 1600, 800, 400 metres buffers, respectively. [a] Indicates time-varying variables included as controls in equations (4.1) and (4.2). [b] Indicates the baseline category excluded in the empirical specifications. Source: MCS.

Table 4.6: Descriptive statistics by availability of fast food restaurants within buffers (cont.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		HOME			SCHOOL		
	All	<1600 mts.	<800 mts.	<400 mts.	<1600 mts.	<800 mts.	<400 mts.
Cohort members' Characteristics							
BMI Wave 3	16.231	16.241	16.269	16.246	16.229	16.226	16.324
Some weekly physical activity	0.669	0.634	0.616	0.588	0.642	0.624	0.63
Cohort members' weekly physical activity							
Not at all [a,b]	0.331	0.366	0.384	0.412	0.358	0.376	0.37
1-2 days [a]	0.472	0.458	0.452	0.446	0.462	0.451	0.462
3-4 days [a]	0.17	0.15	0.14	0.121	0.155	0.15	0.146
5 or + days [a]	0.027	0.026	0.024	0.021	0.025	0.024	0.022
Skip breakfast at least one time per week [a]	0.067	0.071	0.079	0.083	0.069	0.073	0.085
Eats unhealthy food between meals (MCS 7y)	0.447	0.449	0.452	0.454	0.457	0.447	0.453
Drinks sweetened (or artificially sweetened) drinks between meals (MCS 7y)	0.37	0.367	0.357	0.386	0.364	0.368	0.397
Drink sweetened drinks (MCS 11y)	0.809	0.814	0.827	0.836	0.811	0.819	0.827
Drink sweetened drinks every week (MCS 11y)	0.594	0.606	0.613	0.629	0.602	0.614	0.625
Never eats at least 2 portions of fruit (MCS 14y)	0.087	0.089	0.086	0.092	0.085	0.087	0.091
Never eats at least 2 portions of vegetables (MCS 14y)	0.074	0.081	0.088	0.101	0.078	0.081	0.085
Never eats at least 2 portions of fruit or vegetables (MCS 14y)	0.129	0.135	0.14	0.152	0.131	0.134	0.14
Eats Fast Food at least 1-2 days a week (MCS 14y)	0.271	0.295	0.317	0.316	0.291	0.302	0.301
Eats Fast Food at least once a month (MCS 14y)	0.722	0.746	0.764	0.775	0.738	0.743	0.735

Notes: This table shows descriptive statistics at age 7 of availability of fast food restaurants within 400, 800, 1600 metres buffers. Columns 2 & 5; 3 & 6; and 4 & 7 include cohort members with one or more fast food restaurants within 1600, 800, 400 metres buffers, respectively. [a] Indicates time-varying variables included as controls in equations (4.1) and (4.2). [b] Indicates the baseline category excluded in the empirical specifications. Source: MCS.

Table 4.7: Descriptive statistics by availability of fast food restaurants within buffers (cont.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		HOME			SCHOOL		
	All	<1600 mts.	<800 mts.	<400 mts.	<1600 mts.	<800 mts.	<400 mts.
2001 Census Demographics of LSOA area							
Share Female	0.514	0.515	0.515	0.515	0.515	0.515	0.513
Mean Age	37.985	37.592	37.182	36.606	37.617	37.393	37.353
Median Age	37.378	36.556	35.839	35.02	36.694	36.348	36.304
Usual resident Pop: 2001 Density (number of people per hectare)	38.925	47.141	55.132	64.265	45.087	48.464	46.732
Share White	0.904	0.878	0.848	0.825	0.883	0.869	0.874
Share Mixed	0.012	0.014	0.016	0.016	0.014	0.015	0.014
Share Asian/British	0.053	0.069	0.088	0.11	0.066	0.075	0.072
Share Black British	0.023	0.031	0.039	0.039	0.029	0.034	0.032
Share Chinese/Other [a]	0.007	0.008	0.009	0.01	0.008	0.008	0.008
Share born in England	0.841	0.837	0.823	0.81	0.84	0.83	0.832
Share born in Scotland	0.015	0.014	0.014	0.014	0.014	0.014	0.014
Share born in Wales	0.053	0.041	0.038	0.041	0.043	0.044	0.048
Share born in Northern Ireland	0.004	0.004	0.004	0.004	0.004	0.004	0.004
Share born in Republic of Ireland	0.009	0.01	0.011	0.011	0.01	0.01	0.009
Share born in others EU countries	0.012	0.012	0.013	0.013	0.012	0.012	0.012
Share born elsewhere	0.066	0.08	0.096	0.108	0.077	0.085	0.081
Share living in households	0.988	0.989	0.989	0.989	0.989	0.989	0.989
Share living in communal establishments	0.012	0.011	0.011	0.011	0.011	0.011	0.011
Share with owned outright	0.283	0.269	0.258	0.252	0.271	0.267	0.27
Share with owned with a mortgage or loan	0.394	0.378	0.361	0.344	0.385	0.376	0.371
Share with shared ownership	0.006	0.007	0.007	0.007	0.006	0.007	0.007
Share with rented from council (local authority)	0.155	0.171	0.179	0.182	0.168	0.171	0.169
Share with rented from a housing association/registered social landlord	0.059	0.067	0.073	0.082	0.063	0.066	0.07
Share with rented from a private landlord or letting agency	0.073	0.078	0.092	0.101	0.076	0.083	0.083
Share with other tenure [a]	0.031	0.03	0.031	0.033	0.03	0.03	0.031
Share living in a couple: Married	0.513	0.488	0.464	0.454	0.495	0.485	0.488
Share living in a couple: Cohabiting	0.099	0.101	0.102	0.103	0.101	0.102	0.101
Share not living in a couple: Single	0.224	0.239	0.254	0.262	0.235	0.241	0.239
Share not living in a couple: Married	0.01	0.011	0.013	0.015	0.011	0.012	0.012
Share not living in a couple: Separated	0.02	0.021	0.023	0.024	0.021	0.022	0.022
Share not living in a couple: Divorced	0.059	0.062	0.064	0.065	0.061	0.062	0.062
Share not living in a couple: Widowed [a]	0.075	0.078	0.079	0.077	0.076	0.077	0.077
Share households with one person	0.278	0.292	0.306	0.309	0.287	0.292	0.291
Share households with one family only pensioners	0.088	0.084	0.077	0.073	0.084	0.082	0.082
Share households with one family with no children	0.175	0.161	0.152	0.147	0.165	0.162	0.163
Share households with one family with children	0.394	0.392	0.385	0.385	0.394	0.391	0.391
Share households with other type of residents [a]	0.065	0.071	0.08	0.087	0.07	0.074	0.073
Share Part-time Employee	0.122	0.12	0.116	0.115	0.12	0.119	0.12
Share Full-time Employee	0.403	0.4	0.393	0.382	0.402	0.397	0.389
Share Self-employed	0.08	0.07	0.068	0.068	0.073	0.072	0.073
Share Unemployed	0.036	0.039	0.043	0.046	0.038	0.04	0.041
Share Full-time student [a]	0.024	0.024	0.025	0.025	0.024	0.024	0.024
Share Inactive	0.336	0.346	0.355	0.365	0.342	0.348	0.353
Observations	8268	5607	3056	1061	5933	3627	1386

Notes: This table shows 2001 Census Demographics linked with MCS using the cohort member's residence Lower Layer Super Output Areas (LSOA). Lower Layer Super Output Areas small area geographic hierarchy for England and Wales. We show descriptive statistics at age 7 of availability of fast food restaurants within 400, 800, 1600 metres buffers. Columns 2 & 5; 3 & 6; and 4 & 7 include cohort members with one or more fast food restaurants within 1600, 800, 400 metres buffers, respectively. [a] Indicates time-varying variables included as controls in equations (4.1) and (4.2). [b] Indicates the baseline category excluded in the empirical specifications.Source: 2001 Census Demographics.

Tables 4.8 and 4.9 present the average number of fast food restaurants and other food outlets around cohort members' residence and school across time. Several interesting facts emerge. First, we witness a large increase in the number of fast food restaurants around cohort members' homes and schools. At age 7, children in our sample were exposed to an average of 2.5 fast food restaurants within 1600 metres of home, while 7 years later they were exposed to 4, representing an increase of around 60%. This trend is also observed in relation to cohort members' schools, where fast food restaurants within 1600 metres increased by over 40% during this period, from 2.7 to 3.8. Second, the increase in the number of fast food restaurants around cohort members' home and schools is higher between ages 7 and 11, than between ages 11 and 14. Third, not only is the number of fast food restaurants increasing during this period, but so too are other food facilities. On average, at age 7 there were around 15.3 (16.4) other food facilities within 1600 metres of cohort members' homes (schools). By age 14, these numbers had increased by 46.9% (42.2%).

Table 4.8: Availability of fast food restaurants and other food outlets around cohort member's home and across time

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1600 metres			800 metres			400 metres		
	7 years	11 years	14 years	7 years	11 years	14 years	7 years	11 years	14 years
Fast Food Restaurants									
Fast Food	2.532	4.096	3.964	0.632	1.043	1.003	0.154	0.248	0.228
McDonalds	0.123	0.18	0.16	0.019	0.029	0.025	0.002	0.004	0.003
KFC	0.108	0.137	0.14	0.017	0.022	0.021	0.003	0.003	0.003
Burger King	0.028	0.036	0.038	0.002	0.004	0.003	0	0.001	0.001
Wimpy	0.022	0.025	0.018	0.004	0.004	0.004	0.001	0.001	0
Subway	0.071	0.198	0.24	0.009	0.037	0.046	0.002	0.007	0.007
Pizza Hut	0.086	0.162	0.11	0.012	0.035	0.02	0	0.006	0.002
Domino's Pizza	0.085	0.251	0.156	0.013	0.05	0.033	0.002	0.01	0.007
Kebab & Chicken	0.647	1.306	1.309	0.155	0.323	0.325	0.033	0.075	0.065
Fish and chip shops	1.363	1.802	1.793	0.402	0.538	0.526	0.111	0.141	0.14
Others Food Facilities									
Other Food Environment	15.274	22.951	22.432	3.904	5.985	5.659	0.973	1.452	1.363
Restaurants	4.426	6.132	6.298	1.003	1.466	1.456	0.214	0.311	0.304
Bakeries	0.952	1.266	1.268	0.24	0.341	0.323	0.062	0.079	0.073
Butchers	1.095	1.281	1.192	0.304	0.354	0.294	0.078	0.087	0.075
Confectioners	0.209	0.439	0.424	0.046	0.108	0.103	0.008	0.021	0.025
Delicatessens	0.275	0.571	0.588	0.06	0.136	0.147	0.012	0.034	0.033
Fishmongers	0.098	0.194	0.162	0.02	0.046	0.035	0.004	0.011	0.007
Green and new age goods	0.015	0.039	0.025	0.004	0.011	0.006	0.001	0.002	0.002
Grocers; farm shops and pick your own	0.889	1.746	1.502	0.248	0.447	0.366	0.057	0.106	0.087
Organic; health; gourmet and kosher foods	0.384	0.318	0.382	0.089	0.062	0.083	0.021	0.013	0.015
Conv. stores and independent supermarkets	5.374	9.416	9.191	1.517	2.597	2.491	0.422	0.679	0.652
Supermarket chains	1.557	1.547	1.399	0.372	0.417	0.356	0.092	0.11	0.091
Observations	8268	8268	8268	8268	8268	8268	8268	8268	8268

Notes: This table shows descriptive statistics of the POI categories used to create the variables 'fast food restaurants' and 'other food facilities' we use in the regression analysis. Source: Ordnance Survey Point of Interest.

