Socio-economic status and worklessness: educational investments and expectations

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A dissertation submitted in partial fulfillment
of the requirements for the degree of

Doctor of Philosophy
of
University College London (UCL)

UCL Social Research Institute

25th August 2021

Declaration

I hereby declare that, except where explicit attribution is made, the work presented in this thesis is entirely my own.

25th August 2021

Signature *Date*

Word count (excluding front matter, appendices and bibliography): 46,541

Abstract

The link between socio-economic status (SES) and educational outcomes is well established. In this thesis, I improve understanding of different types of educational investment and mechanisms through which dimensions of SES affect young people's education.

First, I use data from the Programme for International Student Assessment (PISA) to research educational investments in 15-year-olds: how do parents in workless households invest their resources in their children's education? Using matching methods comparing children from workless households to those from otherwise similar working households, I find that workless parents invest less money but more time in their child's education, although I find no difference in paying for commercial tutoring.

Second, using longitudinal data from the UK Millennium Cohort Study (MCS), I examine the relationship between household worklessness and educational investments at different ages. Using instrumental variables and fixed effects approaches to reduce bias, I find that workless parents are less likely to pay for childcare (age 1–3) but are equally likely as working parents to pay for tutoring (11–14). While workless parents read to their child (3-7) more frequently, it is unclear whether this difference is causal. I find no link between household worklessness and parents helping their child with reading, writing, or maths (5–7). Contrasting my results from the multinational PISA data, I find no difference in parental homework help for British youths (11–14).

Finally, I look at SES more generally and how it relates to 17-year-olds' expectations about going to university. I explore the role of risk attitudes and time preferences in forming these expectations. I analyse MCS data using regression analysis. Controlling for teenagers' and households' background characteristics over more than 10 years, I find that SES and patience are positively associated with educational expectations, but find no link between risk attitudes and educational expectations.

Impact Statement

My work helps to inform social policy and may aid future research in the following ways.

First, my results suggest that young children growing up in workless households receive fewer monetary investments than their peers whose parents work without necessarily being compensated with greater time investments. Children in workless households could therefore benefit from support through early education programmes, currently mainly available to working parents. In the UK, increasing free-childcare offered to workless parents from the current 15 hours to 30 hours per week, as offered to working parents, could improve early education for children in workless families.

Second, using the most recent data for the UK, my findings confirm that teenagers from lower SES households have lower educational expectations than their peers from more advantaged households. This is true even when accounting for cognitive scores throughout childhood and GCSE exam results. As British social policy has focussed on meritocratic values and equality of opportunity for decades, the persistent gap in educational expectations indicates that more still needs to be done. For example, as I find that young people from low-SES households are more likely to mention the cost of going to university as the main reason not to attend higher education, lowering the perceived or actual financial burden of a university education could encourage these teenagers to go to university.

Third, I find that more patient individuals have higher educational expectations. Policymakers could aim to make young people more patient and, through this, improve university attendance, especially in youth communities that have comparably low patience levels. Studies evaluating the impact of 'buddy programmes' in Germany, in which university students are paired with a disadvantaged teenager in their final year of school, have shown that, among others, participating teenagers became more patient. Incorporating elements into curricula that target time preferences, for example through implementing buddy programmes, might help change time preferences and improve educational outcomes. While time preferences are robustly associated with educational expectations, I find that risk attitudes do not play a role in the formation of educational expectations. This strengthens the argument that – in the UK's current system of university fees combined with income-contingent student loans – university fees do not play a major role in deterring people from going to university through the channel of risk aversion.

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Acknowledgements

I gratefully acknowledge funding from the European Union's Horizon 2020 research and innovation programme and the Marie Skłodowska-Curie European Training Network OCCAM, grant agreement no. 765400.

Any views expressed in the paper are those of the author and not necessarily those of funders or data providers. Any errors remain the author's.

Thanks

Very special thanks to John Jerrim, Jake Anders, and Nikki Sure for their support and thoughtful comments over the past 3 years. I could not have asked for better supervision and guidance.

Many thanks to the OCCAM network for making this PhD project possible. Thank you for great memories, for discussions, laughter, and a constant influx of comments and ideas.

Special thanks to Laura, Pietro, and Room 321 for being superb company in London and Leuven. Without you this journey would have been duller, the weather greyer, and lunch blander.

Thanks, Megan, for your moral support in writing this thesis and great help with proofreading. You have been an amazing companion from near and far.

And finally, my deepest gratitude to my mother, Marga, for supporting me every step along the way.

1. Disadvantage and Investments in Education

1.1. Introduction

The investments made into a young person's education have strong implications for their chances in life. Higher human capital corresponds with higher lifetime earnings (Belfield et al. 2018; Blundell et al. 2000; Psacharopoulos & Layard 1979; Walker & Zhu 2013), life satisfaction (Vemuri & Costanza 2006), and better health (Mirowsky & Ross 1998). A cornerstone of social mobility – the concept at the centre of UK social policy for the past decades – is a more even distribution of human capital development and educational attainment across social classes (UK Social Mobility Commission 2020). However, both in the UK as well as many other European and non-European countries, chances in life are too often determined by parental education, occupation, and income (OECD 2018; UK Social Mobility and Child Poverty Commission 2014). The mechanisms through which social status is passed on from parents to children are therefore of stark interest for researchers to understand and policymakers to overcome.

In this thesis, I provide new evidence about the investments being made in children from workless households as well as the educational trajectories children from lower socio-economic status (SES) take. First, I analyse the association between household worklessness and the amount of money and time parents invest in their child's education across member states of the Organisation for Economic Co-operation and Development (OECD) and additional partner countries. I use the rich international data from the Programme for International Student Assessment (PISA) to compare investments made in 15-year-olds in 70 countries. Second, I focus on children born in the UK around the year 2001, assessed by the Millennium Cohort Study (MCS). I isolate the causal effect of household worklessness on parental investments in their children as young as 9 months up until the age of 14, using different identification strategies. Third, I move away from the specific disadvantage of growing up in a workless household to socio-economic status more generally. In particular, I look at the role of SES and economic preferences (risk attitudes and time preferences) in forming educational expectations at age 17.

1.2. The Importance of Educational Investments

Educational investments in young people can be made by three main groups: the public sector, parents or other primary carers, and young people themselves. It is in the public interest to have a well-educated workforce with high human capital as this helps grow the economy at faster rates (Hanushek & Woessmann 2015). Other documented benefits of education are social trust (Huang et al. 2011)[1] and political engagement (Le & Nguyen 2021)[2]. Investing public resources in human capital formation can therefore come with substantial positive returns on investment. Public investments in education can take many forms and affect different age groups. First and foremost, in countries such as the UK, most children go to tuition-free primary and secondary schools, often until the age of 18. Per pupil in secondary school, the UK government spends around £6,000 per year. But this also includes public spending on early childcare (£4,000 per pupil per year) and tertiary education (more than £8,000 per pupil per year) (Britton et al. 2019). All in all, in 2013, the UK's public expenses on education amounted to 5.7% of GDP (gross domestic product) (UNESCO Institute for Statistics (UIS) 2016).

Parents can also invest their resources into their child's education. In the framework of Becker & Tomes (1986), this is an important factor in 'the rise and fall of families', that is *intergenerational mobility.* The key idea in Becker & Tomes's theory is to have utility maximising parents who are altruistic towards their children. In this model, parents have a certain level of human capital, resulting in income. Given their (known) child's ability endowments, they now have to decide on how many resources they should allocate towards their child's human capital production. The economic situation of households matters, too: poor parents cannot easily borrow to finance educational investments, leading to rich parents getting closer to an optimal

[1] Some studies have found that, despite increasing average education levels, social trust has deteriorated in the US (Putnam 2000) and have questioned the causality of the link between education and social trust (Oskarsson et al. 2017).

[2] While Le & Nguyen (2021) find that education is linked with political interest and information levels, they do not find that education causes higher voter turnout.

investment level. This is largely due to two reasons. On the one hand, giving loans to parents for their children's education is not attractive to banks. While in the medium run the child might get positive returns on increased educational investments through higher wages, the loan would be in the parents' name. As parents do not financially benefit from their children's higher salaries, the returns on investment are no security for the bank's loan. On the other hand, banks might be put off due to information asymmetries: do parents who borrow for educational investments actually invest in education? All of the above translates into parents' decisions on how to allocate their resources (time and money) into their child's human capital development (education).

While models such as Becker & Tomes (1986) and Cunha & Heckman (2007) do not distinguish between different types of investments[3], parental investments can be thought of as time investments and monetary investments (Haveman & Wolfe 1995; Leibowitz 1974). Monetary investments may include paying for childcare tutoring, piano classes, and private school. Time investments can be helping a child with homework or taking the time to read a good-night story, teaching the child to count, or practising the order of the alphabet. Del Boca, Flinn et al. (2014) look at how both time and monetary investments are linked to human capital formation. They conclude that time investments in young children are the most productive investments in a child's education with productivity tapering off as the child reaches school age. Monetary investments, on the other hand, are less effective but their productivity increases with the child's age (Del Boca, Flinn et al. 2014). Not only the productivity of each investment can be part of parents' considerations when allocating resources towards their children's education. Parents are likely to also take into account their own personal productivity in the labour market and the arising opportunity cost of caring for their children. Parents with high salaries might decide to substitute their own time investments with paid-for childcare to not give up on income to care for their children themselves (Aiyagari et al. 2002).

Figure 1.1 shows a diagram of the link between household background, parental educational investments, and young people's human capital formation. In the following two chapters of this thesis, I focus on household worklessness as a determinant of educational investment decisions. Section 1.3 introduces the concept of household worklessness and how this constitutes an interesting and special kind of disadvantage: the work people do largely defines their status in society (see below, Section 1.3),

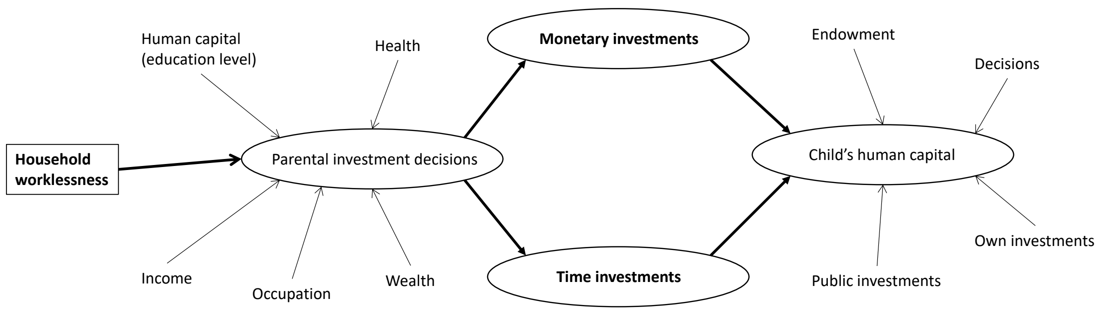
[3]Cunha & Heckman (2007), however, includes the timing of educational investments as investments into the education of young children which are often considered more productive than those into young adults.

leading to workless people facing a different kind of disadvantage than those in low-paid or low-status occupations.

The final pillar of educational investments are those investments people make in themselves (Woodhall 1987). It is a decision to invest time by studying instead of playing video games, reading a book instead of watching TV, or acquiring a vocational qualification whilst having a job. The time young people invest in their own education may even be more productive than the time their parents invest in them (Del Boca, Monfardini et al. 2017). The most relevant investment people make in their own education, in the context of this thesis, is the decision of continuing full-time education at university or leaving school for work. This can be seen as both a time investment – obtaining a degree takes at least three years – and monetary investment – in the UK, university students pay tuition fees. The 'return on investment' of going to university is almost always found to be positive (Belfield et al. 2018; Blundell et al. 2000; Green, Jin et al. 2016; Walker & Zhu 2011; Walker & Zhu 2013). While the extent of the average 'graduate premium' depends substantially on university, subject, and occupation choice (Belfield et al. 2018), it is an investment still strongly encouraged and worked towards by politicians.

Together, these three pillars contribute to the formation of *human capital*. The stratified formation of human capital *within* a society with young people's human capital correlated with that of their parents is an important contributor to the inequality of opportunities. Being well educated opens doors that would otherwise remain closed. Almost all careers perceived as *prestigious* – doctor, lawyer, banker – require a university degree, often from a well-known university. Political power is

Figure 1.1.: Diagram of household worklessness, educational investments, and children's human capital formation



Notes: Diagram based on Becker & Tomes (1986) and Jerrim & Macmillan (2015).

concentrated among the well-educated – only two out of 23 current[4] UK cabinet ministers did not attend university; more than half went to either Cambridge or Oxford – the most prestigious universities in the UK. Educational attainment is key for social mobility in earnings and class. On the other hand, the amount of human capital accumulated in a society can put a country on a higher economic growth trajectory. In their book *The Knowledge Capital of Nations*, Hanushek & Woessmann (2015) point out that countries with higher education levels have seen their GDP grow faster compared with countries with lower education levels. They conclude this link is very strong and causal: higher human capital is the reason why some countries have grown faster than others in the 20th century.

Whether or not people accumulate human capital sufficient to enter better paid professions depends on educational investments from a very young age until they enter the labour market. This is not only true for young people entering higher education, but also for those who do not obtain a degree: doing well at GCSE level results in higher earnings in the late 20s (Belfield et al. 2018). To better understand what affects these investments in young people's education have is the subject of this thesis.