Table 4.9: Availability of fast food restaurants and other food outlets around cohort member's school and across time

	1600 metres			800 metres			400 metres		
	7 years	11 years	14 years	7 years	11 years	14 years	7 years	11 years	14 years
Fast Food Restaurants									
Fast Food	2.683	3.903	3.794	0.747	1.082	0.841	0.2	0.201	0.147
McDonalds	0.137	0.165	0.146	0.017	0.037	0.021	0.002	0.006	0.006
KFC	0.106	0.116	0.106	0.018	0.025	0.019	0.005	0.002	0.002
Burger King	0.031	0.05	0.051	0.002	0.017	0.009	0	0.007	0.001
Wimpy	0.021	0.03	0.022	0.004	0.015	0.006	0.001	0	0
Subway	0.08	0.226	0.28	0.015	0.068	0.069	0.004	0.01	0.013
Pizza Hut	0.098	0.137	0.104	0.016	0.035	0.018	0.003	0.005	0.003
Domino's Pizza	0.092	0.297	0.175	0.02	0.075	0.033	0.005	0.013	0.011
Kebab & Chicken	0.638	1.094	1.099	0.166	0.286	0.222	0.033	0.047	0.037
Fish and chip shops	1.48	1.787	1.813	0.488	0.524	0.443	0.147	0.11	0.074
Others Food Facilities									
Other Food Environment	16.388	22.941	22.979	4.553	6.056	5.047	1.207	1.073	0.973
Restaurants	4.886	6.574	6.902	1.152	1.725	1.377	0.261	0.224	0.242
Bakeries	1.02	1.424	1.438	0.309	0.377	0.338	0.084	0.053	0.059
Butchers	1.162	1.238	1.171	0.381	0.334	0.263	0.11	0.06	0.036
Confectioners	0.23	0.454	0.49	0.056	0.12	0.125	0.011	0.02	0.029
Delicatessens	0.331	0.618	0.624	0.095	0.158	0.139	0.022	0.032	0.033
Fishmongers	0.102	0.198	0.144	0.035	0.043	0.023	0.004	0.003	0.003
Green and new age goods	0.018	0.042	0.032	0.004	0.011	0.007	0.001	0.001	0
Grocers; farm shops and pick your own	0.948	1.498	1.292	0.275	0.333	0.263	0.066	0.061	0.049
Organic; health; gourmet and kosher foods	0.43	0.418	0.432	0.118	0.105	0.087	0.028	0.017	0.018
Conv. stores and independent supermarkets	5.626	8.788	8.843	1.674	2.387	2.036	0.501	0.51	0.429
Supermarket chains	1.634	1.69	1.61	0.454	0.463	0.389	0.12	0.092	0.072
Observations	8268	8268	8268	8268	8268	8268	8268	8268	8268

Notes: This table shows descriptive statistics of the POI categories used to create the variables 'fast food restaurants' and 'other food facilities' we use in the regression analysis. Source: Ordnance Survey Point of Interest.

4.4.2 Benchmark estimates

We start our analysis by estimating equations (4.1) and (4.2). Table 4.10 presents our preferred specification, showing OLS estimates alongside cohort member fixed effects. Note that in section 4.5, we present a robustness analysis, comparing our main estimates with other models as we build up our main specification, analyse the plausibility of our identification strategy and perform falsification tests. In our fixed effects specification, we ask whether changes in cohort members' BMI and body fat are affected by changes in the number of fast food outlets around cohort members' homes and schools. We show estimates bases on exposure to fast food restaurant around cohort members' homes in columns 1-4, and around cohort members' schools in columns 5-6. Panel A shows estimates of equations (4.1) and Panel B shows estimates of equation (4.2). In all specifications we cluster standard errors at the individual level, and all estimates are weighted to account for attrition and survey design.

Looking first at results pertaining to proximity of fast foods in relation to homes, our OLS estimates show a positive and significant association between exposure to fast food outlets and cohort members' BMI and body fat (columns 1 and 3). Overall, we find that OLS estimates are higher than fixed effects estimates across different specifications, indicating the importance of adjusting for selection. In our fixed effects specification (Panel A, columns 2 and 4), we find that an additional fast food outlet within 1600 metres increases cohort members' BMI by 0.04 points, a 0.21% increase over the sample mean of 18.94. We estimate an effect on body fat of 0.08 percentage points, a 0.37% increase with respect to the sample mean of 21.55. Importantly, these results are larger when we focus on fast food outlets within 800 metres. A one unit increase in number of fast food outlets around children's residence increase cohort members' BMI by 0.06 points, a 0.32% increase with respect the sample mean, and their body fat percentage by 0.12 percentage points, a 0.56% increase with respect the sample mean. A similar pattern is observed in Panel B where we show estimates for equation (4.2). Adding one fast food restaurant between 800 and 1600 metres of cohort members' homes increases their BMI and body fat percentage by 0.03 points and 0.07 percentage points respectively. The estimates decrease as the buffer's radius increases, consistent with higher transportation and psychological costs faced by parents and cohort members (Currie et al., 2010).

Results around cohort members' schools (see Table 4.10, columns 5-8) shown similar patterns, but with some notable exceptions. In the fixed effects specification, in columns 6 and 8, our results suggest that increasing the number of fast foods around schools increases cohort members' obesity rates. Specifically, Panel A column 6 shows that adding a fast food restaurant within 1600 metres of cohort members' schools increases BMI by 0.02 points; however, we do not find any effect on body fat (see Panel A, column 8). Interestingly, we find a larger and more consistent effect on BMI when we focus on the number of fast food restaurants within 800 metres of cohort members' schools. Results from equation (1.2) in Panel B show consistent evidence that increasing the number of fast food restaurants between 400 and 800 metres increases both BMI and body fat percentage. Specifically, a unit increase in fast food outlet restaurant between 400 and 800 metres around cohort members' schools increase BMI by 0.08 points and body fat by 0.13 percentage points.[12]

In terms of the magnitude of the associations, our main specification that shows an additional fast food restaurant– respectively within 400, 800, and 1600 metres of cohort members' homes– increase BMI by 0.11, 0.06, 0.04 points, translates into a gain of 365, 165, and 90 grams during the period under consideration. Expressed in z-BMI scores, these estimates are 0.033, 0.017, and 0.008, respectively (See Table 4.19 in Appendix), with the last two statistically significant at 10% level. To put these estimates in context, Qian et al. (2017), using a similar student fixed effects model but over a sample of movers in Arkansas, found that an additional fast food restaurant within 1,600 metres of the child's residence on z-BMI scores was 0.0019. In contrast, Asirvatham et al. (2019) find null effects in a similar specification. Our results could also be interpreted as an increase in the incidence of overweight/obese incidence across time. A marginal increase in fast food restaurants within 800 metres from cohort member's residences increase overweight/obese rate by 0.006 points, a 2.6% increase in the sample rate (Column 4, Panel A in Table 4.19). The same estimates around cohort member's school is 0.009, a 3.9% increase in the sample rate (Column 8, Panel A in Table 4.19). Previous studies, that focus on obesity rates using school-level data in Arkansas and instrumental variable methods, find that an additional fast food restaurant within 1600 metres increase obesity rate by 1.23% (Alviola et al., 2014) and 1.22% (Qian et al., 2017). As a comparison, in the same 1600 metres buffer around schools, we find that an increase of 0.002 points in obesity, an 3.33% with respect to a sample rate of 0.06.

When we restrict our analysis to the sample of cohort members who did not change residence, we are able to separate the effects of fast food openings or closures from the effects due to families moving home, to or from areas with a higher

[12] Note that comparing point estimates between studies is challenging since we are not using the same methods in the identification strategy; however, we find the comparison useful to evaluate the magnitude of our point estimates. Estimates for obesity as dependent variables are available upon request.

or lower density of fast food outlets. In Table 4.11 we present separate fixed effects estimates for families who do and do not change residence. Overall, we find that results are larger and significant in the sample of cohort members who do not change residence (columns 1, 3, 5, and 7), providing suggestive evidence that our results are driven by changes in the supply of fast food outlets, and not due to changes in residence.

Table 4.10: Estimates of the effect of fast food restaurants on BMI and Body Fat percentage

	Home				School			
	BMI		Body Fat (%)		BMI		Body Fat (%)	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)	(6)	(7)	(8)	(9)
Panel A. Equation 1								
Fast food restaurant within 400m	0.127**	0.109	0.258*	0.267	0.108	0.0305	0.0709	-0.0628
	(0.063)	(0.076)	(0.139)	(0.182)	(0.067)	(0.043)	(0.135)	(0.105)
Other food outlets within 400m	-0.0248*	0.00143	-0.0352	0.016	-0.0222	-0.0142	-0.0129	0.0029
	(0.015)	(0.016)	(0.033)	(0.040)	(0.015)	(0.012)	(0.037)	(0.032)
R-squared	0.318	0.656	0.207	0.052	0.318	0.656	0.207	0.051
Fast food restaurant within 800m	0.0727**	0.0577**	0.149**	0.121*	0.0931***	0.0680***	0.160***	0.0956
	(0.035)	(0.025)	(0.067)	(0.065)	(0.029)	(0.022)	(0.058)	(0.059)
Other food outlets within 800m	-0.00473	-0.0001	-0.00147	0.018	-0.00979*	-0.0100*	-0.0133	-0.0107
	(0.011)	(0.006)	(0.022)	(0.013)	(0.005)	(0.005)	(0.014)	(0.015)
R-squared	0.318	0.656	0.208	0.053	0.318	0.656	0.208	0.051
Fast food restaurant within 1600m	0.0382*	0.0367***	0.0694*	0.0812**	0.0167	0.0189*	0.0419	0.0104
	(0.020)	(0.013)	(0.039)	(0.033)	(0.015)	(0.010)	(0.029)	(0.024)
Other food outlets within 1600m	-0.00549	-0.00224	-0.00812	-0.00172	-0.00146	-0.00296	-0.00298	-0.00121
	(0.003)	(0.002)	(0.006)	(0.006)	(0.002)	(0.002)	(0.005)	(0.005)
R-squared	0.318	0.656	0.207	0.053	0.318	0.656	0.207	0.051
Panel B. Equation 2								
Fast food restaurant								
within 400m	0.117*	0.109	0.239*	0.248	0.111*	0.0393	0.0738	-0.05
	(0.063)	(0.077)	(0.137)	(0.184)	(0.067)	(0.044)	(0.135)	(0.106)
between 400m and 800m	0.0556	0.0433	0.116	0.0912	0.0946***	0.0747***	0.182***	0.126**
	(0.039)	(0.030)	(0.080)	(0.079)	(0.030)	(0.023)	(0.061)	(0.062)
between 800m and 1600m	0.0282	0.0291**	0.0446	0.0656*	-0.00836	0.00398	0.00397	-0.0159
	(0.022)	(0.014)	(0.042)	(0.036)	(0.016)	(0.011)	(0.032)	(0.027)
Other food outlets								
within 400m	-0.0366**	-0.00781	-0.0672*	-0.0195	-0.0324**	-0.0168	-0.0341	-0.00532
	(0.017)	(0.017)	(0.037)	(0.043)	(0.016)	(0.011)	(0.037)	(0.030)
between 400m and 800m	0.0121	-0.00229	0.0329	0.0217	-0.00607	-0.00777	-0.0105	-0.0106
	(0.019)	(0.007)	(0.041)	(0.017)	(0.005)	(0.005)	(0.013)	(0.014)
between 800m and 1600m	-0.00773**	-0.00171	-0.0141*	-0.00609	0.00119	-0.00111	0.000336	0.00124
	(0.003)	(0.003)	(0.007)	(0.008)	(0.003)	(0.002)	(0.006)	(0.005)
R-squared	0.319	0.656	0.209	0.053	0.319	0.656	0.208	0.052
Observations	24,725	24,725	24,435	24,435	24,725	24,725	24,435	24,435
Individual FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata and PSU FE	Yes	No	Yes	No	Yes	No	Yes	No
Census 01 LSOA Controls	No	No	No	No	No	No	No	No
Mean Outcome	18.94	18.94	21.55	21.55	18.94	18.94	21.55	21.55
Number of children		8,268		8,267		8,268		8,267

Notes: * denote statistical significance at 10% levels respectively; ** denote statistical significance at 5% levels respectively; *** denote statistical significance at 1% levels respectively

Table 4.11: Estimates of the effect of fast food restaurants on BMI and Body Fat percentage, sample of Movers and Stayers

	Home				School			
	BMI		Body Fat (%)		BMI		Body Fat (%)	
	Stay	Move	Stay	Move	Stay	Move	Stay	Move
	(1)	(2)	(3)	(4)	(6)	(7)	(8)	(9)
Panel A. Equation 1								
Fast food restaurant within 400m	0.0131	0.18	0.132	0.362	0.0977**	-0.0937	-0.0255	-0.118
	(0.068)	(0.113)	(0.159)	(0.277)	(0.047)	(0.086)	(0.114)	(0.211)
Other food outlets within 400m	0.0183	-0.0105	0.0302	0.0088	-0.0226**	0.00192	0.00474	-3.1E-05
	(0.023)	(0.023)	(0.059)	(0.057)	(0.010)	(0.029)	(0.029)	(0.073)
R-squared	0.652	0.667	0.05	0.065	0.652	0.666	0.05	0.063
Fast food restaurant within 800m	0.0404	0.0767**	0.180*	0.0705	0.0592**	0.0786*	0.0574	0.145
	(0.033)	(0.038)	(0.094)	(0.090)	(0.024)	(0.040)	(0.061)	(0.104)
Other food outlets within 800m	0.00788	-0.00486	0.023	0.0211	-0.00616	-0.0156	0.00346	-0.0317
	(0.009)	(0.008)	(0.021)	(0.017)	(0.004)	(0.011)	(0.012)	(0.029)
R-squared	0.652	0.667	0.052	0.064	0.652	0.667	0.05	0.064
Fast food restaurant within 1600m	0.0453***	0.0323*	0.135***	0.0352	0.0203*	0.0178	0.000493	0.0401
	(0.016)	(0.019)	(0.045)	(0.048)	(0.012)	(0.018)	(0.030)	(0.040)
Other food outlets within 1600m	-0.00207	-0.0021	-0.0068	0.00382	-0.00319*	-0.00262	0.00396	-0.0105
	(0.003)	(0.003)	(0.008)	(0.008)	(0.002)	(0.004)	(0.005)	(0.010)
R-squared	0.652	0.667	0.053	0.064	0.652	0.666	0.05	0.063
Panel B. Equation 2								
Fast food restaurant								
within 400m	0.0087	0.183	0.12	0.346	0.0983**	-0.0837	-0.0274	-0.123
	(0.069)	(0.115)	(0.160)	(0.277)	(0.047)	(0.082)	(0.115)	(0.203)
between 400m and 800m	0.0429	0.0429	0.194*	-0.0165	0.0514**	0.110***	0.0806	0.196*
	(0.035)	(0.048)	(0.102)	(0.115)	(0.025)	(0.042)	(0.065)	(0.108)
between 800m and 1600m	0.0478***	0.0134	0.120***	0.0156	0.00923	0.000308	-0.0175	0.00858
	(0.018)	(0.021)	(0.046)	(0.056)	(0.013)	(0.020)	(0.031)	(0.047)
Other food outlets								
within 400m	0.00107	-0.0158	-0.0277	-0.0139	-0.0272***	0.00375	-0.0156	0.0263
	(0.023)	(0.024)	(0.058)	(0.061)	(0.010)	(0.025)	(0.030)	(0.067)
between 400m and 800m	0.00281	-0.00614	0.0268	0.0246	0.00105	-0.0231**	0.00453	-0.0357
	(0.011)	(0.009)	(0.026)	(0.022)	(0.005)	(0.009)	(0.013)	(0.025)
between 800m and 1600m	-0.00328	0.000593	-0.0126	0.00071	-0.00336*	0.00208	0.00442	-0.00623
	(0.004)	(0.004)	(0.010)	(0.012)	(0.002)	(0.004)	(0.005)	(0.009)
R-squared	0.652	0.667	0.053	0.066	0.652	0.668	0.051	0.065
Observations	17,260	7,465	17,066	7,369	17,260	7,465	17,066	7,369
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata and PSU FE	No	No	No	No	No	No	No	No
Census 01 LSOA Controls	No	No	No	No	No	No	No	No
Mean Outcome	18.89	19.06	21.43	21.83	18.89	19.08	21.43	21.83
Number of children	5,770	2,498	5,770	2,497	5,770	2,498	5,770	2,497

Notes: * denote statistical significance at 10% levels respectively; ** denote statistical significance at 5% levels respectively; *** denote statistical significance at 1% levels respectively

4.4.3 Heterogeneity and mechanisms

Previous research in the UK, and elsewhere, portrays a very clear pattern of disparity in adolescent obesity by socioeconomic status (Bann et al., 2018), and so an important question is the extent to which the availability of fast food outlets can further exacerbate these inequalities. To shed light on this, we divide the sample according to maternal education level and specifically, by whether the individual's mother had attained higher education (degree or higher 47.7% of sample) or not

(52.3% of sample).[13]

Table 4.12 present estimates of the effect of fast food outlets around cohort members' homes (columns 1-4) and schools (columns 5-8). We do not find evidence that an increase in the availability of fast food outlets increases BMI or body fat amongst the more highly educated group; however, we find larger and significant effects among cohort members whose mothers had lower educational levels. Evidence that fast food exposure could exacerbate inequalities is found for both specifications (Panel A and B), and around cohort members' residences and schools. In the low education group, increasing in one unit the number of fast food outlets within a 1600 metres from cohort members' residence increases BMI by 0.05 points and body fat percentage by 0.1 percentage points, a 0.26% and 0.45% increase with respect to the sample mean (Table 4.12, Panel A, columns 1 and 2). These results are consistent with the positive and significant effect between 800 and 1600 metres from cohort members' residences (Table 4.12, Panel B, columns 1 and 2). Regarding the effect around cohort member's schools, we find a similar pattern where no effects are found in the high educational group, while positive and significant effects are found for BMI and body fat percentage in the low educational group. Interestingly, we find that a unit increase of fast food outlets in the area between 400 and 800 from schools increase BMI and body fat by 0.6% and 0.8% with respect their respective sample means (Table 4.12, Panel B, columns 5 and 7).

International systematic reviews argue that previous studies have failed to evaluate how age, e.g. transitioning for primary to secondary school, could influence children's interaction with fast food availability (Williams et al., 2014). As children gain autonomy, they face changes in mode of transport and availability of pocket money that may change the association between fast food availability and obesity. To further explore this question, we divide our analysis between cohort member's ages 7-11 and 11-14, which allow us to analyse differences between primary and

[13] We classify cohort members in the high educational group when their mothers had achieved National Vocational Level (NVQ) 4 or 5 at wave 3. Others cohort members are classified in the low education group when their mothers had achieved NVQ 1-3 or none. NVQ 4 level includes bachelor's degrees, graduate certificates, and other higher education diplomas. NVQ 5 level includes master's degrees, Postgraduate certificates/diplomas and Doctorate degrees.

secondary school periods.

In Table 4.13, we present estimates by school period of our main fixed effects model around cohort member's residence (columns 1-4) and schools (columns 5-6). Estimates for the period between ages 7-11 (i.e. primary school) are shown in columns 1, 3, 5 and 7, while estimates for the period between 11-14 (i.e. secondary school) are shown in columns 2, 4, 6, and 8. When we concentrate on children's BMI around cohort member's residence (Panel A, columns 1 and 2), we do not observe differences in the effect of availability of fast food between both periods, i.e. ages 7-11 and 11-14. Adding a fast food restaurant within 1600 metres from cohort member residence increase BMI by 0.028 points at ages 7-11, which is similar to the 0.030 effects at ages 11-14, both statistically significant at 10% level. However, we find some evidence that the effect of availability fast food around cohort member's residence on body fat is larger during primary school than secondary school (Panel A, columns 3 and 4). In contrast, results around cohort member's schools (columns 5 - 8) show larger effects during the secondary school, and null effects during the primary school for both measures of obesity, BMI and body fat. In secondary school, an increase in one fast food restaurant within the 1,600 metres school-buffer increase cohort member's BMI by in 0.07 points and Body fat by 0.11 percentage points, a 0.35% and 0.5% increase with respect the sample mean in the corresponding period. We found larger and statistically significant results within 800 metres from secondary school.