1.3. Worklessness and Socio-Economic Status

Inequality research and studies focussing on the intergenerational transmissibility of disadvantage often look at *socio-economic status*: is the social and economic positioning in society passed on from parents to children and how strong is this relationship? The construct socio-economic status aims to capture a household's income, wealth, education level, occupation, and employment status and condense it into one concept. While generally a very useful construct capturing different aspects of disadvantage, I begin by looking at a very specific aspect of socio-economic status: household worklessness.[5] Household worklessness is regularly defined as a household in which no working age household member works for money. In the past two decades, between one in five and one in 10 UK children grew up in a workless household – among the highest rates in Europe (Eurostat 2020b).

[4] June, 2021.

[5] This is often referred to as *joblessness*, emphasising that people without a job may just as well do very important and hard work such as caring for a relative or children. In the remainder of this thesis, I use *worklessness*, in line with the jargon used in much of the wider UK-related worklessness research and policy briefs.

Worklessness is a special disadvantage[6] in four ways. First, workless households are often also low-income households, resulting in income-related disadvantage. The resulting tight budget constraint makes spending and investing in education more challenging. Second, not having a job may be socially isolating. Not being able to exchange arising opportunities, to know which schools to pick, which tutor to hire, or how to get a child into university, may limit parents' ability to aid their child's education. Third, time not spent on a job may be free to be invested in a child's education. Homework help, reading to the child, or helping them with maths, may be tasks working parents would like to be able to help their child with but cannot do so because of time constraints. Fourth, children in workless households see their parents not having a job. Their peers in working households see their parents leave for their jobs at specific times of the day – regardless of their occupation's social status. Children with workless parents do not share this experience.

However, this is most certainly an oversimplification of worklessness. Worklessness is often not a choice but results from poor health, caring for a relative, or unemployment. These possible reasons for worklessness might also reduce the amount of time parents can actually spend on their child's education. Hence, a child growing up in a workless household potentially faces a unique and multidimensional disadvantage.

Children growing up in workless households have increasingly become a subject of academic research and have been identified as a disadvantaged group of interest for policymakers (Macmillan 2014; Parsons et al. 2014; Schoon 2014; DWP 2017; DWP 2018). In Chapters 2 and 3, I add to the existing literature around children growing up in workless households and examine the investments made in their education, both internationally (Chapter 2) and in the UK (Chapter 3).

While worklessness is a very specific form of disadvantage, socio-economic status is a more general construct consisting of household income, wealth, education level, employment status, and occupation (Baker 2014). Hence, low SES does not merely capture, for example, low household income but also includes low education level, possibly unemployment or a 'low status' occupation. On the other end of the spectrum one expects to find high-income, university-educated individuals in prestigious occupations such as being a doctor. A highly successful plumber might rank highly on income but likely lacks the status coming with a university degree.

[6] Worklessness may also be a sign of stark *advantage*. Individuals who have either inherited or accumulated a sizeable wealth might not need to work (anymore) and may be retired from paid employment. However, in the literature as well as my own research there is no indication that this group is sizeable among workless households.

Rose & Pevalin (2003) discuss how these status categories translate into employment relations and autonomy at the workplace: 'service relations' having autonomy and benefitting both employer and employee typically in more senior roles; 'labour contracts' on the other hand being a mere exchange of effort for money, typically closely supervised. This focus of socio-economic status on employment relations highlights how different the above discussed class of workless households is in terms of socio-economic status.

Having a higher socio-economic status is found to be linked to many positive outcomes in life. For example, higher status individuals are healthier (Smith 1998) and happier (Pinquart & Sörensen 2000) and live longer lives (Ingleby et al. 2021). On top of that, socio-economic status is often passed on from one generation to the other. Children growing up in low-SES households are disadvantaged not only through a less comfortable life, but their opportunities in life are on average fewer than for their higher status peers.

The circumstances in which young people grow up likely shape how they perceive the world around them, what opportunities they deem to be realistic, and what seems out of reach. In Chapter 4 of this thesis, I look at how socio-economic status throughout childhood – from toddler until teenager – affects the formation of educational expectations. In the context of educational investments in general and – more specifically – the expectation of going to university, previous literature has shown a clear disadvantage for low-SES pupils (Anders 2015; Anders 2017; Boneva & Rauh 2017; Kajonius & Carlander 2017; Salazar et al. 2020). I add to this literature by looking at very recent data from the UK as well as by including *economic preferences* into the analysis.

1.4. Risk Attitudes and Time Preferences

Human decision-making is complex, and shedding some light into this black box often proves a challenge. Going through life there are many decisions to be made. Shall I study or play with friends? Do I want to go to university or work right after school? Where is this university going to be? Am I willing to live in another country for a while? State school or private school? In all these decisions one would expect people willing to take risks to act differently from those afraid of uncertainty. Similarly, a patient person could be expected to act differently from one who wants to see results immediately.

Economists have incorporated human attitudes towards risk and preferences of the sooner over the later in theoretical models for almost a century (Samuelson 1937; Von Neumann & Morgenstern 1947). In the field of normative decision theory, researchers ask how rational individuals should decide under uncertainty – given their utility function and the information that is available to them (Peterson 2017). Descriptive decision theorists aim at building models that help accurately predict real human behaviour under uncertainty – for example through prospect theory (Kahneman & Tversky 1979). Similarly, inter-temporal discounting is part of many theoretical models (e.g. Hall 1988) and researchers have proposed theoretical models different from Von Neumann & Morgenstern (1947) in order to better predict inter-temporal decisions (e.g. Loewenstein 1988).

More recently, the emergence of behavioural economists conducting experiments in *econ labs* has provided data for economic preferences and how heterogeneously they are distributed (Falk et al. 2018). Ever since, researchers have studied the link between individuals' economic preferences and their behaviour in health, finance, education, and other areas (Belzil & Leonardi 2013; Guiso & Paiella 2004; Norum 2008; van der Pol 2011). Moreover, the distribution of economic preferences can be viewed as part of a society's cultural identity (Becker, Enke et al. 2020). In their Global Preference Survey, Falk et al. (2018) map the global distribution of economic preferences in 76 countries. Using this data, Hanushek, Kinne et al. (2020) explain variations in student achievement in the PISA study with differences in average risk attitudes and time preferences across countries.

As economic preferences have such a profound impact on individuals' and societies' development, it is of great importance to understand how these preferences are formed. Prior research has linked the formation of economic preferences in children to socio-economic status (Deckers, Falk, Kosse, Pinger et al. 2017). Results suggest that higher SES may be linked to more patience and less risk taking. However, economic preferences do not have to stay the same over time. In intervention studies, economic preferences – especially time preferences – were changed (Resnjanskij et al. 2021). Teaching the importance of the future over the present and making young people aware that decisions now may improve life further down the road, possibly alter economic preferences and may therefore affect behaviour.

In Chapter 4 of this thesis, I not only look at socio-economic status as an explanatory variable but also include risk attitudes and time preferences in my analyses. This helps me understand how, in the context of the UK, risk attitudes and patience are linked with young people's educational expectations. While the existing literature often relies on cross-sectional data which might not be representative of the overall population or aims at comparing different countries and cultures, my study makes use of a representative birth cohort study with information about each cohort member reaching back until the year 2001. Thus, I contribute to the literature with results with strong external validity for the UK. My findings therefore strengthen our understanding of the link between economic preferences and life outcomes. Furthermore, my results may support the case for seeking policies that directly aim to change economic preferences and, through this channel, improve equality in society.

1.5. Thesis Outline

The remainder of this thesis is structured as follows. In Chapter 2, I analyse the link between household worklessness and educational investments in 15-year-olds living in 70 countries around the globe. Using PISA 2012 data, I apply propensity score matching methods to compare educational investments made in children from workless backgrounds to otherwise similar teenagers living in households with at least one parent in paid employment. This contributes to the existing literature in two ways. First, to my knowledge, this is the first study using large-scale international data to analyse the ramifications household worklessness has on children's lives. Most of the previous research has been around workless households in the UK and US. Second, household worklessness as well as educational investments have been identified as factors affecting intergenerational mobility. I contribute to the literature by building a link between these areas of research. My analyses indicate that workless parents invest less of their money in their children's education. However, controlling for a rich set of background characteristics, I do not find an association between household worklessness and paid-for commercial tutoring. Furthermore, workless parents – especially workless single parents – spend more time helping their child doing homework.

In Chapter 3, I focus on children from a workless background in the United Kingdom only. Using longitudinal data from the Millennium Cohort Study, I analyse the link between household worklessness and educational investments from the age of 9 months until 14 years. This further adds to understanding the link between household worklessness and educational investments. First, I aim at isolating the causal link between worklessness and educational investments, using an instrumental variable approach, fixed effects regression, as well as information about future worklessness spells. This helps identify the added disadvantage – especially for those children at the margin – of living in a workless household. Second, looking at different age appropriate indicators for monetary and time investments from as young as 9 months until age 14, I provide a broad overview of different types of educational investments and the impact household worklessness has on them. Results indicate that workless parents report having more time with their children at all ages. Worklessness causes parents to be less likely to pay for childcare (age 1 and 3). Compared to working households, that is households in which at least one parent is in employment, workless parents tend to read to their child more frequently. My results on whether this association is in fact caused by worklessness are inconclusive. I find no difference in helping the child with reading, writing, maths (age 5 and 7), and help with homework (age 11 and 14) – contrasting my previous results obtained from analysing PISA data. This is possibly due to different populations being observed: the PISA study has an international focus on pupils from 70 countries[7] while the MCS focusses on British children only. Finally, workless parents pay for extra lessons at similar rates as working parents (age 11 and 14), confirming similar results from Chapter 2.

Third, in Chapter 4, I look at the link between socio-economic status and economic preferences with the expectations 17-year-olds have of going to university. Investing both at least 3 years of their time and almost £30,000 in student fees alone is a huge commitment young people can make. I analyse how socio-economic status experienced through childhood as well as risk attitudes and time preferences are linked to educational expectations. In using very recent data from the UK after the increase in student fees, my research offers an up-to-date view on the link between socio-economic status and the expectation of going to university. Furthermore, in adding information about risk attitudes and time preferences to my analysis, I contribute to the understanding of which character traits are associated with educational decisions and the expectations of future decisions. Controlling for rich background information including cognitive and behavioural scores, I find that both SES and time preferences (i.e. impatience) are significantly associated with the reported educational expectations: higher SES and more patience are associated with higher educational expectations. However, I do not find an association between risk attitudes and educational expectations in any model analysed: whether an adolescent is risk loving or risk averse does not change their expectations about going

[7] Referring to PISA 2012.

to university. This indicates that young people do not perceive taking a loan to go to university as a financial risk. Risk-averse teenagers have the same educational expectations as their more risk-taking peers. This may be because in the UK student loan repayments are income contingent, which may lead to taking up a student loan to go to university being viewed as low-risk educational investment.

Finally, Chapter 5 summarises the results of this thesis and discusses their relevance for further research and policy-making. My thesis explores where worklessness, socio-economic status, and economic preferences may lead to differences in educational investments and where they do not. Understanding this may help policy-makers to find new ways of targeting disadvantaged groups and improving children's prospects in life. Furthermore, in having added to the wider international and UK-specific literature, I reflect on how future research may add to my findings.

2. Monetary and Time Investments in Children's Education: How Does it Differ in Workless Households?

2.1. Introduction

Public attention is frequently drawn towards various issues arising from unemployment and worklessness. For instance, in Germany, families living off social benefits ('Hartz IV') are subject to regular media coverage, especially highlighting insufficient funds for children and their education (Öchsner 2018; Schäfer 2019). Adults not working and households with no adult household member in employment (i.e. workless households) have been identified as a vulnerable group, both by policy makers and researchers (e.g. McClelland 2000; Mynarska et al. 2015).

Aside from public interest, a broad range of scientific literature explores the connections between socio-economic background and education. Links between parents' income and children's educational achievement have been researched in the past decades (e.g. Black & Devereux 2010; Blanden, Gregg et al. 2007; Chevalier et al. 2013; Gregg et al. 2017; Taubman 1989). Two main mechanisms have been identified linking parental income with their child's school performance: parental stress and parental investment (e.g. Conger et al. 1992; Yeung et al. 2002). On the one hand, low income puts stress on parents and therefore limits their ability for 'good parenting'. On the other hand, low income budget constraints reduce the potential for parents' monetary educational investments in their children.

Economists have modelled parental investments in a child's education as investments in human capital. Models, such as those introduced by Becker & Tomes (1986) and Aiyagari et al. (2002), suggest that utility-maximising parents caring for their children's future utility level choose to invest money in their child's education depending on their own wealth and productivity. Solon (2004) suggests that higher income parents not only have greater possibilities to invest in their children, but also have a greater incentive to do so: when assuming that parents derive non-zero utility from their children's future earnings, Solon finds that higher income parents give up a higher amount of personal consumption to invest in their child's education.