Table 4.12: Heterogeneity by education: Estimates of the effect of fast food restaurants around cohort member's residence and school

	Home				School			
	BMI		Body Fat (%)		BMI		Body Fat (%)	
	below level 4 NVQ	level 4 or more NVQ	below level 4 NVQ	level 4 or more NVQ	below level 4 NVQ	level 4 or more NVQ	below level 4 NVQ	level 4 or more NVQ
	(1)	(2)	(3)	(4)	(6)	(7)	(8)	(9)
Panel A. Equation 1								
Fast food restaurant within 400m	0.136	0.00746	0.297	0.101	0.0729	-0.0502	0.014	-0.208
	(0.103)	(0.069)	(0.242)	(0.187)	(0.061)	(0.053)	(0.148)	(0.128)
Other food outlets within 400m	0.00181	-0.00155	0.0367	-0.0323	-0.0234	0.00673	-0.0388	0.0867***
	(0.022)	(0.018)	(0.056)	(0.047)	(0.017)	(0.013)	(0.045)	(0.034)
R-squared	0.641	0.691	0.063	0.042	0.64	0.691	0.062	0.044
Fast food restaurant within 800m	0.0753**	-0.000296	0.122	0.092	0.0984***	0.0184	0.159*	-0.00418
	(0.033)	(0.031)	(0.085)	(0.083)	(0.030)	(0.025)	(0.083)	(0.059)
Other food outlets within 800m	-0.000658	0.000926	0.0348**	-0.0231	-0.0178**	0.00306	-0.0291	0.0181*
	(0.008)	(0.007)	(0.016)	(0.019)	(0.007)	(0.004)	(0.022)	(0.010)
R-squared	0.641	0.691	0.065	0.043	0.641	0.691	0.063	0.043
Fast food restaurant within 1600m	0.0456***	0.00826	0.103**	0.0104	0.0491***	-0.0168	0.0432	-0.0219
	(0.017)	(0.016)	(0.043)	(0.042)	(0.015)	(0.010)	(0.040)	(0.026)
Other food outlets within 1600m	-0.00299	-0.00037	-0.000601	-0.00312	-0.00840***	0.00340**	-0.00842	0.00684**
	(0.003)	(0.003)	(0.007)	(0.007)	(0.003)	(0.001)	(0.009)	(0.003)
R-squared	0.641	0.691	0.065	0.042	0.641	0.691	0.062	0.043
Panel B. Equation 2								
Fast food restaurant								
within 400m	0.137	0.00602	0.267	0.122	0.0861	-0.045	0.0303	-0.207
	(0.104)	(0.069)	(0.245)	(0.188)	(0.060)	(0.053)	(0.146)	(0.128)
between 400m and 800m	0.0562	-0.00025	0.0863	0.0841	0.106***	0.0375	0.192**	0.0353
	(0.039)	(0.034)	(0.102)	(0.089)	(0.033)	(0.027)	(0.092)	(0.067)
between 800m and 1600m	0.0347*	0.0105	0.0933*	-0.012	0.0338**	-0.0286**	0.00605	-0.0306
	(0.019)	(0.018)	(0.048)	(0.047)	(0.017)	(0.012)	(0.042)	(0.031)
Other food outlets								
within 400m	-0.0092	-0.00375	-0.0141	-0.032	-0.0182	-0.00326	-0.0396	0.0715**
	(0.024)	(0.018)	(0.060)	(0.050)	(0.015)	(0.013)	(0.042)	(0.034)
between 400m and 800m	-0.00354	0.000363	0.0396*	-0.0233	-0.0167**	0.00209	-0.0248	0.00742
	(0.009)	(0.009)	(0.022)	(0.025)	(0.007)	(0.006)	(0.022)	(0.013)
between 800m and 1600m	-0.00214	-0.00032	-0.00948	0.00304	-0.00595**	0.00381*	-0.00273	0.00405
	(0.004)	(0.003)	(0.011)	(0.009)	(0.003)	(0.002)	(0.008)	(0.005)
R-squared	0.641	0.691	0.067	0.043	0.642	0.692	0.064	0.044
Observations	12,917	11,808	12,764	11,671	12,917	11,808	12,764	11,671
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata and PSU FE	No	No	No	No	No	No	No	No
Census 01 LSOA Controls	No	No	No	No	No	No	No	No
Mean Outcome	19.14	18.74	22.11	20.95	19.14	18.74	20.95	20.95
Number of children	4,322	3,946	4,322	3,945	4,322	3,946	3,945	3,945

Notes: * denote statistical significance at 10% levels respectively; ** denote statistical significance at 5% levels respectively; *** denote statistical significance at 1% levels respectively

Table 4.13: Heterogeneity by school period: Estimates of the effect of fast food restaurants around cohort member's residence and school on BMI and Body Fat percentage

	Home				School			
	BMI		Body Fat (%)		BMI		Body Fat (%)	
	7 and 11	11 and 14	7 and 11	11 and 14	7 and 11	11 and 14	7 and 11	11 and 14
	(1)	(2)	(3)	(4)	(6)	(7)	(8)	(9)
Panel A. Equation 1								
Fast food restaurant within 400m	0.0385	0.119	0.012	0.334	-0.00261	0.0594	-0.191*	0.163
	(0.065)	(0.099)	(0.149)	(0.260)	(0.046)	(0.058)	(0.112)	(0.165)
Other food outlets within 400m	0.0203	-0.0351	0.0771*	-0.071	-0.0000618	-0.029	0.0503*	-0.0521
	(0.016)	(0.026)	(0.043)	(0.071)	(0.011)	(0.018)	(0.029)	(0.064)
R-squared	0.575	0.507	0.081	0.024	0.575	0.507	0.08	0.024
Fast food restaurant within 800m	0.034	0.0448	0.145*	0.0519	0.0228	0.102**	-0.0338	0.220**
	(0.030)	(0.033)	(0.084)	(0.093)	(0.021)	(0.040)	(0.059)	(0.108)
Other food outlets within 800m	0.00938	-0.0121	0.0189	0.0101	-0.00345	-0.0172	0.00948	-0.0284
	(0.006)	(0.009)	(0.017)	(0.022)	(0.003)	(0.011)	(0.012)	(0.031)
R-squared	0.575	0.507	0.083	0.024	0.575	0.508	0.08	0.026
Fast food restaurant within 1600m	0.0284**	0.0306*	0.105**	0.0506	-0.00847	0.0665***	-0.0358	0.109**
	(0.014)	(0.018)	(0.041)	(0.049)	(0.009)	(0.017)	(0.031)	(0.043)
Other food outlets within 1600m	-0.000555	-0.00494	-0.00664	-0.00317	0.00137	-0.0103***	0.00723	-0.0175**
	(0.002)	(0.004)	(0.006)	(0.011)	(0.001)	(0.003)	(0.005)	(0.009)
R-squared	0.575	0.507	0.083	0.024	0.575	0.509	0.08	0.026
Panel B. Equation 2								
Fast food restaurant								
within 400m	0.0273	0.128	-0.0241	0.314	-0.00139	0.104*	-0.188*	0.24
	(0.066)	(0.099)	(0.151)	(0.265)	(0.046)	(0.061)	(0.112)	(0.174)
between 400m and 800m	0.0355	0.0316	0.186**	0.0217	0.0285	0.106***	-0.00321	0.216**
	(0.032)	(0.039)	(0.093)	(0.110)	(0.023)	(0.041)	(0.063)	(0.108)
between 800m and 1600m	0.0258	0.0239	0.0935**	0.0441	-0.0178	0.0564***	-0.0342	0.0814
	(0.016)	(0.020)	(0.041)	(0.055)	(0.011)	(0.020)	(0.032)	(0.050)
Other food outlets								
within 400m	0.00634	-0.0361	0.0374	-0.0895	-0.00248	-0.0265**	0.0439	-0.0476
	(0.016)	(0.026)	(0.043)	(0.073)	(0.011)	(0.013)	(0.029)	(0.054)
between 400m and 800m	0.00937	-0.00961	0.0201	0.0291	-0.00444	-0.0129	0.000288	-0.0126
	(0.009)	(0.011)	(0.025)	(0.024)	(0.004)	(0.012)	(0.012)	(0.032)
between 800m and 1600m	-0.00319	-0.00113	-0.0155**	-0.00764	0.00296	- 0.00891***	0.00696	-0.0181**
	(0.003)	(0.005)	(0.007)	(0.014)	(0.002)	(0.003)	(0.006)	(0.008)
R-squared	0.576	0.508	0.084	0.025	0.575	0.51	0.081	0.027
Observations	16,511	16,457	16,316	16,286	16,511	16,457	16,316	16,286
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata and PSU FE	No	No	No	No	No	No	No	No
Census 01 LSOA Controls	No	No	No	No	No	No	No	No
Mean Outcome	17.74	20.19	21.42	21.92	17.74	20.2	21.42	21.92
Number of children	8,268	8,268	8,264	8,261	8,268	8,268	8,264	8,261

Notes: * denote statistical significance at 10% levels respectively; ** denote statistical significance at 5% levels respectively; *** denote statistical significance at 1% levels respectively

4.5 Robustness checks

4.5.1 Robustness check

As a first robustness check, we estimate a variety of different empirical specifications, where we adjust the estimates in ways indicated in the tables. Table 4.14 shows estimates based on exposure to fast food restaurant around cohort members' residences, and Table 4.15 around cohort members' schools. Panel A in Tables 4.14 and 4.15 shows estimates of equation (4.1) and Panel B shows estimates of equation (4.2). Our main estimates, from the previous section, are shown in column 6 for ease of comparison. In both tables, column 1 shows unconditional estimates where we only control for other food outlets. Column 2 adds time-varying individual controls described in previous sections, year of the survey dummies, and area fixed effects. Column 3 replaces area fixed effects for 2001 Census Lower Layer Super Output Area (LSOA) variables. Together, these first three columns provide estimates that exploit changes in the number of fast food restaurants across time and between cohort members living in different areas in the UK. Columns 4, 5 and 6 exploit within individual variation in exposure to fast food restaurants. Column 4 adds cohort members' fixed effects and year of the survey dummies to the unconditional estimates in column 1. Column 5 adds to column 4, individual time-varying controls and 2001 Census LSOA variables[14], providing estimates for the subsample of cohort members who were living in England and Wales during 2000-2001.

When we compared our main estimates (in column 6) with other models, several interesting results emerge. First, our fast food estimates are more precise when we include controls, indicating that time-varying variables such as family socio-economic characteristics or healthy activities, e.g. the frequency of physical activity or whether the child eats breakfast, are useful absorbing predictors of obesity (columns 4 and 6). Second, point estimates decrease once we add individual fixed effects, reflecting the fact that previous results based on cross-sectional analysis, which fail to control for time-invariant unobserved factors, overestimate the association between obesity measures and the availability of fast food outlets. Third, overall, we find positive effects across different specifications, providing further

[14]In models that we do not include cohort members' fixed effects, we additionally control for area fixed effects, cohort members' gender, and a 2^{nd} degree polynomial of cohort members' age. Area fixed effects are defined as the strata and PSU of the MCS. Additionally, for a subsample of children living in England and Wales during 2000-2001, we control for characteristics of the geographical area using 2001 Census Demographics of Lower Layer Super Output Area (LSOA). Specifically, we control for the share of females; share of five ethnic groups (White, Mixed, Asian/British, Black/British); 2001 usual resident population density (number of people per hectare); share of people with different house tenure (outright, owned with a mortgage or loan, shared ownership, rented from council (local authority), rented from a housing association/registered social landlord, rented from a private landlord or letting agency); share of people living in a couple (married and cohabiting) and share of people not living in a couple (single, married, separated, divorced); share of households with different family structures (with one person, with one family only pensioners, with one family with no children, and with one family with children); share of people with different labour status (part-time employee, full-time employee, self-employed, unemployed, inactive).

credibility to our main results.

Another possible concern that could bias our results is measurement error in the number fast food restaurants around the cohort member's residence and school. However, there are two reasons why this is unlikely that this issue is driving our results. First, attenuation bias due to classical measurement error in fixed effects regression should bias downwards our point estimate, giving us a conservative estimate of the effect of fast food outlets. Second, by focusing on major fast food chains, instead of using the aggregate PoI categories we prevent potential misclassification due to changes in PoI versions.

4.5.2 Analysis of the plausibility of our identification strategy and falsification tests

To test the plausibility of our identification strategy we first ask whether, conditional on cohort member fixed effects, the availability of fast food outlets is correlated with time-varying individual-level characteristics. If we find that cohort member or maternal demographics are correlated with the number of fast food outlets, our identification assumption could fail. Specifically, we estimate this placebo analysis using as outcomes the following variables: the presence of two parents or carers in the household, OECD equivalent weekly family income, whether the highest educational level of cohort member's mother is NVQ level 4 or 5, whether cohort member does not practice exercise during the last week, and whether cohort member skips breakfast at least one time per week. However, results in Tables 4.16, 4.17, and 4.18 provide evidence that, for a large group of time-varying variables, there is no correlation with the availability of fast food restaurant around both specifications (equations (4.1) and (4.2)), or around cohort members' residences and schools.

We estimate a placebo exercise by running our preferred specification but replacing our fast food variable by the number of facilities in other PoI categories that arguably should not be associated with cohort members' obesity. Specifically, we use the categories 'IT, marketing and media services', 'Employment and career agencies', 'Consultancies', and 'Construction services.' Figures 4.2 and 4.3 show the results of this exercise for equation 4.1, and Figures 4.4 and 4.5 for equation

4.2. Across all specifications, we do not find evidence that commercial facilities near cohort members' residences or schools are associated cohort members' BMI nor Body fat percentage, providing evidence of the reliability of our main findings.

4.6 Conclusion

In this paper, we analysed the relationship between individual exposure to fast food outlets and children's BMI and body fat. Using a rich and unique longitudinal study collected in the UK and a fixed effects research design we show that increase in fast food outlets near home and school increase children's BMI and body fat during childhood. While we find consistent and statistically significant detrimental effects of exposure to fast food outlets, point estimates are relatively small. This results is similar to what previous studies have found (Alviola et al., 2014; Asirvatham et al., 2019; Currie et al., 2010; Qian et al., 2017). We find that a marginal increase of fast food restaurants within 800 metres from children's residences increases cohort members' BMI by 0.06 points, a 0.32% increase with respect the sample mean. Similarly, it increases cohort members' body fat and overweight/obese incidence by 0.12 and 0.006 percentage points – which respectively represent a 0.56% and 2.6% increase in the sample mean. Our results also indicate that access to fast food restaurants surrounding schools increase adolescent weight, where a marginal increase in fast-food restaurants within 800 metres increase BMI and the incidence of overweight/obesity by 0.37% and 3.5% with respect the sample mean. Investigating potential mechanisms, we explore differences by maternal education and primary/secondary schooling. Our findings suggest that detrimental effects of availability of fast food outlets vary by maternal education and they could be linked to the literature of health inequality (Deaton, 2003b; Marmot, 2010). If behavioural mechanisms interacting with socioeconomic status – such as nutrition knowledge (Parmenter et al., 2000) or working conditions (Griffith et al., 2016) – play a role in changing unhealthy decisions, then increasing the supply of fast food restaurants could exacerbate the effects on adolescent obesity. Besides, our results strengthen and complement previous cross-sectional evidence in the UK which demonstrate that access to fast food amplify socioeconomic inequalities in adults (Burgoine et al., 2016). We also find larger effects around 800 metres during secondary school, between ages 11-14, rather than during primary school, between ages 7-11. We hypothesize that these effects could be in part associated with an increase in the autonomy of adolescents as they growth; however, further research is needed in this area.

The extent our results have a causal interpretation depends on the plausibility of our identification strategy. One concern is that selection into less or more deprived areas across time could bias our results; however, we show suggestive evidence that our results are not driven by changes of residence during the analysed period. Another concern is potential unobservable time-varying factors correlated with access to fast food restaurants and children's BMI. To mitigate this concern, we control with several child and maternal time-varying indicators, besides we further control with other food facilities, which are plausibly correlated with unobserved time-varying local economic conditions and infrastructure. Additionally, we present evidence that our results are robust to different specifications and show falsification tests in favour of our empirical specification. Although this evidence alleviates concerns about identification, we cannot completely rule out self-selection and omitted variable bias.

4.7 Figures and tables of chapter 4

Table 4.14: Estimates of the effect of fast food restaurants around cohort member's residence on BMI and Body Fat percentage

	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: BMI						Dependent variable: Body Fat (%)					
Panel A. Equation 1												
Fast food restaurant within 400m	0.243***	0.127**	0.135**	0.114	0.1	0.109	0.326**	0.258*	0.291**	0.272	0.236	0.267
	(0.081)	(0.063)	(0.064)	(0.078)	(0.078)	(0.076)	(0.156)	(0.139)	(0.132)	(0.179)	(0.192)	(0.182)
Other food outlets within 400m	0.0214	-0.0248*	-0.0284*	0.000151	0.00916	0.00143	0.0681*	-0.0352	-0.05	0.0246	0.0371	0.016
	(0.018)	(0.015)	(0.015)	(0.016)	(0.017)	(0.016)	(0.040)	(0.033)	(0.034)	(0.041)	(0.044)	(0.040)
R-squared	0.003	0.318	0.292	0.648	0.656	0.656	0.002	0.207	0.184	0.023	0.058	0.052
Fast food restaurant within 800m	0.196***	0.0727**	0.0684*	0.0596**	0.0588**	0.0577**	0.312***	0.149**	0.133*	0.121*	0.11	0.121*
	(0.044)	(0.035)	(0.037)	(0.026)	(0.027)	(0.025)	(0.071)	(0.067)	(0.071)	(0.067)	(0.070)	(0.065)
Other food outlets within 800m	0.000521	-0.00473	-0.00621	-0.000761	0.00357	-0.0001	0.00613	-0.00147	-0.00463	0.0201	0.0309**	0.018
	(0.009)	(0.011)	(0.011)	(0.006)	(0.006)	(0.006)	(0.018)	(0.022)	(0.025)	(0.014)	(0.015)	(0.013)
R-squared	0.007	0.318	0.292	0.648	0.657	0.656	0.006	0.208	0.184	0.023	0.059	0.053
Fast food restaurant within 1600m	0.121***	0.0382*	0.0429**	0.0379***	0.0361***	0.0367***	0.193***	0.0694*	0.0748**	0.0860***	0.0799**	0.0812**
	(0.021)	(0.020)	(0.018)	(0.013)	(0.013)	(0.013)	(0.037)	(0.039)	(0.037)	(0.033)	(0.035)	(0.033)
Other food outlets within 1600m	-0.00842***	-0.00549	-0.00772***	-0.00198	-0.000393	-0.00224	-0.0132**	-0.00812	-0.0134**	-0.000527	0.00222	-0.00172
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
R-squared	0.011	0.318	0.292	0.649	0.657	0.656	0.008	0.207	0.185	0.024	0.059	0.053
Panel B. Equation 2												
Fast food restaurant												
within 400m	0.214***	0.117*	0.123*	0.116	0.101	0.109	0.276*	0.239*	0.265*	0.255	0.215	0.248
	(0.077)	(0.063)	(0.065)	(0.078)	(0.077)	(0.077)	(0.149)	(0.137)	(0.135)	(0.181)	(0.191)	(0.184)
between 400m and 800m	0.154***	0.0556	0.0396	0.044	0.0459	0.0433	0.252***	0.116	0.0716	0.0883	0.0852	0.0912
	(0.042)	(0.039)	(0.039)	(0.031)	(0.030)	(0.030)	(0.075)	(0.080)	(0.085)	(0.079)	(0.082)	(0.079)
between 800m and 1600m	0.106***	0.0282	0.0399**	0.0301**	0.0287**	0.0291**	0.168***	0.0446	0.0662*	0.0720**	0.0701*	0.0656*
	(0.024)	(0.022)	(0.019)	(0.014)	(0.014)	(0.014)	(0.044)	(0.042)	(0.039)	(0.036)	(0.037)	(0.036)
Other food outlets												
within 400m	-0.0338*	-0.0366**	-0.0328*	-0.00969	-0.00146	-0.00781	-0.0151	-0.0672*	-0.0635*	-0.0135	0.00268	-0.0195
	(0.020)	(0.017)	(0.017)	(0.018)	(0.018)	(0.017)	(0.045)	(0.037)	(0.036)	(0.044)	(0.045)	(0.043)
between 400m and 800m	0.00135	0.0121	0.0109	-0.00462	-0.000645	-0.00229	0.00639	0.0329	0.0325	0.0174	0.0297	0.0217
	(0.018)	(0.019)	(0.019)	(0.007)	(0.007)	(0.007)	(0.040)	(0.041)	(0.041)	(0.017)	(0.018)	(0.017)
between 800m and 1600m	-0.00895**	-0.00773**	-0.0106***	-0.000692	-8.33E-05	-0.00171	-0.0170**	-0.0141*	-0.0209***	-0.00382	-0.00411	-0.00609
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.007)	(0.007)	(0.009)	(0.008)	(0.008)
R-squared	0.011	0.319	0.293	0.649	0.657	0.656	0.008	0.209	0.186	0.024	0.06	0.053
Observations	24,804	24,725	21,643	24,804	21,643	24,725	24,510	24,435	21,430	24,510	21,430	24,435
Individual FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Individual Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Strata and PSU FE	No	Yes	No	No	No	No	No	Yes	No	No	No	No
Census 01 LSOA Controls	No	No	Yes	No	Yes	No	No	No	Yes	No	Yes	No
Mean Outcome	18.95	18.95	18.95	18.95	18.95	18.95	21.56	21.56	21.56	21.56	21.56	21.56
Number of children				8,268	7,256	8,268				8,267	7,255	8,267

Notes: * denote statistical significance at 10% levels respectively; ** denote statistical significance at 5% levels respectively; *** denote statistical significance at 1% levels respectively

Table 4.15: Estimates of the effect of fast food restaurants around cohort member's school on BMI and Body Fat percentage