These theoretical findings have been supported by empirical studies, which establish the proposed link between parental income and monetary investments in a child's education. Richer parents are found to spend more money on their child's primary and secondary education compared to less wealthy parents (Mauldin et al. 2001). In the United States, the proportion of income allocated to the education of a child below the age of 24 has been around 5% for most households between the 1970s and 2000s (Kornrich & Furstenberg 2013). Households belonging to the lowest 10% in terms of income spent around 20% of their income on their child's education. Although in absolute terms poor households spend less than rich households, allocating a greater share of household income on their child's education imposes greater restrictions on the household's budget compared to richer households. Parental education level appears to be an important factor in explaining future educational success (e.g. Black, Devereux & Salvanes 2005) and is also found to be strongly associated with the amount of money parents spend on their child's education (Mauldin et al. 2001).

However, monetary investments are not the only investments that parents can make in their child's education; they can also use their own time. In the economic model of Aiyagari et al. (2002), parental time investments are deemed to be efficient only if made by individuals with low productivity levels elsewhere in the economy, while high-skilled parents' rational choice is to pay for childcare. One result from this model is that highly productive parents do not invest their time caring for their child (and with that, investing in their child's education) unless forced to do so by an imperfect childcare market.

Some empirical studies, however, find results in contrast to the theoretical predictions by Aiyagari et al. (2002): as with monetary investments, richer and better-educated parents tend to allocate more of their time towards their child's education compared to those less wealthy and well educated (Guryan et al. 2008). This result is even more striking given that Guryan et al. observe that better educated parents also spend more time at work. Thus, parents who have high 'human capital' to pass on to their children also spend more time doing so. Possible reasons discussed in Guryan et al. (2008) include a) highly educated parents viewing professional childcare services as poor substitutes for their own time; b) higher educated parents might have a greater relative preferences for spending time on childcare rather than leisure; and c) returns from time investment are greater for highly educated parents.

Another important factor for time investments identified in previous empirical research is family composition. Children growing up with two parents receive more time investments than those living with a single parent (Kalil et al. 2014).

Several studies have analysed parental occupational status and time investments. Parents who are not in employment tend to spend more time investing in their child's education (Guryan et al. 2008). Furthermore, for mothers who do not hold employment when their child is younger than 5 years old, Bernal (2008) finds a positive effect on the child's cognitive abilities. While these studies focus on individual parents not working, Parsons et al. (2014) focus on workless households, i.e. households in which no adult household member is in employment. They observe that on average parents in workless households tend to spend less time reading to their young children or taking them to the library (ibid) as compared to working households.[1]

Literature that has explored the link between parental occupation status and a child's outcomes has had two main foci: firstly, estimating the link between parents' worklessness and children's school performance, or more generally, their educational trajectories. In the context of the United Kingdom, the DWP (2017) recently analysed children from workless households and their performance in school. This study found that one in eight children lives in a workless household. In their educational career, children from a workless background appear to struggle more often and perform worse; the findings led the British government to widen the scope of their *Troubled Families Programme*.[2] Also, parental worklessness is found to be associated with lower parental education levels and single parenthood as well as lower educational attainment of young children (Parsons et al. 2014).

The other major focus of this literature has been on more general economic intergen-

[1] This result is a simple correlation, not controlling for household, parent, or child characteristics.

[2] The Troubled Families Programme is an initiative first introduced in 2012 to help families facing multiple problems (e.g. worklessness, low income, mental health issues, or disability) to 'turn around'. In the programme running 2015–2021, almost three in five supported households were workless. One of the aims of the programme is to support children's development and get parents back into paid work. For more information, see Loft (2020).

erational effects of worklessness. Section 1.3 introduced worklessness as a special kind of disadvantage that may influence the way children grow up. As such, it has also been identified as a factor for social mobility. Especially in weak labour markets, adolescence in a workless household increases the probability of becoming workless later on in life (Friedman et al. 2017; Macmillan 2014, findings for the UK). A strong association between worklessness and educational attainment is observed in many European countries (Macmillan, Gregg et al. 2018). Especially for boys, there appears to be a link between growing up with a workless background and being jobless and poor later on in life, especially in countries in which the attainment gap is found to be strong. However, even though worklessness correlates between generations in many countries, many studies do not detect causal effects (Mäder, Riphahn et al. 2015, for intergenerational transmission of worklessness between fathers and sons). Schoon (2014) does not find evidence for a 'culture of worklessness' with a causal link between growing up in a workless household and being unemployed as a young adult. While much of the literature focusses on the relationship between fathers and sons, Berloffa et al. (2017) find that maternal worklessness is associated with a lower risk of youth unemployment in many European countries.

Overall, the current literature on parental worklessness does not focus on its implications on educational investments, and similarly the academic discussion of parental educational investments leaves out worklessness. In this study, I contribute to the existing literature in the following ways.

First, worklessness and both monetary and time investments in education have been identified as potential mechanisms affecting educational attainment and intergenerational mobility. However, there remains a gap in understanding how worklessness and educational investments are linked. While studies such as Parsons et al. (2014) and DWP (2017) find differences in educational performance between children from workless and working background families, this study aims to shed light on specific mechanisms which lead to such differences.

Second, building on Macmillan, Gregg et al. (2018), I use the extensive background data of the PISA study to look at parents' worklessness and its implications. This gives my study an international perspective and allows me to observe heterogeneity between countries. Where the existing literature on monetary and time investments in education mainly uses country-specific datasets – with most research conducted for the United States and more recently the United Kingdom – this study includes a wide range of OECD and partner countries covered by the PISA study.

In short, the literature introduced above suggests that parents with more money spend more on their child's education and parents not in employment spend more time with their child. However, other factors such as parental education levels need to be taken into account. Figure 2.1 sums up which factors are likely to affect the amount of money and time parents invest in their child's education – which influences a child's educational attainment. While parental characteristics such as education and occupation levels can affect monetary and time investments in a child's education directly (e.g. highly educated parents tend to spend more time with their child), they are also linked to the propensity of a household to become workless. In this study, I am interested in how monetary and time investments are different in workless households, correcting for observable family characteristics (i.e. β in the figure).

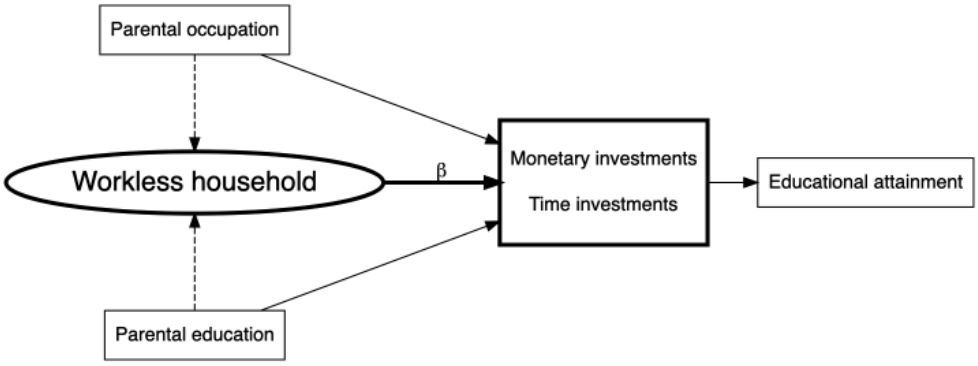
As workless parents may have less money but more time to spend, the hypothesis I test in this paper is that workless parents invest less money – but more time – in their child's education. My findings partly confirm the first part of this hypothesis: while workless households generally spend less money on children's education, I do not find that children in workless households are less likely to receive commercial out-of-school lessons. Overall, workless parents – especially single parents – tend to spend more time helping their child with its homework, confirming the second part of my hypothesis. However, results are not clear-cut and differ across subsets of the PISA data.

The remainder of this paper is structured as follows. In Section 2.2, the data from the PISA study is introduced. I highlight differences in the characteristics between children with workless and working parents in Section 2.3. Section 2.4 introduces the empirical method. This includes the preprocessing of the data using a matching approach, ensuring only children from workless and working households that are similar in observed background characteristics are compared, as well as the subsequent analysis of the matched sample. A detailed description of the results can be found in Section 2.5 with additional robustness checks in Section A.3. Finally, Section 2.6 discusses the paper's key findings and reflects on the advantages and limitations of researching worklessness and investments in education using the PISA data.

2.2. Data

In this paper, I use data from the 2012 PISA cycle. Since its launch in 2000, PISA has assessed 15-year-old school children's reading, mathematics and science skills.

Figure 2.1.: Parental worklessness and investments in their child's education.



Notes: β indicates the strength of the association between a workless household and parental investments in their child's education. Figure based on Jerrim & Macmillan (2015) and Leibowitz (1974).

The PISA study is conducted every 3 years in all OECD countries as well as a growing number of partner countries.

After participating in the PISA tests, all students answer questions about themselves, their family background, learning habits, and more. Starting with PISA 2006, some participating countries also ask parents to fill in a questionnaire containing questions similar to those in the student questionnaire as well as additional information on the family's financial background, educational spending, and time spent with their children. In 2012, participating countries and regions with parent questionnaire data are: Belgium, Chile, Croatia, Germany, Hong Kong, Hungary, Italy, Macau, Mexico, Portugal and South Korea. For more information about all participating countries and jurisdictions, and their sample sizes, see Table A.1. This study makes use of the detailed information provided by the student background questionnaire and – where available – parent questionnaire.

The background questionnaire has varied significantly over the years, such that not all information required for the analysis of parental worklessness and their educational investments is available in each PISA cycle. Parents' occupational status (workless or working) is provided by the student questionnaires of PISA cycles 2000, 2003, 2009 and 2012. Only the PISA 2012 data contains items related to both parental homework help and *commercial* out-of-school lessons from both the student and parent questionnaires, making it the best-suited to research into how workless parents invest their time and money in their child's education. In total, around 480,000 pupils from 65 countries or jurisdictions were surveyed by PISA in 2012, of which around 100,000 pupils in 11 countries also returned a parent questionnaire.

Key for all analyses conducted throughout this paper is measurement of parental worklessness. Following Macmillan, Gregg et al. (2018) and in line with the definition used by the UK government (ONS 2019), a household is considered workless if none of the parents[3] living in the household hold any kind of employment. Conversely, a household is not workless if at least one parent is in employment. Hence, it is possible to find a parent currently not in employment in a working household.[4] It is important to note that within the scope of this thesis I focus on the binary distinction between household worklessness and working households. However, one can possibly also think about worklessness as a more continuous concept: when parents only work very few hours per week, this could be labeled as *underemployment* and children growing in an underemployed household may face disadvantage as compared to households in which one or two parents work full-time. However, in the remainder of this thesis, I focus on household worklessness as a binary concept and add to the existing literature in this field.

To observe household worklessness, it is necessary to know which parents are living with the child as well as details about those parents' employment situation. This information is only available through the student questionnaire, not the parent questionnaire. Thus, a variable indicating a workless background can only be created if the respective questions have been answered by the student.[5]

This definition of worklessness together with the use of PISA data has some shortcomings. For one, worklessness of a household is only measured at one point in time at which the child is 15 years old. This does not reflect the complexity of the occupational biographies of parents but merely reduces it to a single-point-in-time measure. Furthermore, the reasons for worklessness are unknown and therefore the characterisation of the group of children growing up in workless households remains potentially heterogeneous. In this study, it is not possible to differentiate between voluntary worklessness (due to, for example, retirement or wealth) and involuntary worklessness, e.g. after losing a job or due to illness.

[3]This includes step-parents and legal guardians.

[4]This definition is in line with Parsons et al. (2014) and I refer to working (i.e. non-workless) households as households in which at least one adult is in employment. However, it is important to note that other publications such as Office for National Statistics (2016) limit the term *working household* to households in which all adults are in employment.

[5]This excludes Israel from this study as households composition is not assessed. Also, due to a very small amount of workless background children (only 10 observations), I exclude Liechtenstein from further analysis.

The PISA dataset provides several background characteristics which I use throughout this paper, first to describe different characteristics of children with workless and working parents (Section 2.3) and then as control variables (Section 2.5). The background characteristics used throughout this study contain students' gender, both parents' occupation and education level, a family's immigration background, and whether it is a single- or two-parent household. For workless parents, I use their last held employment to determine occupation level. In doing so, I match workless parents to working parents who previously held similar occupations. As shown in Section 2.3, children of workless and working parents differ in various ways. Table 2.1 lists all background variables I use throughout this study.

Parental occupation is reported by the students (and parents in countries with a parent questionnaire) in form of an open question. If a parent is not working, students are asked to name the last-held occupation:

> *What is your mother's (father's) main job?*
> *(If she (he) is not working now, please tell us her (his) last main job.)*
>
> *(e.g. school teacher, kitchen-hand, sales manager)*
>
> Please write in the job title. *(PISA 2012 student questionnaire)*

The occupations are then ultimately coded into a continuous quantitative variable using the International Socio-Economic Index of Occupational Status (ISEI) (OECD (Organization for Economic Cooperation and Development) 2014). Parental education level is assessed in both parent and student questionnaire by using a multiple choice question. Jerrim & Micklewright (2014) show that children's reports of their parents' occupation are generally accurate while, for parental education level, children and parents show 'moderate' agreement in their responses.

For the analyses of educational investments as observed from the student questionnaire, I only use background information reported by students. I use background information reported by parents only when focussing on dependent variables from the parent questionnaire. This is done to ensure consistent data sources (both across countries and within countries).

Monetary investments can be observed indirectly in the student questionnaire and directly in the parent questionnaire. In the student questionnaire, around two-

Table 2.1.: Description of variables used for matching.