	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: BMI						Dependent variable: Body Fat (%)					
Panel A. Equation 1												
Fast food restaurant within 400m	0.0545	0.108	0.0984	0.0269	0.0321	0.0305	0.221	0.0709	0.072	-0.0767	-0.0808	-0.0628
	(0.090)	(0.067)	(0.063)	(0.044)	(0.045)	(0.043)	(0.156)	(0.135)	(0.126)	(0.105)	(0.109)	(0.105)
Other food outlets within 400m	-0.0328	-0.0222	-0.0116	-0.0138	-0.0119	-0.0142	0.0238	-0.0129	0.00641	0.00643	0.00721	0.0029
	(0.024)	(0.015)	(0.016)	(0.012)	(0.012)	(0.012)	(0.046)	(0.037)	(0.039)	(0.032)	(0.034)	(0.032)
R-squared	0	0.318	0.292	0.648	0.656	0.656	0	0.207	0.184	0.022	0.057	0.051
Fast food restaurant within 800m	0.161***	0.0931***	0.1000***	0.0702***	0.0668***	0.0680***	0.342***	0.160***	0.165***	0.0897	0.0839	0.0956
	(0.036)	(0.029)	(0.027)	(0.023)	(0.024)	(0.022)	(0.062)	(0.058)	(0.055)	(0.060)	(0.064)	(0.059)
Other food outlets within 800m	-0.00791	-0.00979*	-0.00902	-0.0103*	-0.0092	-0.0100*	-0.0132	-0.0133	-0.0119	-0.00979	-0.00769	-0.0107
	(0.008)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.016)	(0.014)	(0.015)	(0.015)	(0.016)	(0.015)
R-squared	0.003	0.318	0.292	0.649	0.657	0.656	0.004	0.208	0.185	0.022	0.057	0.051
Fast food restaurant within 1600m	0.0826***	0.0167	0.0276**	0.0189*	0.0162	0.0189*	0.131***	0.0419	0.0537*	0.00753	0.00404	0.0104
	(0.019)	(0.015)	(0.013)	(0.010)	(0.010)	(0.010)	(0.030)	(0.029)	(0.029)	(0.025)	(0.025)	(0.024)
Other food outlets within 1600m	-0.00239	-0.00146	-0.00298	-0.00318	-0.00234	-0.00296	-0.00495	-0.00298	-0.00555	-0.000947	0.000459	-0.00121
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
R-squared	0.007	0.318	0.292	0.648	0.656	0.656	0.004	0.207	0.184	0.022	0.057	0.051
Panel B. Equation 2												
Fast food restaurant												
within 400m	0.0622	0.111*	0.0927	0.0354	0.0413	0.0393	0.218	0.0738	0.0581	-0.0648	-0.0686	-0.05
	(0.088)	(0.067)	(0.063)	(0.044)	(0.045)	(0.044)	(0.151)	(0.135)	(0.127)	(0.106)	(0.110)	(0.106)
between 400m and 800m	0.189***	0.0946***	0.101***	0.0778***	0.0731***	0.0747***	0.363***	0.182***	0.181***	0.122*	0.117*	0.126**
	(0.045)	(0.030)	(0.029)	(0.024)	(0.025)	(0.023)	(0.069)	(0.061)	(0.059)	(0.063)	(0.067)	(0.062)
between 800m and 1600m	0.0553**	-0.00836	0.00552	0.00328	0.000982	0.00398	0.0649*	0.00397	0.0209	-0.018	-0.0211	-0.0159
	(0.022)	(0.016)	(0.015)	(0.011)	(0.012)	(0.011)	(0.036)	(0.032)	(0.033)	(0.028)	(0.028)	(0.027)
Other food outlets												
within 400m	-0.0915***	-0.0324**	-0.0199	-0.0159	-0.0152	-0.0168	-0.048	-0.0341	-0.00811	-0.00124	-0.00407	-0.00532
	(0.023)	(0.016)	(0.017)	(0.011)	(0.011)	(0.011)	(0.040)	(0.037)	(0.038)	(0.030)	(0.031)	(0.030)
between 400m and 800m	-0.0151	-0.00607	-0.00529	-0.00775	-0.00755	-0.00777	-0.0279*	-0.0105	-0.00808	-0.00986	-0.00851	-0.0106
	(0.009)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.017)	(0.013)	(0.015)	(0.015)	(0.016)	(0.014)
between 800m and 1600m	0.00525	0.00119	-0.0016	-0.00144	-4.74E-04	-0.00111	0.00347	0.000336	-0.0049	0.0012	0.00284	0.00124
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
R-squared	0.01	0.319	0.292	0.649	0.657	0.656	0.005	0.208	0.185	0.022	0.057	0.052
Observations	24,804	24,725	21,643	24,804	21,643	24,725	24,510	24,435	21,430	24,510	21,430	24,435
Individual FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Individual Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Strata and PSU FE	No	Yes	No	No	No	No	No	Yes	No	No	No	No
Census 01 LSOA Controls	No	No	Yes	No	Yes	No	No	No	Yes	No	Yes	No
Mean Outcome	18.95	18.95	18.95	18.95	18.95	18.95	21.56	21.56	21.56	21.56	21.56	21.56
Number of children				8,268	7,256	8,268				8,267	7,255	8,267

Notes: * denote statistical significance at 10% levels respectively; ** denote statistical significance at 5% levels respectively; *** denote statistical significance at 1% levels respectively

Table 4.16: Estimates of effect of fast food restaurants around cohort member's residence on child and mother demographics: Placebos Equation 4.1

	Two parents/carers in the household	OECD equivalised weekly family income	Mother has NVQ level 4 or 5	Kid does not exercise	Kid skip breakfast at least one time per week	Two parents/carers in the household	OECD equivalised weekly family income	Mother has NVQ level 4 or 5	Kid does not exercise	Kid skip breakfast at least one time per week	Two parents/carers in the household	OECD equivalised weekly family income	Mother has NVQ level 4 or 5	Kid does not exercise	Kid skip breakfast at least one time per week
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
FF 1600m	-0.0004	-0.0043	0.0011	-0.0042	0.0019										
	(0.002)	(0.662)	(0.001)	(0.003)	(0.002)										
OF 1600m	-0.0003	-0.0360	-0.0002	-0.0002	0.0002										
	(0.001)	(0.132)	(0.000)	(0.001)	(0.001)										
FF 800m						-0.0013	1.8440	0.0028	-0.0095	0.0057					
						(0.006)	(1.403)	(0.002)	(0.006)	(0.005)					
OF 800m						0.0005	-0.3100	-0.000905**	-0.0009	0.0000					
						(0.002)	(0.324)	(0.000)	(0.002)	(0.001)					
FF 400m											0.0001	1.6650	0.0060	-0.0180	-0.0054
											(0.009)	(2.735)	(0.005)	(0.012)	(0.011)
OF 400m											0.0002	0.3440	-0.00250**	-0.0010	0.0028
											(0.004)	(0.786)	(0.001)	(0.003)	(0.003)
Observations	24,804	24,804	24,804	24,748	24,733	24,804	24,804	24,804	24,748	24,733	24,804	24,804	24,804	24,748	24,733
R-squared	0.012	0.28	0.037	0.146	0.293	0.011	0.28	0.038	0.146	0.293	0.011	0.28	0.038	0.145	0.292
Number of children	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
F test	0.387	0.0978	0.616	3.105	1.004	0.0484	0.875	2.567	3.976	1.104	0.00302	0.589	2.986	1.56	0.53
p-value (F test)	0.679	0.907	0.54	0.0449	0.367	0.953	0.417	0.0768	0.0188	0.331	0.997	0.555	0.0506	0.21	0.589

Notes: Each column is a different regression defined as equation 4.1. Column names denote the following five time-varying dependent variables: a binary variable whether two parents or carers live in the household; OECD equivalised weekly family income; a binary variable whether the highest educational level of child's mother is NVQ level 4 or 5, whether child does not practice exercise during the last week; and whether child skip breakfast at least one time per week. Labels 'FF' and 'OF' in rows refer to our measure of the number of fast food and other food outlets. Columns 1-5, 6-10, and 11-15 show estimates of specification around 1600, 800, and 400 metres from child' residence. Each regression controls for individual fixed effects, years of survey dummies, and a 2^{nd} degree polynomial of child' age. Standard errors are cluster at child level. * denote statistical significance at 10% levels respectively; ** denote statistical significance at 5% levels respectively; *** denote statistical significance at 1% levels respectively.

Table 4.17: Estimates of effect of fast food restaurants around cohort member's school on child and mother demographics: Placebos Equation 4.1

	Two parents/carers in the household	OECD equivalised weekly family income	Mother has NVQ level 4 or 5	Kid does not exercise	Kid skip breakfast at least one time per week	Two parents/carers in the household	OECD equivalised weekly family income	Mother has NVQ level 4 or 5	Kid does not exercise	Kid skip breakfast at least one time per week	Two parents/carers in the household	OECD equivalised weekly family income	Mother has NVQ level 4 or 5	Kid does not exercise	Kid skip breakfast at least one time per week
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
FF 1600m	0.0011	-1.191*	0.0002	-0.0018	-0.0005										
	(0.001)	(0.617)	(0.001)	(0.002)	(0.002)										
OF 1600m	-0.0003	0.1100	-0.0001	0.0005	0.0002										
	(0.000)	(0.091)	(0.000)	(0.000)	(0.000)										
FF 800m						-0.0032	-1.9860	-0.0008	-0.0035	-0.0004					
						(0.005)	(1.411)	(0.002)	(0.004)	(0.004)					
OF 800m						0.0006	0.2400	-0.0002	0.0005	0.0008					
						(0.001)	(0.230)	(0.000)	(0.001)	(0.001)					
FF 400m											0.0036	0.0179	0.0047	-0.0137	-0.0027
											(0.007)	(2.603)	(0.003)	(0.009)	(0.007)
OF 400m											-0.0009	-0.7390	-0.00169**	0.0023	0.0012
											(0.002)	(0.689)	(0.001)	(0.003)	(0.002)
Observations	24,804	24,804	24,804	24,748	24,733	24,804	24,804	24,804	24,748	24,733	24,804	24,804	24,804	24,748	24,733
R-squared	0.012	0.28	0.037	0.145	0.292	0.012	0.28	0.038	0.145	0.293	0.011	0.28	0.038	0.145	0.292
Number of children	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
F test	0.408	2.121	0.222	1.135	0.245	0.273	0.991	1.599	0.319	1.047	0.174	0.734	2.409	1.147	0.181
p-value (F test)	0.665	0.12	0.801	0.322	0.783	0.761	0.371	0.202	0.727	0.351	0.84	0.48	0.0899	0.318	0.834

Notes: Each column is a different regression defined as equation 4.1. Column names denote the following five time-varying dependent variables: a binary variable whether two parents or carers live in the household; OECD equivalised weekly family income; a binary variable whether the highest educational level of child's mother is NVQ level 4 or 5, whether child does not practice exercise during the last week; and whether child skip breakfast at least one time per week. Labels 'FF' and 'OF' in rows refer to our measure of the number of fast food and other food outlets. Columns 1-5, 6-10, and 11-15 show estimates of specification around 1600, 800, and 400 metres from child' school. Each regression controls for individual fixed effects, years of survey dummies, and a 2^{nd} degree polynomial of child' age. Standard errors are cluster at child level. * denote statistical significance at 10% levels respectively; ** denote statistical significance at 5% levels respectively; *** denote statistical significance at 1% levels respectively.

Table 4.18: Estimates of effect of fast food restaurants around cohort member's residence and school on child and mother demographics: Placebos Equation 4.2

	Home					School				
	Two parents/carers in the household	OECD equivalised weekly family income	Mother has NVQ level 4 or 5	Kid does not exercise	Kid skip breakfast at least one time per week	Two parents/carers in the household	OECD equivalised weekly family income	Mother has NVQ level 4 or 5	Kid does not exercise	Kid skip breakfast at least one time per week
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Fast food restaurant within 400m	-0.00171	2.154	0.00668	-0.0179	-0.00402					
	(0.010)	(2.767)	(0.005)	(0.012)	(0.011)					
between 400m and 800m	-0.00111	1.574	0.00203	-0.00764	0.00799					
	(0.006)	(1.525)	(0.002)	(0.007)	(0.006)					
between 800m and 1600m	-0.000194	-0.627	0.000553	-0.00226	0.000759					
	(0.003)	(0.761)	(0.001)	(0.003)	(0.003)					
Other food outlets within 400m	0.000734	0.493	-0.00257**	0.00175	0.00127					
	(0.003)	(0.849)	(0.001)	(0.003)	(0.003)					
between 400m and 800m	0.00207	-0.456	-0.000849	-0.000584	-0.00115					
	(0.002)	(0.414)	(0.001)	(0.002)	(0.001)					
between 800m and 1600m	-0.000973	0.0489	0.000128	-0.000258	0.000439					
	(0.001)	(0.166)	(0.000)	(0.001)	(0.001)					
Fast food restaurant within 400m						0.00232	-0.583	0.00484	-0.0131	-0.0034
						(0.007)	(2.636)	(0.003)	(0.009)	(0.007)
between 400m and 800m						-0.00433	-2.197	-0.0018	-0.00141	0.00028
						(0.005)	(1.501)	(0.002)	(0.005)	(0.004)
between 800m and 1600m						0.00229	-1.017	0.000546	-0.00125	-0.000725
						(0.002)	(0.664)	(0.001)	(0.002)	(0.002)
Other food outlets within 400m						-0.000678	-0.784	-0.00148*	0.00174	0.00034
						(0.001)	(0.756)	(0.001)	(0.003)	(0.002)
between 400m and 800m						0.00125	0.536*	-0.000159	-0.000341	0.000992
						(0.002)	(0.278)	(0.000)	(0.001)	(0.001)
between 800m and 1600m						-0.000599*	0.0529	0.0000408	0.000619	-0.00000641
						(0.000)	(0.115)	(0.000)	(0.000)	(0.000)
Observations	24,804	24,804	24,804	24,748	24,733	24,804	24,804	24,804	24,748	24,733
R-squared	0.013	0.28	0.038	0.146	0.293	0.012	0.28	0.038	0.145	0.293
Number of children	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268	8,268
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F test	0.507	0.636	1.786	1.663	0.769	0.814	1.392	1.251	0.764	0.623
p-value (F test)	0.803	0.702	0.0978	0.126	0.594	0.559	0.214	0.277	0.599	0.712

Notes: Each column is a different regression defined as equation 4.2. Column names denote the following five time-varying dependent variables: a binary variable whether two parents or carers live in the household; OECD equivalised weekly family income; a binary variable whether the highest educational level of child's mother is NVQ level 4 or 5, whether child does not practice exercise during the last week; and whether child skip breakfast at least one time per week. Colu[5ex]mns 1-5 and 6-10 show estimates of specification around child' residence and school, respectively. Each regression controls for individual fixed effects, years of survey dummies, and a 2^{nd} degree polynomial of child' age. Standard errors are cluster at child level. * denote statistical significance at 10% levels respectively; ** denote statistical significance at 5% levels respectively; *** denote statistical significance at 1% levels respectively.

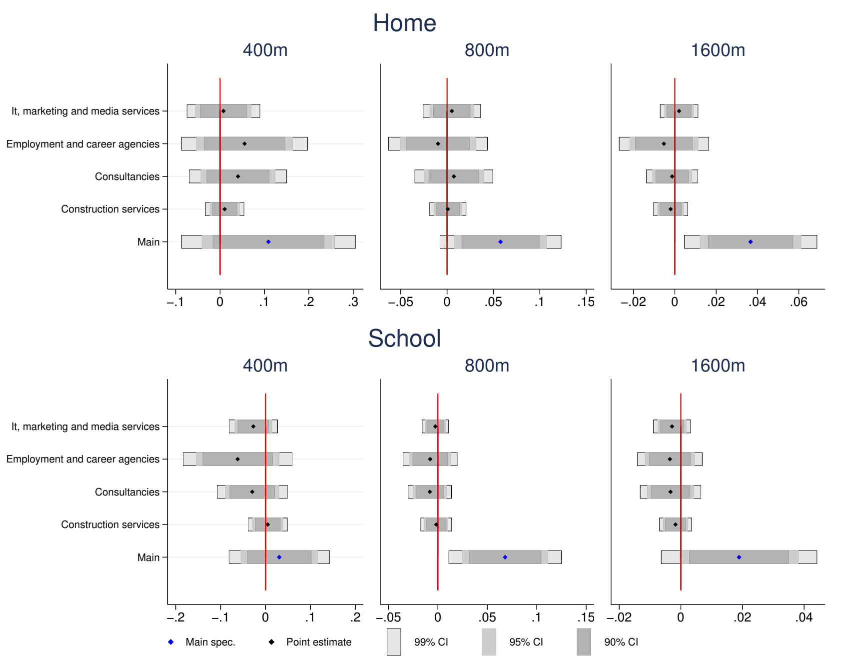

Figure 4.2: Placebo estimates for child's BMI, equation 4.1

Notes: This figure shows estimates for equation 4.1 (β) using our preferred cohort member fixed effects specification. Each point estimate denotes a different regression using cohort members' BMI as dependent variable. The model in equation 4.1 is estimated considering the number of fast food outlets within the distances 0-400, 0-800 and 0-1600 metres. Models are estimated for cohort member's residence and school separately. Our preferred specification is labelled as 'Main'. Other estimates in this figure replace the number of fast food restaurants by the numbers of other placebo PoI facilities within 0-400, 0-800, and 0-1600 metres from cohort member's residence and school. We plot estimates using placebo exposure to facilities in the following PoI categories: 'IT, marketing and media services', 'Employment and career agencies', 'Consultancies', and 'Construction services'.

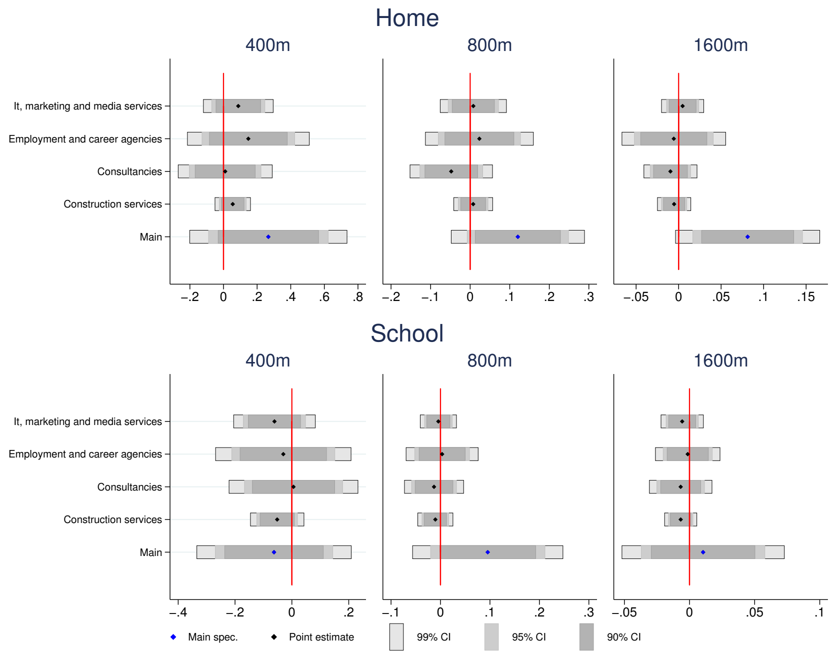

Figure 4.3: Placebo estimates for child's Body Fat, equation 4.1

Notes: This figure shows estimates for equation 4.1 (β) using our preferred cohort member fixed effects specification. Each point estimate denotes a different regression using cohort members' Body Fat percentage as dependent variable. Equation 4.1 is estimated considering the number of fast food outlets within the distances 0-400, 0-800 and 0-1600 metres. Models are estimated for cohort member's residence and school separately. Our preferred specification is labelled as 'Main'. Other estimates in this figure replace the number of fast food restaurants by the numbers of other placebo PoI facilities within 0-400, 0-800, and 0-1600 metres from cohort member's residence and school. We plot estimates using placebo exposure to facilities in the following PoI categories: 'IT, marketing and media services', 'Employment and career agencies', 'Consultancies', and 'Construction services'.

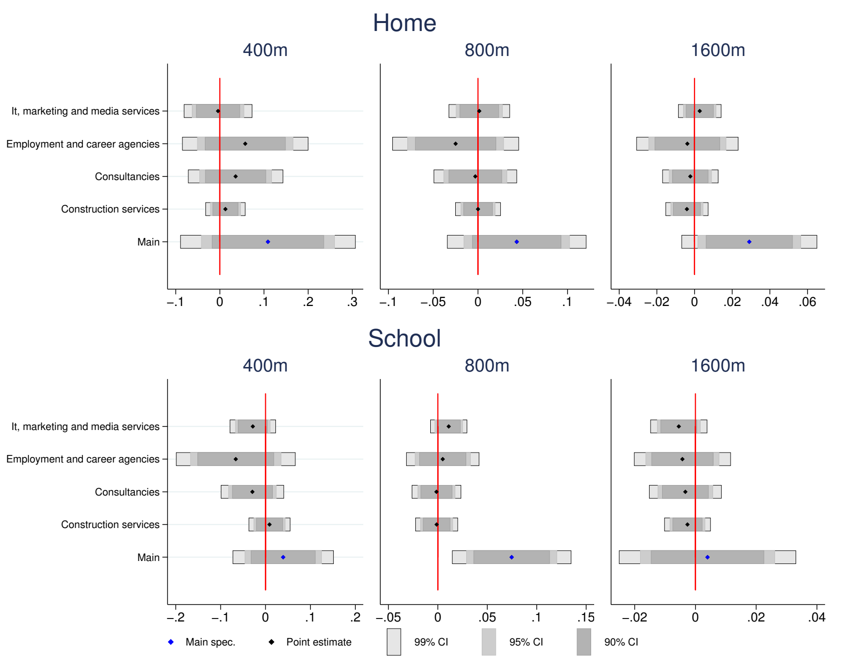

Figure 4.4: Placebo estimates for child's BMI, equation 4.2

Notes: Estimates in the figure denote results using cohort members' BMI as dependent variable.This figure shows estimates for equation 4.2 using our preferred cohort member fixed effects specification. Our preferred specification is labelled as 'Main'. Other estimates shown in this figure replace the number of fast food restaurants by the numbers of other placebo PoI facilities within 0-400, 400-800 and 800-1600 metres from child's residence and school. We plot estimates using placebo exposure to facilities in the following PoI categories: 'IT, marketing and media services', 'Employment and career agencies', 'Consultancies', and 'Construction services'. For example, for cohort member's home and PoI category 'IT, marketing and media services', the figure shows three point estimates corresponding to the number of facilities within 0-400 (left top panel), 400-800 (middle top panel) and 800-1600 metres (right top panel), which refer to the γ_1, γ_2 and γ_3 parameters in equation 4.2.