Variable	Type	Source	Formula symbol
Mothers' occupation level	Continuous	SQ / PQ	O_m
Fathers' occupation level	Continuous	SQ / PQ	O_f
Gender	Binary	SQ	G
Immigration status	Binary	SQ	I
Mothers' education	Categorical	SQ / PQ	E_m
Fathers' education	Categorical	SQ / PQ	E_f
Single parent household	Binary	SQ	S
Mother's age	Categorical	PQ	A_m
Father's age	Categorical	PQ	A_f

Notes: SQ *means the variable is measured through the student questionnaire and* PQ *indicates it is observed from the parent questionnaire. Parental education levels are observed in six categories of the International Standard Classification of Education (ISCED) and recoded into three categories,* low, medium *and* high *to ensure comparability between student and parent questionnaire as well as between countries. Parental age is observed in categories* younger than 36, 36-40, 41-45, 46-50 *and* 51 or older.

thirds of students are randomly assigned booklets[6] containing the following question:

> *Thinking about all school subjects: on average, how many hours do you spend each week on the following?*
>
> *d) Attend out of school classes organised by a commercial company, and paid for by your parents*
>
> *e) Study with a parent or other family member*
>
> *(PISA 2012 student questionnaire)*

I use the former part of the question (d) as a proxy variable for monetary investments – given that such classes are usually expensive and represent a sizeable financial commitment by parents in their offspring's education (Dang & Rogers 2008; Kassotakis & Verdis 2013). Demand for such services is likely linked to (unobserved) prior test scores or grades. I cannot control for this in this study. I use the second item (e) to measure parental time investments. The response rate of students presented with this question is 87% commercial tutoring and 90% for parental homework help.

The parent questionnaire provides a more direct view on parents' monetary investments by asking specifically for the amount of money parents spend on their child's education annually:

[6] As this assignment is completely random, meaning that pupils in the same classroom might be assigned different booklets, this does not limit my analysis. See Section 2.2.1 for a discussion of missing data in general.

In the last twelve months, about how much would you have paid to educational providers for services?

- *Nothing*
- *More than **0** but less than **W***
- ***W** or more but less than **X***
- ***X** or more but less than **Y***
- ***Y** or more but less than **Z***
- ***Z** or more*

(PISA 2012 parent questionnaire – monetary investments)

Each country decides on the values for **W**, **X**, **Y**, and **Z**. I account for these differences by recoding the item in three categories – *low*, *medium*, *high* – to ensure comparability across countries.[7] The correlation between parental accounts of how much money they spend on their child's education and children's accounts of how many hours of commercial tutoring they receive depends on the overall prevalence of commercial tutoring. In countries such as Germany, Hong Kong, and South Korea, where more than 25% of pupils receive commercial tutoring, I find that hours of tutoring and parental investments are correlated with a Spearman's correlation coefficient between 0.3 and 0.45. In countries where commercial tutoring is not very common (e.g. Belgium and Hungary) parental investments and tutoring are not correlated.

Furthermore, parents are asked how frequently they help their child with its mathematics homework:

How often do you or someone else in your home [help your child with his/her mathematics homework]?

- *Never or hardly ever*
- *Once or twice a year*
- *Once or twice a month*
- *Once or twice a week*
- *Every day or almost every day*

[7] My recoding of this variable aims at aligning category sizes between countries. A detailed discussion of this can be found in Appendix A.2.1.

(PISA 2012 parent questionnaire – time investments)

I use this variable to complement the analysis of the time investment variable from the student questionnaire (option *e* from student questionnaire). However, the item from the parent questionnaire is limited to mathematics homework only. A potential minor limitation of the measures for time investment arises from the phrasing of the question: it is not restricted to parental homework help but allows also for help from other people living in the household, such as grandparents or siblings. The response rate for the questions from the parent questionnaire is 85% and 86%, respectively.

2.2.1. Missing Data

As in many other surveys, the PISA study suffers from missing data. Table 2.2 shows the proportion of missing data in selected variables from the student questionnaire. Particularly high rates of missing data can be observed for worklessness as well as fathers' – and especially mothers' – occupation levels. As the workless variable can only be constructed if the household composition is known, missing values in household composition cause missing values in the workless variable. Furthermore, if a child is living with, for example, their grandparents or in a foster home, this results in a missing value for worklessness. The return rate of the parent questionnaire is high in most countries (87%), noteworthy exceptions being Belgium and Germany with response rates of 49% and 58%, respectively.

A closer look at missing values in the parental occupation variables from the student questionnaire reveals some interesting patterns. First, mothers' occupation is frequently missing in some countries, such as the United Arab Emirates (62%), Tunisia (69%), Jordan (78%) and Turkey (82%), much higher rates than for fathers' occupation (between 13% and 26%) or parental education (between 2.6% and 5.8%). This indicates that in these countries mothers' occupation may be unknown because it is less common for mothers to be employed.[8] Second, in single-parent households, information for the remote parent not living with the child is missing more frequently. Thirty-two percent of children living with a single mother don't report their fathers' occupation compared to only 9% in a two-parent households

[8]According to World Bank data (World Bank 2019b; World Bank 2019c), female labour force participation in countries with high amounts of missing data for mothers' occupation is much lower than for males. The correlation coefficient between the difference of female and male labour force participation and the difference of missing data for mothers and fathers in PISA is 0.87, indicating a strong correlation between the two. In short: in countries where women are employed at lower rates than men, children report mothers' occupation less frequently than fathers'.

(similar, but less pronounced for single fathers). As most single-parent households are in fact single-mother households, this affects missing data in fathers' occupation more.

Analysing only students with complete information could potentially cause bias as observations are not likely to be left out at random. I use *multiple imputation* to impute missing values (Rubin 1987), using the R-package *mice* (van Buuren & Groothuis-Oudshoorn 2011). In the following paragraphs, I describe how I adjust for potential missing data mechanisms in my imputation algorithm for both data from the student and parent questionnaire. While the questionnaires are mostly the same in all participating countries, both the extent to which missing data occurs and the mechanisms that cause them may differ between countries. As a result, I perform multiple imputation for all participating countries separately. Furthermore, I do not impute households' occupation status (workless or working), as this is the explanatory variable of interest in this study. Missing values in this variable are mainly caused by unknown or unusual (i.e. no parent present) household composition. Last, by design of PISA 2012, only around two-thirds of all students were assigned questionnaire booklets containing the outcome variables *commercial tutoring* and *parental homework help*. I exclude students who did receive questionnaires not containing the outcome variables from further analysis of dependent variables from the student questionnaire without causing bias as they are missing completely at random. All of the above results in a student population of interest of 270,175 observations from 63 countries, of which 101,555 (37.6%) require some degree of imputation. For the analysis of the parent questionnaire, out of a total of 101,175 observations from 11 countries, 46,903 (46.4%) require imputation on at least one of the variables of interest.

As discussed previously, information about the remote parent is often missing in single-parent households. To take this into account, I apply different imputation

Table 2.2.: Missing data

	Household comp.	Workless household	Mothers' education	Fathers' education	Mothers' occupation	Fathers' occupation	Immigration status
OECD	.09	.13	.05	.08	.20	.13	.03
Partner countries	.11	.20	.03	.05	.33	.17	.03
Total	.10	.15	.04	.07	.25	.14	.03

Notes: Rate of missing observations for selected variables from the student questionnaire.

algorithms for children in two-parent households and single-parent households.[9]

In countries with a parent questionnaire, both parents and students report on parental occupation level and parental education level. I make use of this additional information when imputing. To account for the proportion of missing data in the dataset at hand, I create 30 imputed datasets which I use for all subsequent steps of analysis. I then reconcile the results by using *Rubin's Rule*.

2.3. Differences Between Children in Workless and Working Families

2.3.1. Background Variables

The background variables provided by the PISA study provide insights into each participating child's personal background. This section focusses on the circumstances children with workless parents grow up in and how this compares to those from a working background. In doing so, this helps to provide a better understanding of the similarities and differences between these two heterogeneous groups of children that will be used in the analyses conducted later on in this study.

The PISA study covers many countries and jurisdictions with different prevalence of worklessness. Around 7% of students in OECD countries and 14% in partner countries report living in a workless household (see Table A.1 for worklessness rates in each participating country). On average, workless-background children in OECD countries score 38 points lower on the PISA test in mathematics (36 in reading and 37 in science) than their peers from a working background. In partner countries, the difference is slightly less pronounced with a difference in mathematics score of around 25 points (25 in reading, 23 in science). PISA scores for children from a workless background are the same as for those from working households only in Macau, Singapore, Thailand and Albania.

Next, Table 2.3 reports summary statistics for parents' occupation level in OECD

[9]For Japan, Perm (Russia), and Iceland there are too few observations of either single- or two-parent households to split the dataset up and I impute the pooled dataset.

and partner countries for workless and working household parents.[10] First, note that for both workless and working parents the observed occupation levels range from 11 (e.g. subsistence farmers) to 89 (e.g. judges). This means that at least some parents with the highest occupation levels are workless and some with the lowest are in employment, ensuring common support in this variable. Overall, parents in workless households are over-represented in lower occupation levels. The median workless household mother has an occupation level of around 28 (e.g. sales assistant), whereas the median for working household mothers is 45 (e.g. secretary). For fathers from a workless household, the median value is 28 (e.g. elementary worker), whereas those from a working household have a median occupation level of 36 (e.g. electrician). Thus, on average, workless parents' last job was in 'lower' occupations compared to parents in a working household.

Very similar observations can be made for parental education level, where workless parents have lower education levels compared to those in employment. In OECD countries, around 17-18% of parents from a working household have a low education level[11] compared to 34-35% in workless households. A similar but less pronounced

Table 2.3.: Summary statistics for parents' occupation level in OECD countries for workless-background and working-background children.

(a) Mother's occupation level

	min	25%	median	mean	75%	max	N
not workless	11	27	45	46	65	89	203,306
workless	11	23	28	36	50	89	10,077
Total	11	25	44	45	65	89	213,383

(b) Father's occupation level

	min	25%	median	mean	75%	max	N
not workless	11	26	36	44	62	89	219,519
workless	11	21	28	34	44	89	13,700
Total	11	26	35	43	62	89	233,219

Notes: Occupation levels of mothers (upper table) and fathers (lower table) in workless and working households, classified using the ISEI scale. Reported figures are minimum, 25th percentile, median, mean, 75th percentile, maximum and the number of observations (N). The number of observations differs for mothers and fathers because of missing information on the occupation (last) held. No weights applied.

[10] Being working (i.e. 'not workless') refers to the household not the individual parent. If the mother holds a full-time job and the father is workless, this previous occupation level contributes to the 'not workless' distribution.

[11] ISCED 2 or lower, equivalent to 9 years of schooling or less in the United States (see Miller 2007, for US equivalents).

pattern can be observed for participating partner countries.

The living and family conditions of children from a workless background differ in various other ways. Around half of all children living in a workless household in an OECD country are raised by a single parent as opposed to only around 12% in working households. In general, parents in workless households appear to be older on average,[12] and are more likely to have an immigrant background. Furthermore, workless households appear to have a lower annual income.[13]

2.3.2. Parental Investments in Education

As described in greater detail in Section 2.2, monetary investments are observed from the student questionnaire using the proxy variable *commercial tutoring*. As shown in Table 2.4, around 16% of students in OECD countries and more than 34% in partner countries attend at least 1 hour of commercial tutoring per week. The raw difference between workless-background and working-background children appears to be very small on average in both OECD and partner countries.

The differences between countries in terms of prevalence of commercial out-of-school lessons is shown in Figure 2.2. While in countries such as Norway, Sweden and Denmark only a very small proportion of around 4% of students report attending any commercial tutoring, around half of students the OECD countries South Korea and Greece and up to almost 80% of students in Malaysia, Vietnam and Indonesia report attending at least 1 hour per week in commercial out-of-school lessons. Overall, in most OECD countries commercial tutoring seems to be far less common than in non-OECD countries.

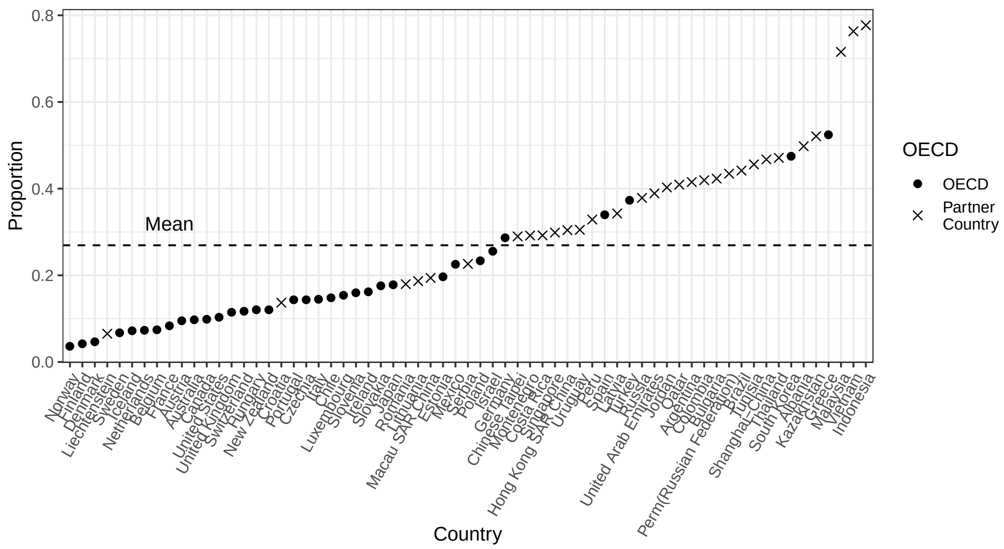
Table 2.4.: Commercial tutoring for children from a workless and working background.

	not workless	workless
OECD	0.161	0.163
Partner Country	0.371	0.348

Notes: Difference in the prevalence of at least 1 hour per week of commercial tutoring in workless and working households, not adjusted for any background characteristics. Senate weights applied.