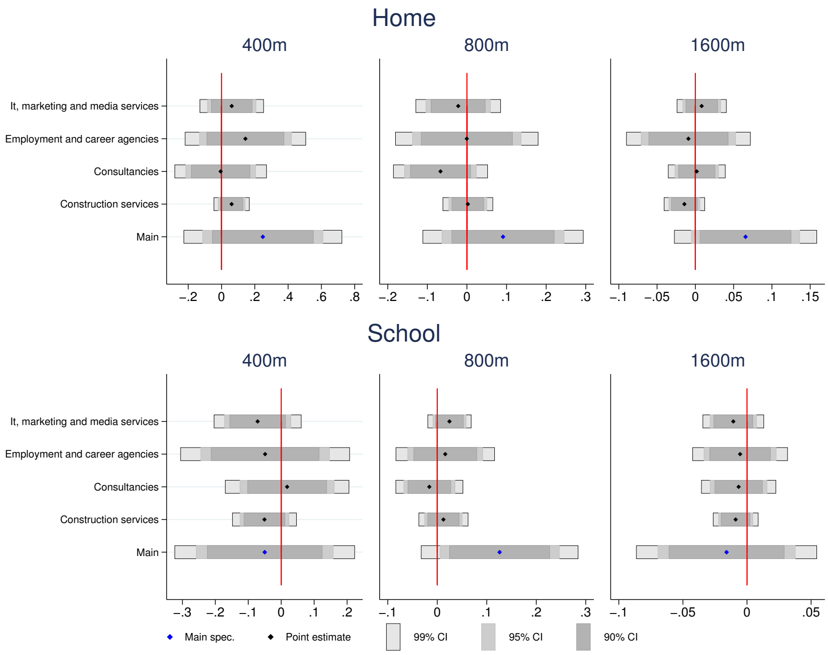

Figure 4.5: Placebo estimates for child's Body Fat, equation 4.2

Notes: Estimates in the figure denotes results using cohort members' Body Fat percentage as dependent variable. This figure shows estimates for equation 4.2 using our preferred cohort member fixed effects specification. Our preferred specification is labelled as 'Main'. Other estimates shown in this figure replace the number of fast food restaurants by the numbers of other placebo PoI facilities within 0-400, 400-800 and 800-1600 metres from child's residence and school. We plot estimates using placebo exposure to facilities in the following PoI categories: 'IT, marketing and media services', 'Employment and career agencies', 'Consultancies', and 'Construction services'. For example, for cohort member's home and PoI category 'IT, marketing and media services', the figure shows three point estimates corresponding to the number of facilities within 0-400 (left top panel), 400-800 (middle top panel) and 800-1600 metres (right top panel), which refer to the γ_1, γ_2 and γ_3 parameters in equation 4.2.

Table 4.19: Estimates of the effect of fast food restaurants on z-BMI and Overweight/Obesity rate

	Home				School			
	z-BMI		Overweight/Obesity		z-BMI		Overweight/Obesity	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Equation 1								
Fast food restaurant within 400m	0.0438*	0.0325	0.0146	0.0158	0.0377*	0.0146	0.0177**	0.0144**
	(0.024)	(0.028)	(0.010)	(0.013)	(0.021)	(0.013)	(0.008)	(0.007)
Other food outlets within 400m	-0.00928*	0.00201	-0.00291	-0.000646	-0.00967**	-0.00508	-0.00408**	-0.00402**
	(0.005)	(0.005)	(0.002)	(0.002)	(0.005)	(0.004)	(0.002)	(0.002)
R-squared	0.073	0.063	0.066	0.034	0.073	0.062	0.066	0.034
Fast food restaurant within 800m	0.0279**	0.0165*	0.00750*	0.00587*	0.0300***	0.0198***	0.00767**	0.00916**
	(0.011)	(0.009)	(0.004)	(0.004)	(0.009)	(0.007)	(0.004)	(0.004)
Other food outlets within 800m	-0.003	0.000954	-0.000608	-3.50E-05	-0.00330**	-0.00325**	-0.000898	-0.00167*
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
R-squared	0.073	0.063	0.066	0.034	0.073	0.063	0.066	0.034
Fast food restaurant within 1600m	0.0130**	0.00795*	0.00322	0.00258	0.00446	0.00308	0.00121	0.002
	(0.007)	(0.004)	(0.002)	(0.002)	(0.005)	(0.003)	(0.002)	(0.001)
Other food outlets within 1600m	-0.00192*	0.000258	-0.000454	6.39E-05	-0.00036	-0.000681	-0.000149	-0.000463
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
R-squared	0.073	0.064	0.066	0.034	0.073	0.062	0.066	0.034
Panel B. Equation 2								
Fast food restaurant								
within 400m	0.0422*	0.03330	0.01400	0.01640	0.0387*	0.01690	0.0177**	0.0152**
	(0.024)	(0.028)	(0.010)	(0.013)	(0.021)	(0.013)	(0.008)	(0.007)
between 400m and 800m	0.0228*	0.01210	0.00556	0.00319	0.0306***	0.0206***	0.00621*	0.00802**
	(0.012)	(0.010)	(0.005)	(0.005)	(0.010)	(0.008)	(0.004)	(0.004)
between 800m and 1600m	0.00872	0.00484	0.00192	0.00136	-0.00408	-0.00188	-0.00091	-0.00011
	(0.007)	(0.004)	(0.002)	(0.002)	(0.006)	(0.004)	(0.002)	(0.002)
Other food outlets								
within 400m	-0.0124**	-0.00203	-0.00404*	-0.00177	-0.0135***	-0.00532	- 0.00501***	-0.00388**
	(0.006)	(0.005)	(0.002)	(0.003)	(0.005)	(0.003)	(0.002)	(0.002)
between 400m and 800m	0.00146	-0.00062	0.00094	-0.00057	-0.00167	-0.00252*	-0.00006	-0.00101
	(0.005)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
between 800m and 1600m	-0.00207*	0.00068	-0.000563*	0.00036	0.00060	-0.00001	0.00006	-0.00016
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
R-squared	0.074	0.064	0.066	0.034	0.074	0.063	0.066	0.035
Observations	24,714	24,714	24,725	24,725	24,714	24,714	24,725	24,725
Individual FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata and PSU FE	Yes	No	Yes	No	Yes	No	Yes	No
Census 01 LSOA Controls	No	No	No	No	No	No	No	No
Mean Outcome	0.433	0.433	0.23	0.23	0.433	0.433	0.23	0.23
Number of children		8,268		8,268		8,268		8,268

Notes: ** denote statistical significance at 5% levels respectively; *** denote statistical significance at 1% levels respectively.

Table 4.20: PoI categories used in definition of Other Food Outlets

Group description	Category description	Class description
Retail	Food, drink and multi item retail	Butchers
		Confectioners
		Delicatessens
		Fishmongers
		Green and new age goods
		Grocers, farm shops and pick your own
		Organic, health, gourmet and kosher foods
		Convenience stores and independent supermarkets
		Supermarket chains

Table 4.21: PoI categories used in falsification tests

Group description	Category description	Class description
Commercial services	Construction services	Metalworkers including blacksmiths
		Building contractors
		Construction completion services
		Construction plant
		Cutting, drilling and welding services
		Demolition services
		Diving services
		Electrical contractors
		Gardening, landscaping and tree surgery services
		Glaziers
		Painting and decorating services
		Plasterers
		Plumbing and heating services
		Pool and court construction
		Restoration and preservation services
		Road construction services
		Roofing and chimney services
		Fencing and drystone walling services
		Building and component suppliers
Commercial services	Consultancies	Architectural and building related consultants
		Business related consultants
		Computer consultants
		Construction service consultants
		Feng shui consultants, furnishers and shop fitters
		Food consultants
		Image consultants
		Interpretation and translation consultants
		Security consultants
		Telecommunications consultants
		Traffic management and transport related consultants

Table 4.22: PoI categories used in definition of Falsification tests (cont.)

Group description	**Category description**	**Class description**
Commercial services	Employment and career agencies	Careers offices and armed forces recruitment
		Domestic staff and home help
		Driver agencies
		Employment agencies
		Modelling and theatrical agencies
		Nursing agencies
Commercial services	It, advertising, marketing and media services	Advertising services
		Artists, illustrators and calligraphers
		Computer security
		Computer systems services
		Concert/exhibition organisers and services
		Database services
		Desktop publishing services
		Electronic and internet publishers
		Film and video services
		General computer services
		Internet services
		Literary services
		Mailing and other information services
		Marketing services
		Plate makers, print finishers and type setters
		Press and journalism services
		Printing and photocopying services
		Recording studios and record companies
		Telephone, telex and fax services
		Television and radio services

Chapter 5

Conclusions

In this thesis, I have studied how health throughout life is affected by a variety of socio-demographic and environmental factors. In each chapter, I have exploited quasi-random variations to estimate policy-relevant causal parameters, providing new evidence to the literature on health economics. By focusing my analysis on rich longitudinal studies for the UK and Chile, the empirical research across all of the chapters controls for individual time-invariant unobserved factors that have typically confounded the evaluation of health determinants in the previous literature.

A common factor across the chapters is that vulnerable populations– such as ill children, adolescents with a lower socio-economic background, and working women– are more sensitive to changes to their environments. For instance, an increase in air pollution exposure is more detrimental for children with respiratory problems. An increase in the number of fast food restaurants impacts disproportionally the obesity of adolescents whose mothers have achieved lower education levels. Similarly, the reduction in working hours – induced by the Chilean labour reform– reduced smoking behaviours among workers without tertiary education and increased physical activity and reduced smoking behaviours among working women. The disproportionate impacts of socio-demographic inequalities on health and healthy behaviours among vulnerable populations continues to be an area of ongoing research.

Although throughout the chapters I provide some evidence about how unhealthy environments can further exacerbate health inequalities over life, further research is needed. Below, I outline what I consider to be areas of future work on each of the topics addressed in this thesis: labour market reforms, environmental pollution and obesogenic environments.

In the first chapter, I establish how the reduction from 48 to 45 hours in working hours changed unhealthy behaviours in less-educated workers and women. However, it is not clear whether these effects persisted in the long term. Using EPS data from subsequent waves, a long-term evaluation of the reform could shed light on the impact on physical activity and smoking behaviours, as well as on other health outcomes that have not previously been evaluated, such as drinking behaviours, mental health and chronic conditions. There are several methodological challenges to carrying out this evaluation due to the lack of data on these health outcomes in the EPS before the reform; however, the evaluation would be possible by linking the EPS with administrative health records. This constitutes part of my current research agenda. Furthermore, evaluating the long-term effects of the reduction in working hours would allow for conducting an economic evaluation based not only on its impact on labour outcomes but also on its long-term impacts on population health.

There has been an increase in the literature that studies the impact of environmental pollution on labour productivity, cognitive performance, mental health and other outcomes that have not previously been associated with environmental risks. Furthermore, in recent years, a particular emphasis has been placed on evaluating these effects throughout life; however, there is still little evidence of these impacts during adolescence or early adulthood. Given this gap, future work should focus on evaluating the effects of pollution on cognitive performance during adolescence. For this, longitudinal data from the United Kingdom, such as the Millennium Cohort Study or Next Steps, are well suited to study the role that socio-economic inequalities play in mediating the impact of environmental risks.

Finally, in terms of obesogenic environments and health during adolescence, the focus was on ages 7 to 14– a period in which parents mostly influence eating decisions. However, as young people gain independence and additional financial resources to make their own eating choices (e.g. pocket money), other factors such as mode of travel, travel routes between school and home and peer pressure begin to play an important role in eating choices. Exploring whether changes in the obesogenic environment during adolescence affect obesity is part of my future research plan. Exploiting the longitudinal and cohort structure of the Millennium Cohort Study and Next Steps, I would assess the role of obesogenic environments in adolescent obesity and health inequalities.

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