[12]Information only available for countries with a parent questionnaire.
[13]Information available for countries with a parent questionnaire except Italy.

Figure 2.2.: Proportion of children with at least 1 hour of commercial tutoring per week across countries.



Notes: Countries on the horizontal line sorted from smallest to greatest proportion of commercial tutoring. The dashed line shows the average proportion. Student weights applied.

In the parent questionnaire, educational expenses are measured more directly.[14] On average, around 35% of working parents fall into the lowest expense category, whereas more than 45% of workless parents only spend low amounts on their child's education. Working parents are in turn over-represented in the medium- and high-expense category. The raw difference between workless and working parents is comparably high in Chile, Hong Kong, Hungary and Portugal. A very small raw difference can be observed in Belgium and Denmark.

I measure parental time investments in their child's education using the reported number of hours per week spent studying with a parent or other family member. In OECD countries, the rate of students reporting that they spend at least 1 hour per week studying with a parent or family member is around 45% and for partner countries slightly above 50% (see Table 2.5). Similarly, for countries with a parent questionnaire, parents report how regularly they assist their child with its *mathematics* homework. Around 50% of parents report helping their child with its mathematics homework at least a few times per year, around a quarter of parents report helping on a weekly basis (see Table 2.6). Overall, there are only small raw differences between children from a workless and those from a working household.

[14]Data from the parent questionnaire on education expenses provided in the PISA dataset is regrouped as described in Appendix A.2.1 in order to ensure comparability across countries.

Table 2.5.: Parental homework help for children from a workless and working background.

	not workless	workless
OECD	0.436	0.447
Partner Country	0.524	0.542

Notes: Difference in the prevalence of at least 1 hour per week of parental homework help in workless and working households, not adjusted for any background characteristics. Senate weights applied.

Table 2.6.: Parental mathematics homework help for children from a workless and working background.

	Never or hardly ever	Once or twice a year	Once or twice a month	Once or twice a week	Every day or almost every day	N
not workless	0.457	0.112	0.189	0.178	0.0637	$80,723$
workless	0.495	0.0919	0.155	0.181	0.0761	$7,611$

Notes: Frequency with which parents report helping their child with his or her mathematics homework for workless and working households. The last column shows the number of observations N. *Data available for countries with a parent questionnaire. All values are raw values and have not been adjusted for any background characteristics. Senate weights applied.*

2.4. Methods

This section introduces the methods used to understand how monetary and time investments in a child's education differ if parents are workless compared to households in which at least one parent is in employment. Section 2.3 has shown how workless and working households differ in many background characteristics, while educational investments are roughly the same regardless of parental occupation status, if not adjusting for any of the differences in background characteristics. Now the aim is to take into account all those background characteristics in order to assess the association between worklessness and parental educational investments were those other characteristics to be equalised.

For this, I use a combination of two methods: First, I use a *matching* approach to construct a sample of pupils from workless households that can realistically be compared with the sample of pupils from working households. The basic intuition is that for each child from a workless household I find a sufficiently alike counterpart, in terms of their observable characteristics, in a workless household. All those identified in this way are included in the matched sample. Workless-background children who do not have a counterpart growing up in similar circumstances but with working parents (and vice versa) are discarded.

Second, I apply linear and logistic regression modelling to the matched dataset. This helps account for any remaining imbalance in terms of observable characteristics and improves the precision of the measured association between parental occupation status and parental educational investments (Ho et al. 2007; Stuart 2010).

2.4.1. Matching

As described in Section 2.3, children from a workless background are different on average from those whose parents are in employment in many regards. Household characteristics such as parental occupation and education, single parenthood and immigration status are likely to affect both the probability of worklessness and the outcomes of interest related to educational investments.

In this study, I use matching as a tool to construct a comparison group of pupils from working backgrounds with whom we can meaningfully compare pupils from workless backgrounds. Even though growing up in a workless household is not a 'treatment' in the normal sense, matching helps reduce bias and model dependency in the estimation of the association between worklessness and educational investments (Ho et al. 2007). Sometimes, regression modelling alone is used to achieve similar aims. However, when comparing a 'treatment' group with a very dissimilar comparison group, this can suffer from problems with extrapolation, leading to unreliable estimates for the regressors in the model. This is potentially the situation here, given how different workless and working households may be.

In the matching literature, it is often recommended to apply different matching specifications and use the best-balanced dataset for further analysis. The robustness of results can then be tested across a range of techniques that produce datasets with a similar good balance.[15] However, it is not that clear how to define the best balance (Stuart 2010). Ideally, it would be possible to compare the multidimensional distribution of all matching variables between 'treatment' and 'comparison' group and settle for the approach that minimises this difference. As this is not feasible in practice, researchers are left with no incontestable way of comparing different matched datasets.

[15] In the context of PISA data and matching, for example Rutkowski et al. (2018) use different matching techniques and report results as robustness checks.

Because of these limitations and the fact that most matching approaches applied to this dataset resulted in very similar balance improvements, I present the matching methods used for the analyses in the main body and the resulting satisfactory balance improvements of this matching approach in this section. I present the results obtained from the subsequent analysis of this matched dataset in Section 2.5. Additionally, Appendix A.3 shows robustness checks using differently matched samples, including information about balance improvements from these matching methods.

As with my imputation of missing data, I run the matching algorithm separately for each country as well as for single- and two-parent households. As there are too few observations for Japan, Iceland and Perm (Russia), I do not split the dataset up between single- and two-parent households but instead add a dummy variable indicating household composition. For the implementation of matching in this study, I use the R package *MatchIt* (Ho et al. 2011). This package implements many matching methods and allows for detailed specifications.

2.4.1.1. Matching methods applied

Next, I introduce the matching methods and specifications used for preprocessing the data from both student and parent questionnaire for further analyses.[16] An overview of available matching techniques and advice on the implementation in practice can be found in Stuart (2010), which has set the foundation for the following paragraphs.

For all analyses presented in the main body of this paper I use one-to-one nearest neighbour matching: for each observation in the *workless* group, this method finds the closest match from the *working* group, according to a distance measure, here the *propensity score*. The propensity score is the probability that an observation with certain characteristics belongs to the 'treatment' – i.e. *workless* – group. As the true propensity score cannot generally be observed, most commonly the propensity score is estimated using a binary response model where the dependent variable is the treatment status (i.e. workless or working). I use a logistic regression of the following form to estimate the propensity score:

$$\text{logit}(ps) = \gamma_0 + \vec{\gamma}_1 B_{(\cdot)}, \tag{2.1}$$

where $\gamma_1 B_{SQ}$ includes all relevant background variables when matching data from the student questionnaire: parental education, parental occupation, and immigration

[16] For information about matching methods used as robustness checks, see Appendix.

status as well as – for Perm (Russia), Iceland, and Japan – a dummy variable indicating a single-parent household. Similarly, $\gamma_1 B_{PQ}$ includes all variables from the student questionnaire and additionally mothers' and fathers' age.[17] Rosenbaum & Rubin (1984) introduce the use of the propensity score for matching as it helps overcome the *curse of dimensionality*.[18]

One-to-one nearest neighbour propensity score matching is the most commonly applied matching method and it offers a wide range of additional specifications from which to choose. The background variables may predict worklessness differently in each country and for different household compositions (single- or two-parent): single parenthood was found to be strongly associated with worklessness in previous studies (e.g. Macmillan, Gregg et al. 2018), as only one parent needs to be workless instead of two. I take this into account by running the matching algorithm separately for each country and household composition[19], including the estimation of the propensity score. Also, for each country and household composition, I set the algorithm to discard those workless-background and working-background children from matching, which are outside the common support of the propensity score. Matching is carried out without replacement. This means that, once an observation from the comparison group has been matched, it cannot be matched to another workless-background child, even if it were the closest match in terms of propensity score. This prevents one working-background child being matched to several workless-background children.

This matching approach results in countries with a large PISA sample and higher worklessness rates contributing more to my analyses. While I partly account for this by analysing different subsets of the data, I also perform robustness checks applying senate weights. See Appendix A.3 for details.

[17]Hence,

$$\vec{\gamma}_1 B_{SQ} = \delta_1 G + \delta_2 I + \delta_3 O_m + \delta_4 O_f + \vec{\delta}_5 E_m + \vec{\delta}_6 E_f (+\delta_7 S),$$

and

$$\vec{\gamma}_1 B_{PQ} = \delta_1 G + \delta_2 I + \delta_3 O_m + \delta_4 O_f + \vec{\delta}_5 E_m + \vec{\delta}_6 E_f + \vec{\delta}_7 A_m + \vec{\delta}_8 A_f (+\delta_9 S).$$

For an overview of all variables and their formula symbols, see Table 2.1.

[18]The curse of dimensionality is an issue common to the analysis of data with many covariates: depending on the statistical method used, more covariates (i.e. higher dimension) cause the data to be too sparse which causes the method to perform poorly or fail.

[19]Except Perm (Russia), Iceland, and Japan, where I pool single- and two-parent households due to small number of observations and require exact matching on household composition.

2.4.1.2. Balance improvement

As the main purpose of matching in this setting is to create a balanced dataset in which workless-background and working-background children are very similar in their background characteristics, I check the balance improvement due to matching. Different measures can be used to check the balance of a dataset before and after matching. I mainly use the *absolute standardised bias in means*[20] (reported in this section) combined with visually checking the distribution of the propensity score and mothers' and fathers' occupation levels before and after matching (see Appendix).

Table 2.7 shows the change in standardised bias of all relevant variables of interest for the student questionnaire. A standardised bias smaller than 0.25 is considered to be balanced enough for further analyses (Ho et al. 2007; Stuart 2010). Before matching, most variables in both two-parent and single-parent households are unbalanced. Matching improves balance very well for all variables, reducing the standardised bias well below the 0.25 threshold with all variables having a standardised bias between 0.00 and 0.05. Moreover, the distributions of the propensity score and mothers' and fathers' occupation level of the matched dataset are well balanced over their full support (see Appendix): slight imbalances remain only for low occupation levels of fathers.

Table 2.8 shows the standardised bias in data from the parent questionnaire before and after matching. Before matching, many variables in both two-parent and single parent households are unbalanced, especially mothers' and fathers' occupation level. Despite initial imbalance being stronger in two-parent households, matching succeeds in bringing all variables' standardised bias in means well below the 0.25 threshold with almost no imbalance remaining. However, some notable imbalance remains for single parent households after matching: the standardised bias in means is brought well below 0.25 with variables measuring mothers' occupation and education level retaining an imbalance of above 0.10.

[20] The absolute standardised bias in means is computed as follows:

$$SB = \frac{|\bar{x}_T - \bar{x}_C|}{\tilde{s}_T}, \tag{2.2}$$

where $\bar{x}_T$ and $\bar{x}_C$ denote the mean value of variable x for treatment (workless) and comparison (working) group, respectively, and $\tilde{s}_T$ denotes the observed standard deviation of the treatment group.

Table 2.7.: Absolute standardised bias in means before and after matching – student questionnaire.

	Two-parent household			*Single-parent household*		
Variable	Before	After	Improvement	Before	After	Improvement
Gender	0.06	0.01	78.89%	0.03	0.01	75.46%
Immigration status	0.01	0.01	10.91%	0.12	0.01	90.32%
Occupation level father	0.59	0.03	95.68%	0.16	0.01	96.16%
Occupation level mother	0.56	0.01	97.58%	0.35	0.01	95.83%
Education level father - low	0.51	0.03	94.39%	0.23	0.03	87.27%
Education level father - medium	0.10	0.02	81.62%	0.06	0.01	83.78%
Education level father - high	0.53	0.02	97.08%	0.18	0.04	79.01%
Education level mother - low	0.60	0.02	97.03%	0.38	0.05	87.85%
Education level mother - medium	0.13	0.01	92.87%	0.01	0.00	64.40%
Education level mother - high	0.63	0.01	97.93%	0.41	0.05	87.23%

Notes: Matched dataset generated as described in this section; i.e. one-to-one nearest neighbour propensity score; matching algorithm run separately for each country and household composition. All numbers are averaged over all 30 imputations.
Two-parent household*: Workless-background children discarded for lack of common support: 89-158. Unmatched workless-background children: 0. Total number of observations in matched dataset: 31,652-31,786.*
Single-parent household*: Workless-background children discarded for lack of common support: 564-746. Workless-background children unmatched: 499-560. Total number of observations in matched dataset: 16,428-16,684. Variation in figures due to random differences between the 30 imputed datasets.*

Table 2.8.: Absolute standardised bias in means before and after matching – parent questionnaire.

	Two-parent household			*Single parent household*		
Variable	Before	After	Improvement	Before	After	Improvement
Gender	0.08	0.01	90.27%	0.05	0.03	38.16%
Immigration status	0.02	0.01	49.05%	0.01	0.01	28.77%
Occupation level father	0.68	0.01	97.84%	0.26	0.06	77.28%
Occupation level mother	0.69	0.01	98.53%	0.48	0.11	78.10%
Education level father - low	0.52	0.01	97.39%	0.28	0.07	74.84%
Education level father - medium	0.27	0.01	95.24%	0.10	0.04	59.87%
Education level father - high	0.40	0.01	97.84%	0.23	0.05	78.87%
Education level mother - low	0.60	0.01	98.05%	0.44	0.12	71.80%
Education level mother - medium	0.34	0.01	96.83%	0.20	0.08	58.95%
Education level mother - high	0.46	0.01	97.78%	0.34	0.08	76.36%
Father Age <36	0.02	0.01	38.98%	0.05	0.02	40.27%
Father Age 36-40	0.04	0.01	64.32%	0.01	0.03	-821.85%
Father Age 41-45	0.13	0.01	93.82%	0.12	0.03	72.85%
Father Age 46-50	0.26	0.01	96.11%	0.11	0.03	75.05%
Father Age >51	0.30	0.01	96.87%	0.18	0.04	76.30%
Mother Age <36	0.10	0.01	88.93%	0.04	0.02	58.05%
Mother Age 36-40	0.03	0.01	61.45%	0.01	0.03	-744.65%
Mother Age 41-45	0.20	0.01	94.93%	0.15	0.01	90.11%
Mother Age 46-50	0.11	0.01	89.62%	0.06	0.01	82.83%
Mother Age >51	0.23	0.01	95.92%	0.19	0.05	72.28%

Notes: Matched dataset generated as described in this section; i.e. one-to-one nearest neighbour propensity score matching; algorithm run separately for each country and household composition. All figures in the table are averaged over all 30 imputations.
Two-parent household*: Workless-background children discarded for lack of common support: 9-36. Unmatched workless-background children: 0. Total number of observations in matched dataset: 10,590-10,644.*
Single-parent household*: Workless-background children discarded for lack of common support: 78-129. Workless-background children unmatched: 247-285. Total number of observations in matched dataset: 6,014-6,090. Variation in figures due to random differences between the 30 imputed datasets.*

2.4.2. Regression Modelling

The matched datasets can now be analysed using the same methods one would have applied to an unmatched dataset with the advantage of reduced model dependency. This is the recommended approach throughout the matching literature in order to find the best estimates for the association of interest (e.g. Ho et al. 2007; Stuart 2010).

When analysing the student questionnaire, I focus on the probability of receiving commercial (C_{binary}) and parental (P_{binary}) out-of-school lessons and how it differs between workless-background and working-background children. I analyse two-parent and single-parent households separately. These models can be represented as follows:

M1 – commercial tutoring

$$\Pr[C_{binary} = 1] = G(\beta_0 + \beta_1 WL + \vec{\gamma}_1 B_{SQ} + \epsilon_{M_{1.1}}) \tag{2.3}$$

M2 – parental homework help

$$\Pr[P_{binary} = 1] = G(\beta_0 + \beta_1 WL + \vec{\gamma}_1 B_{SQ} + \epsilon_{M_{2.1}}), \tag{2.4}$$

where $\gamma_1 B_{SQ}$ controls for the observable background characteristics also used for matching, i.e. gender, immigration status, mothers' and fathers' occupation level as well as their education level (see Table 2.1). The link function $G(\cdot)$ translates the linear core into probabilities. If G is the identity function, a *linear probability model* is estimated using Ordinary Least Squares (OLS). In the main body of this paper I report results from the linear probability model, as they are easy to interpret and can be estimated best given the data structure at hand.[21] WL denotes the households' occupation status (workless or not-workless) and ϵ represents the error term. As an additional robustness check, I analyse the number of hours spent attending out-of-school lessons. For details and results, see Section A.3.

M3 – monetary investments; and M4 – time investments The dependent variables obtained from the parent questionnaire are ordinal: parents report on their

[21] A logistic regression with country fixed effects cannot be computed with cluster robust standard errors. Therefore, given the structure of the data, I report results from a linear probability model only.

educational expenses and helping their child with its homework in distinct ranked categories. I use two approaches to analyse this data. In the first approach, I use different cut-points[22] to recode the ranked categories into a binary variable, which I then analyse using a linear probability model:

$$\Pr[V = 1] = \beta_0 + \beta_1 WL + \vec{\gamma}_1 B_{PQ} + \epsilon_{M_{3/4}}, \tag{2.5}$$

where the background variables summarised in $\vec{\gamma}_1 B_{PQ}$ are parental education and occupation, mothers' and fathers' age, and students' immigration status and gender. The dependent variable V represents all binary versions of the original variable using different cut-points.

However, by transforming an ordinal outcome variable into multiple binary ones, valuable information from the data is lost within each logistic regression. Therefore, I use an *ordered logistic regression* as a second approach which aims at avoiding this issue by using the full information of the categorical dependent variable in a single model, instead of scattering this information across several logistic regressions. In both approaches, logistic regression with cut-points and ordered logistic regression, I use the same background variables as shown above. I report results from the ordered logistic regression together with the results from different cut-points.

With all linear probability models, I apply country fixed effects to compute the standard errors for the estimates. This is done by introducing country dummies as covariates in the regression. When analysing the data from the parent questionnaire with an ordered logistic regression, I include country dummies in the estimation as country fixed effects cannot be implemented. All reported standard errors (and resulting p-values and confidence intervals) are computed clustering at the country level.[23]

I apply models using data from the student questionnaire (M1 to M4) to the fully matched samples for two-parent and single-parent households as well as to several subsets of this. Most importantly, I separately analyse OECD countries and partner

[22]For clarification, consider a dependent variable consisting of three ranked categories, $A < B < C$. This variable can now be transformed into a binary dependent variable by merging two of the original categories. The first option is to merge A and B to a new category such that the resulting new depending variable γ takes value 1 if category A or B holds true, and 0 in case of category C. The second option would be to merge B and C, such that $\gamma = 1$ if category A holds true, and 0 otherwise.

[23]From the way PISA data is collected, it would be most natural to cluster at school level. Due to the comparably small number of observations in some countries and my matching approach, this is not feasible. Therefore, I cluster on country level instead.

countries. As described at several points in Section 2.3, OECD and partner countries differ in many regards. For instance, it is less common in OECD countries to receive any form of out-of-school lessons. Furthermore, I distinguish between countries with high public spending on education (above median according to UNESCO Institute for Statistics (UIS) (n.d.)) and countries with low education expenditure (below median). Lastly, I state countries with a parent questionnaire separately to allow for comparison with additional results obtained for those countries.

Note that the analyses for each subset do not involve a different matching approach, as all matching is performed within countries.

2.5. Results

In this section I present my estimates for the association between parental worklessness and money and time parents invest in their child's education. I obtain my estimates by first preprocessing the data with *matching* techniques and subsequently using regression analyses for estimation (see Section 2.4). I present the point estimates for the regression coefficients of the worklessness variable (β_1) as well as corresponding standard errors and significant levels. When reporting results from an ordered logistic regression from the analysis of the parent questionnaire, I report the *average marginal effect* rather than the actual model coefficients to ensure comparability with the results from the linear probability models. The marginal effects of worklessness show by how much the probability of being in a higher category of the dependent variable differs if parents are workless instead of working, depending on a broad range of background characteristics.

First, I present results around monetary educational investments in Section 2.5.2. Results for time investments are shown in Section 2.5.3. Note that robustness checks (heterogeneity analysis, variations in regression, no matching, differently matched sample; see Section A.3) are in line with the findings presented in this section. I provide an overview of these robustness checks in Section 2.5.4.

2.5.1. Conditional Associations

To examine the effect of including different sets of background variables in the analysis, I present estimated associations between household worklessness and respective outcome variables when loading more variables into the analysis. The regression methods used are as described in Section 2.4. However, as the focus of this paragraph is to examine how estimates are affected by included control variables, I do not run separate analyses for different subsets of the data.

Table 2.9 shows which variables are added in each step. In Model C1, I measure the association between household worklessness and respective outcome variables using country fixed effects only. In further models I add more control variables: gender and immigration status (Model C2), parental education (C3), and parental occupation (C4).

Table 2.9.: Conditional associations adding control variables

	Model			
Control	C1	C2	C3	C4
Country fixed effects	x	x	x	x
Demographics Gender Immigration status Parental age (PQ only)		x	x	x
Parental education			x	x
Parental occupation				x

Table 2.10 shows the estimated association between household worklessness and the outcome variables of interest, controlling for an increasing number of background characteristics (see Table 2.9). In two-parent households, all estimates remain stable and there are no substantial differences in magnitude or statistical significance level depending on the control variables included. This is a desired feature of preprocessing the data with matching methods: model dependency and therefore also dependency on control variables included should be reduced. Observing that model dependency for two-parent households has been completely eliminated confirms the observation made in Section 2.4 that the matched dataset is indeed very balanced.

In single-parent households, loading more background variables into the model slightly changes the point estimates for some of the outcome variables. For example, when looking at money spent as reported in the parent questionnaire, point estimates when only adding country fixed effects (model C1) and when adding demographic control variables are around 0.01 greater in magnitude than when adding parental education level. While the overall results are very similar regardless of included background variables, these slight changes in point estimate when adding parental education and occupation indicate that preprocessing with help of matching has resulted in imperfect – albeit strongly improved – balance. Again, this confirms my observations made in Section 2.4: particularly balance improvements in the mothers' education level in single parent households were well below balance improvements other imbalanced variables.

Table 2.10.: Conditional associations of household worklessness with respective outcome variables

	Two-parent household				*Single-parent household*			
Outcome Variable	C1	C2	C3	C4	C1	C2	C3	C4
Monetary investments								
Comm. tutoring	-.010	-.010	-.009	-.009	-.009	-.009	-.008	-.008
	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)
Money spent (PQ)								
low | med & high	-.040***	-.040***	-.039***	-.039***	-.053***	-.054***	-.042**	-.040**
	(.012)	(.012)	(.013)	(.013)	(.017)	(.017)	(.017)	(.017)
low & med | high	-.026***	-.026***	-.025***	-.025***	-.036***	-.037***	-.027**	-.024**
	(.010)	(.010)	(.009)	(.009)	(.014)	(.014)	(.011)	(.011)
Time investments								
Homework help	.013**	.013**	.013**	.013**	.025***	.025***	.026***	.026***
	(.007)	(.007)	(.007)	(.007)	(.009)	(.009)	(.009)	(.009)
Homework help – maths (PQ)								
A | B C D E	.004	.004	.005	.005	-.017	-.015	-.009	-.008
	(.011)	(.011)	(.011)	(.011)	(.025)	(.025)	(.023)	(.023)
A B | C D E	.004	.002	.003	.003	-.017	-.020	-.015	-.015
	(.011)	(.014)	(.013)	(.013)	(.025)	(.022)	(.020)	(.020)
A B C | D E	.009	.009	.009	.009	.005	.006	.009	.009
	(.009)	(.009)	(.009)	(.009)	(.017)	(.017)	(.016)	(.016)
A B C D | E	.003	.003	.003	.003	-.000	-.000	.001	.001
	(.007)	(.007)	(.006)	(.006)	(.010)	(.010)	(.009)	(.009)
Country fixed effects	x	x	x	x	x	x	x	x
Demographics		x	x	x		x	x	x
Parental education			x	x			x	x
Parental occupation				x				x

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Regression on matched sample run separately for two-parent and single-parent households. Linear probability models for parent questionnaire data (indicated with PQ) with different cut-points for the categorical dependent variable, indicated by ' | *'. Abbreviations for parental maths homework help: A: 'Never or hardly ever'; B: 'Once or twice a year'; C: 'Once or twice a month'; D: 'Once or twice a week'; E: 'Every day or almost every day'. Standard errors clustered at country level. Country fixed effects.*

2.5.2. Monetary Investments

In this section and the following, I present regression analyses including all control variables. Models M1 and M3 estimate the association between parental worklessness and their monetary investments in their child's education (see Section 2.4).

Table 2.11 shows the results from a linear probability model M1 applied to *all countries*, *OECD countries*, *partner countries*, and *countries with a parent questionnaire*. Data from the student questionnaire is used with a binary variable indicating whether or not a child attends commercial tutoring as a dependent variable. The point estimates of the association between worklessness and commercial tutoring are mostly negative, close to 0, with none being statistically significant.

Next, I analyse the data from the parent questionnaire using model M3. Table 2.12 presents the estimates for the association of worklessness with parental educational expenses. As educational expenses are measured in ordered categories, I present both the results of linear probability models with different cut-points of the categorical expense variable as well as the results of an ordered logistic regression (see Section 2.4). The results indicate that workless-background children living in both single-parent and two-parent households are more likely to be in a lower expense category compared to their working-background peers. My estimates suggest that children from a workless background are 2.4–2.5 percentage points more likely to be in the lowest expense category and around 3.9–4.0 percentage points less likely to be in the

Table 2.11.: M1 – Association between worklessness and commercial tutoring from a linear probability model applied to different subsets of the matched PISA data.

	Two-parent household		*Single-parent household*	
Data	Estimate	Standard error	Estimate	Standard error
All countries	-0.009	0.008	-0.008	0.008
OECD	-0.009	0.011	-0.001	0.009
Partner countries	-0.010	0.011	-0.016	0.013
PQ	0.004	0.011	-0.015	0.012
Observations	31,783–31,917		16,653–16,925	

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Regression on matched sample run separately for two-parent and single-parent households. Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, and immigration status. Standard errors clustered at country level. Country fixed effects.

highest expense category. There appears to be no difference between children living in a single-parent or two-parent household.

Robustness checks confirm these results with similar or stronger point estimates (see Section A.3). It is noteworthy that the analysis of the student questionnaire did not show any difference in the prevalence of commercial tutoring in countries with a parent questionnaire. This suggests that commercial tutoring does not capture overall spending on a child's education: in countries with a parent questionnaire, there appears to be robust negative association between parental worklessness and educational expenses as a whole, while this difference cannot be detected when focussing on commercial tutoring only – a specific kind of educational expense.

2.5.3. Time Investments

In this section I present the results from models M2 and M4, estimating the association between parental occupation status and parents' time investments in education.

Table 2.13 shows the results from analysing the student questionnaire. I find a statistically significant association between parental worklessness and parental homework help in both two-parent and single-parent households. In two-parent

Table 2.12.: M3 – Association between parental worklessness and monetary investments using data from the parent questionnaire.

	Two-parent household		*Single-parent household*	
Regression	Estimate	Standard error	Estimate	Standard error
low | medium, high	-0.039***	0.013	-0.040**	0.017
low, medium | high	-0.025***	0.009	-0.024**	0.011
Ordered logistic regression	-0.036***	0.010	-0.037***	0.013
Observations	10,590–10,644		6014–6090	

$*\ p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$

Notes: First two rows – linear probability models with different cut-points for the categorical dependent variable: between low income and merged medium and high income (first row) and between merged low and medium income and high income (second row). Standard errors clustered at country level. Country fixed effects.
Third row – ordered logistic regression. For comparability, I report the average marginal effect *and the corresponding standard error, which allows the magnitude of the regression coefficients to be compared. Standard errors clustered at country level. Country dummies included (no country fixed effects).*
Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, immigration status, and mothers' and fathers' age.

households, I find this association only in OECD countries, where children living in a workless household are around 2 percentage points more likely to be helped by their parents with their homework. The estimate for partner countries and countries with a parent questionnaire is small and not significant. In single-parent households, I find a significant association in partner countries (5% level) and OECD countries (10% level). Here, children from a workless background are between 2 and 3 percentage points more likely to receive parental homework help, compared to children with similar background characteristics who live in a working household. However, I do not find this association in countries with a parent questionnaire.

As Table 2.14 shows, I find no difference in parental *mathematics* homework help between workless-background and working-background children when analysing data from the parent questionnaire. The dependent variable is categorical and indicates how regularly parents report helping their child with their mathematics homework. The point estimates are close to 0 and insignificant for all cut-off points of the linear probability models as well as for the ordered logistic regression, both for two-parent and single-parent households.

These results suggest that overall there is a positive association between parental worklessness and time investments in a child's education. Unsurprisingly, this association appears to be stronger in single-parent households compared to two-parent households: many two-parent households only have one parent in full-time employment which leaves time for the other parent to help the child with their homework.

However, the subset of countries with a parent questionnaire does not show any association between parental worklessness and parents helping their child doing homework. This indicates that the association between worklessness and parental homework help – while being overall positive – differs between countries, with no association on average in parent questionnaire countries.

2.5.4. Robustness Checks

To check how strongly my results depend on model specifications and country selection, I perform a wide range of robustness checks. For a detailed discussion of all robustness checks, see Appendix A.3.

The robustness checks can be categorised in three categories. First, I perform a

Table 2.13.: M2 – Association between worklessness and parental homework help from a linear probability model applied to different subsets of the matched PISA data.

	Two-parent household		*Single-parent household*	
Data	Estimate	Standard error	Estimate	Standard error
All countries	0.013**	0.007	0.026***	0.009
OECD	0.021**	0.010	0.021*	0.012
Partner countries	0.007	0.009	0.031**	0.015
PQ	0.001	0.012	0.013	0.018
Observations	31,783–31,917		16,653–16,925	

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Regression on matched sample run separately for two-parent and single-parent households. Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, and immigration status. Standard errors clustered at country level. Country fixed effects.

Table 2.14.: M4 – Association between parental worklessness and parental mathematics homework help using data from the parent questionnaire.

	Two-parent household		*Single-parent household*	
Regression	Estimate	Standard error	Estimate	Standard error
A | BCDE	0.005	0.011	-0.008	0.023
AB | CDE	0.003	0.013	-0.015	0.020
ABC | DE	0.009	0.009	0.009	0.016
ABCD | E	0.003	0.006	0.001	0.009
Ordered logistic regression	0.006	0.010	-0.004	0.020
Observations	10,590–10,644		6014–6090	

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: First four rows – linear probability models with different cut-points for the categorical dependent variable, indicated by ' | '. Abbreviations: A: 'Never or hardly ever'; B: 'Once or twice a year'; C: 'Once or twice a month'; D: 'Once or twice a week'; E: 'Every day or almost every day'. Standard errors clustered at country level. Country fixed effects.
Last row – ordered logistic regression. For comparability, I report the average marginal effect *and the corresponding standard error, which allows the magnitude of the regression coefficients to be compared. Standard errors clustered at country level. Country dummies included (no country fixed effects).*
Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, immigration status, and mothers' and fathers' age.

heterogeneity analysis in which I divide the countries into different categories such as high and low GDP per capita. In doing so, I break up the differentiation presented in the main analysis which distinguishes between OECD and non-OECD countries only. Second, I use different model specifications and matching methods. I run my analyses treating the outcome variables as continuous, apply coarsened exact matching (CEM) as opposed to propensity score matching, and I analyse the sample without the use of matching at all. Third, I use weights to see how results are affected if each country contributes to the analysis equally as compared to equal weights to each child with a workless background.

2.5.4.1. Monetary investments

None of my robustness checks detects any statistically significant difference in commercial tutoring between children in workless households and their peers without a workless background. This holds true for any subsets of the data analysed in the heterogeneity analysis, when looking at the number of hours per week of commercial tutoring, using CEM, and when applying senate weights. Only when analysing the full pre-matching sample I do find a statistically significant (5% level) association in two-parent households in countries with a parent questionnaire. However, the overwhelming evidence from my robustness checks confirms that there is not substantial and robust association between household worklessness and commercial tutoring.

My results on money spend on education (parent questionnaire) indicate that there is a statistically significant difference between workless and working households. When looking at countries separately, seven out of 11 countries show a statistically significant association (at least 10% level). This indicates that while there is an overall association, there possibly are differences between countries. As numbers of observations of workless households per country are too small for meaningful inferences, further research at country level would be necessary to draw further conclusions. While no matching or CEM do not impact the results, using senate weights reduces statistical significance levels. However, point estimates remain at a comparable level with larger standard errors.

2.5.4.2. Time investments

Robustness checks of the association between household worklessness and homework help (student questionnaire) are mixed. The heterogeneity analysis indicates that my results depend on countries included. However, point estimates consistently remain positive with larger standard errors in certain subsets of the data reducing statistical significance. Results do not seem to be driven by countries with large populations as using senate weights almost exactly reproduces the results presented in the main section with larger point estimates. Similarly, using CEM results in similar estimates as presented in the main body: in OECD countries I find a statistically significant difference for two-parent households while in partner countries I find a difference in single-parent households. Lastly, when analysing the full dataset without matching, I find a strongly statistically significant association between household worklessness and homework help.

When looking at parents' reports, I find that most robustness checks confirm that parents in workless households do not report higher amounts of mathematics homework help. Only in two out of 11 countries, I do see a difference significant on the 10% level. Senate weights or CEM do not change results. Only when using the full sample without matching, I do find that there may be a very weakly statistically significant association. Altogether, these robustness checks confirm the findings from the main analysis of no association between household worklessness and parental mathematics homework help.

2.5.5. Summary of Results

The results from my regression analyses presented above combined with robustness checks (Appendix A.3) are summarised in Table 2.15. First, when looking at all countries, I do not find a difference in prevalence of commercial tutoring between workless and working households. Second, while workless children in parent questionnaire countries do not receive less commercial tutoring, their parents report lower spendings on education. Third, over all countries I find a weak positive association between household worklessness and parental homework help in two-parent households and a robust positive association in single-parent households. This indicates that overall in single-parent households children with workless parents receive larger time investments. However, this is not true in countries with a parent questionnaire, where both children and parents do not report a higher prevalence of parental homework help. Hence, time investments in the form of homework help may be higher in workless-background children overall, but this difference is country dependent.[24] Hence, both differences in the institutions in the (public) education system and cultural differences possibly matter for the association between household worklessness and time investments through homework help.

2.6. Conclusion

Children living in workless households are often surrounded by a particular economic and social disadvantage, potentially putting strains on their educational careers. While workless parents may have more time to spend on their child's education, they might face tighter economic constraints. This potentially changes how parents decide to invest in their child's education by spending their financial and time resources.

I studied these hypotheses using PISA 2012 and applied different statistical methods to estimate for association between parental worklessness and these two different kinds of educational investments.

I find that parental worklessness is associated with lower overall spending on education in both two-parent and single-parent households. However, offering their child access to commercial tutoring appears not to be a channel through which workless parents spend fewer resources compared to otherwise similar working parents. This may be because paying for extra lessons is an educational investment more common for parents at the higher end of the SES distribution as opposed to the households at the margin of worklessness researched in this study. On the other hand, workless parents

Table 2.15.: Overview of results

	Two-parent household		*Single-parent household*	
	All countries	Countries with PQ	All countries	Countries with PQ
Commercial tutoring	Null	Null	Null	Null
Money spent	–	Negative	–	Negative
Homework help	Weak positive	Null	Positive	Null
Homework help (maths)	–	Null	–	Null

[24]In Chapter 3 of this thesis, I find only a weak link between household worklessness and homework help in UK children, which does not hold in robustness checks.

– especially single-parents – appear to spend more time helping their child with their homework compared to working parents with otherwise similar characteristics. While I find this pattern in many subsets of the data analysed, I do not find higher time investments into workless-background children in countries with a parent questionnaire, i.e. Belgium, Chile, Croatia, Germany, Hong Kong, Hungary, Italy, Macau, Mexico, Portugal, and South Korea – regardless of whether students or parents report on this. Overall, my results suggest that children from workless households on average receive lower monetary investments in their education, while in some countries, children – especially those from single-parent households – receive higher time investments. The observation that my results in part dependent on the set of countries analysed indicates that that potentially both cultural differences and differences in education systems contribute to worklessness being a factor for the educational investments analysed in this study.

However, these results come with limitations. First, while the methods I use go beyond an analysis of correlations – comparing children growing up in workless and working households with otherwise very similar background characteristics – it would not be appropriate to interpret the results as *causal*. This is because I do not observe possible confounding factors such as prior achievement or parental motivation and ability.

Second, despite PISA offering a unique international perspective on the ramifications of worklessness, country-level interpretation of my results is limited and often not possible. Mainly, my sample size varies substantially between countries. While Italy and Mexico have a sizeable population of children with a workless background in their comparably large overall sample, the sample size for countries such as Japan is too small to draw meaningful conclusions. This combined with noisy self-reported data does not allow for a by-country analysis of the association between household worklessness and educational investments.

Third, I am lacking a time dimension in the data to see and analyse different patterns of worklessness. Similarly, I don't have detailed information about potential reasons for worklessness, such as age, illness, wealth, or unemployment.

Fourth, in this chapter and throughout this thesis I look at worklessness in a binary sense: a household can be workless or working. In doing so, I add to the wider worklessness literature. However, this does not allow for a deeper understanding of differences in occupational choices parents make. As highlighted in this chapter, in many cultures mothers are far less likely to be in work than fathers, posing questions about the impact of female labour force participation on their children's outcomes. Further, working parents may only work few hours per week and be underemployed as a result. This is not captured in my analyses.

Last, the proportion of workless households from the PISA study is a coarse estimate. For the UK, PISA data suggests that around 7% of children grow up in a workless household, compared to around 12% according to DWP (2017) and 17% according to Eurostat (2020b) (all numbers for 2012, the year of PISA data collection – see also Chapter 3 for more details on children in workless households in the UK). This indicates that either the PISA sample does not accurately represent the population of workless-background children in the UK (and possibly other countries), or that there is substantive measurement error for household worklessness. If measurement error is to blame, all estimates are possibly biased towards zero.

Results from my study as well as country-level analyses could help guide how policy makers approach the education of children growing up in workless households. For instance, in countries in which monetary investments by workless parents are lower compared to working households, social policy could help reduce this difference. This could be through subsidies for educational expenses or by ensuring parental expenses for children's education are not necessary and become less common regardless of the household's employment situation. My research presented in this study suggests that possible lower monetary investments may not be compensated for with higher time investments. Hence, policies currently targeted at working parents (e.g. after school childcare) could be expanded to include all children regardless of their parents' employment situation.

This Chapter opens up topics for further research on the link between household worklessness and educational investments which I aim to address in the next chapter of this thesis. First, while the above study analysed a large set of countries, focussing on one nation with comparable cultural traits and educational policies can add to the literature in this field. In Chapter 3, I focus on household worklessness and educational investments in the UK-context. Second, using data from the MCS, in Chapter 3 I look at educational investments into children as young as 9 months up to the age of 14. This adds to my results from analysing educational investments in 15-year-old teenagers participating in the PISA study. Last, MCS data is longitudinal and therefore adds a time dimension to my analyses. This allows me to get closer to causal estimates of the effect household worklessness has on parental time and money investments in their child's education.

3. Investments in the Education of Children Growing up in Workless Households in the UK

3.1. Introduction

The environment children grow up in shapes their present and future lives. Living conditions, parental income, parents' ability to help with school work, parents' jobs and education, health condition, and political views all influence a child's life. The extent of these parental influences is being researched in outcomes such as social mobility (Friedman et al. 2017; Gugushvili et al. 2017), smoking behaviour (Pedersen & Soest 2017), or voting preferences (Akee et al. 2018; Bougher 2018).

In this study, I focus on children in the UK growing up in workless households – meaning households in which no parent works for money. This is of particular relevance in the context of the UK. In 2010, around 18% of UK children lived in workless households, almost twice the rate of the EU average (Eurostat 2020b). After a steady decline in the proportion of children in workless households since 2010, in 2019 around 10.5% of children in Britain lived in workless households, still exceeding the EU-27 average by almost 2 percentage points (Eurostat 2020b).

In workless households, resources parents are able to use for their child's education are likely to be different from working[1] households (e.g. McClelland 2000; Mynarska et al. 2015). This paper provides insights into the ramifications worklessness has on the investments parents make into their child's education. By using nationally

[1] As in Chapter 2, I refer to a household as working if at least one parent is in employment. Thus, any non-workless household is considered working.

representative data from the United Kingdom, the MCS[2], I am able to see how children in workless households compare to their peers in working households at different ages from as young as 9 months to the age of 14. In particular, I am interested in getting closer to obtaining the causal effect a change in household worklessness has on educational investments and subsequent outcomes.

As discussed previously in Chapter 2, the literature around the link between parental worklessness and children's outcomes has mainly focussed on two aspects: school performance and intergenerational effects of worklessness. Children growing up in workless households are found to struggle more often in school and perform worse (Macmillan, Gregg et al. 2018; DWP 2017), with lower educational attainment found in young children already (Parsons et al. 2014). Having grown up in a workless household as a child is associated with outcomes later in life, too. Especially boys from such a background are more likely to be poor later on in life, in particular in countries where the attainment gap is large (Macmillan, Gregg et al. 2018).

Parents allocate their time and money towards their child's education, investing in their human capital. Models such as Aiyagari et al. (2002), Becker & Tomes (1986) and Solon (2004) explore incentives and budget constraints and resulting trade-offs parents face: spending time to work and earn money which then can be spent on the child's education versus directly spending time on advancing the child's education. Caucutt et al. (2020) find that higher educated mothers generally invest more resources in their child's education. Despite working, their time allocation is not lower than for lower educated mothers. Furthermore, Caucutt et al. (2020) conclude that investing time and money serve as substitutes in building a child's skills, highlighting that productivity of time and other investments does not depend on parental education levels. Lastly, Caucutt et al. show that differences in prices and wages explain a large proportion of variation in investment decisions between parents.

In Chapter 2, I discussed how parents invest their money and time in their child's education depending on whether they are in employment or not. I used PISA 2012 data measuring both the household's employment status (workless or not workless) and monetary and time investments in a child's education at a single point in time at the age of 15. The analysis includes more than 60 countries and therefore provides a very general global perspective on the ramifications of parental worklessness on

[2] University of London 2017a; University of London 2017b; University of London 2017c; University of London 2017d; University of London 2017e; University of London 2019; University of London 2020.

investments made in a child's education. However, both cross-sectionality and internationality of the data used in that paper have some disadvantages. First, changes over time in family composition (single-parent and two-parent household) as well as changes in employment status cannot be understood as they remain unobserved due to the cross-sectionalitey of the data. This leads to a single point-in-time measurement of employment status. Second, there are no results at country level, but the data is pooled over many of the participating countries. As educational policy, as well as policies targeting the labour market, are often based at country level, a more country-specific analysis could be useful. Third, while the results show some very interesting and robust associations between parental worklessness and educational investments, no claims about a *causal* link between worklessness and educational investments are made.

In this chapter, I move away from the international perspective and focus on British children in workless households. Using the longitudinal (panel) MCS data for this study, I wish to address two main questions.

How do educational investments differ between workless and working households at different ages? While in Chapter 2 I only look at children aged 15, the MCS data contains several measures for educational investments from the age of 9 months up to the age of 14 years. This allows for a much more detailed view on how children in workless households compare to children in working households at different points in their educational careers.

Is there a causal link between worklessness and educational investments? Understanding if there is a *causal* link between entering the state of worklessness (or leaving it) and educational investments is important, especially with rates of workless households likely to increase due to the current Covid-19 crisis. To do so, I use three different methods: (1) fixed effects regression focussing on households transitioning in and out of worklessness over time; (2) an instrumental variable approach using labour force data of occupation-level worklessness; and (3) future spells of worklessness to reduce bias (Gottschalk 1996; Müller et al. 2017).

I find that worklessness causes parents to have significantly more time with their child, and parental worklessness to be associated with more frequent reading to young children. I do not find household worklessness to be causally linked to parents helping their child with reading, writing, or maths more regularly (age 5-7), nor does household worklessness cause children to receive more homework help (age 11-14). The latter finding is in contrast to Chapter 2 which finds a significant association between parental worklessness and increased homework help at age 15.[3] Furthermore, workless parents are less likely to pay for childcare (age 1-3). Similar to my analyses in Chapter 2, I find that worklessness is not causally associated with lower expenses for extra lessons (age 11-14).

The remainder of this chapter is structured as follows. In Section 3.2, I introduce the data from the Millennium Cohort Study. Section 3.3 then introduces the empirical models and the methods I use to estimate both the non-causal associations of worklessness with the outcome variables of interest, as well as the causal estimates of worklessness. In Section 3.4, I present the results of these analyses. I conclude by summarising and discussing the results and their implications in Section 3.5.

3.2. Data

3.2.1. The Millennium Cohort Study

For this study I use data from the Millennium Cohort Study (MCS) (University of London 2017a; University of London 2017b; University of London 2017c; University of London 2017d; University of London 2017e; University of London 2019). A nationally representative sample of around 19,000 children born in 2000-2002 in England, Scotland, Wales, and Northern Ireland are followed through their lives with regular interviews of parents, teachers, and the cohort members themselves.

I use the first six MCS sweeps, which allows me to analyse worklessness and investments in education from as early as 9 months until the age of 14. The number of participating households decreases with each sweep, from 18,522 participating households in Sweep 1 (age 9 months) to 11,714 in Sweep 6 (age 14). This is mostly due to families not responding to requests to participate in later sweeps of the MCS. To account for the potential attrition bias resulting from this as well as the sampling

[3] There are two possible explanations for the difference in findings. First, I use propensity score matching (PSM) in Chapter 2 and regression methods in this chapter. However, robustness checks on the unmatched sample estimate the association to be stronger and more significant than those presented in the main analysis. Second, Chapter 2 includes more than 60 countries (and subsets of these) in the analysis. As the heterogeneity analysis suggests, the association between household worklessness and parental homework help is dependent on the countries included in the analysis. Thus, the differences in results are likely explained by focussing on UK teenagers only in this chapter.

process,[4] I use the sweep-specific weights to report averages and distributions as well as for my regression analyses.

3.2.2. Worklessness

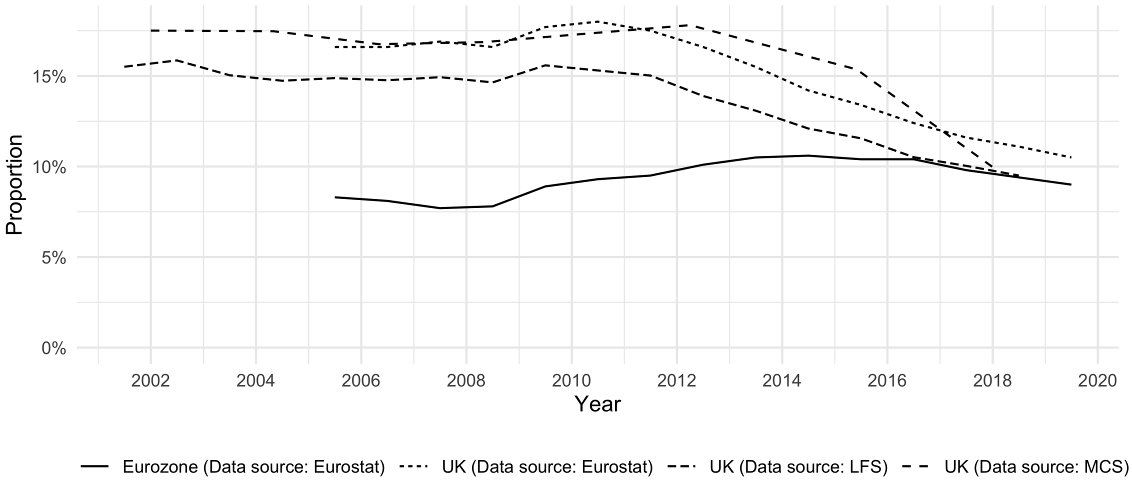
The main explanatory variable of interest in this study is worklessness: how do educational investments by workless parents compare to working parents? Workless households are regularly defined as households in which no adult household member (age 16 or older) works for money (DWP 2018) or in which no parent is working (Schoon 2014). In this study – as in Chapter 2, I consider a household to be workless if none of the primary carers (called 'Main' and 'Partner' in the MCS data) are in work. For better comparability of workless and working households, I exclude cases in which grandparents take the role of the primary carers (between 0.0% of observations in the Age 9 Months Sweep and 1.0% in the Age 14 Sweep). A household is considered workless regardless of the reasons for not working which could include unemployment,[5] health issues, caring for the family, or other reasons. This is in line with the academic literature (Barnes et al. 2012; Friedman et al. 2017; Parsons et al. 2014; Schoon 2014) and the definition of worklessness in UK government publications (DWP 2017; DWP 2018).

UK Department for Work and Pensions (2017) finds that between 2006 (around MCS Sweep 3, age 5) and 2011 (around Sweep 5, age 11) the proportion of UK children growing up in a workless household was stable at around 16% and has dropped to around 10% in 2016 (around Sweep 6, age 14). Similarly, Eurostat (2020b) reports that between 2008 (Sweep 4, age 7) 2015 (Sweep 6, age 14) between 13% and 18% of minors lived in workless households. Using MCS data, I estimate the (weighted) proportion of households in the MCS being workless to fall between 17% (age 5 and 7) and 20% (age 11). As mentioned previously, the estimated household worklessness rate from the PISA study stands out as substantially lower at around 7%. In the PISA study, children report on their parents' employment status while in the MCS parents themselves are asked about their current employment situation. Children might not be well informed about their parents' current employment or might not

[4]Families in Scotland, Wales, and Northern Ireland, as well as disadvantaged households, are oversampled

[5]Commonly defined as people who are not working but looking for a job and prepared to start a new job within the next weeks.

Figure 3.1.: Children in workless households in the UK



Notes: Data sources: University of London (2017a), University of London (2017b), University of London (2017c), University of London (2017d), University of London (2017e), University of London (2019) and University of London (2020); ONS (2020); Eurostat (2020b). Own calculations of rate of children in workless households for MCS and LFS data. Eurostat and LFS lines represent the proportion of all children aged 0–17 living in a workless household. MCS line represents the proportion of cohort members (aged between 1 in 2001/02 and 17 in 2018) living in a workless household.

report accurately for other reasons resulting in this discrepancy.[6]

Figure 3.1 shows that throughout the 2000s the UK has had a substantially higher rate of children in workless households than the Eurozone average.[7] In the past decade, this gap has been closing. However, according to Eurostat data, the UK still trails the Eurozone countries by a considerable margin. Overall, my calculations using the MCS data are in line with my calculations using the Labour Force Survey (ONS 2020), the official Eurostat data (Eurostat 2020b), as well as governmental publications such as DWP (2017), UK Department for Work and Pensions (2017) and DWP (2018).

As the MCS follows the same children as they grow older, changing household circumstances also influence worklessness. For instance, single parenthood is strongly associated with being workless: only one instead of two parents needs to be not

[6] I do not consider small differences in year of birth or sampling issues as the main reason for the difference in estimates of the proportion of children growing up in workless households. This is because both Eurostat and Labour Force Survey based estimates include all children below the age of 17. However, it cannot be ruled out that the PISA sample does not capture children from workless households at a representative rate.

[7] The difference is comparable for subgroups such as the EU28/EU27, with data availability of the Eurozone-19 countries reaching furthest back to 2005.

working to fall in the workless household category. Figure 3.2 shows the prevalence of worklessness across sweeps as well as the proportion of single-parent households. The solid line indicates that the proportion of single-parent households increases over time from around 15% in the Age 9 Months Sweep to 30% in the Age 14 Sweep. The overall worklessness level (dotted line) and the worklessness level of two-parent households (long-dashed line) remain rather constant with a notable increase between age 7 and age 11, possibly due to the financial crisis. However, the proportion of single-parent households being workless households decreases from well above 70% to below 40%. While the proportion of worklessness among single-parent households is much higher than in two-parent households, it decreases the older the cohort members get. However, this does result in a lower overall worklessness level as more households become single-parent households.

3.2.3. Outcome Variables

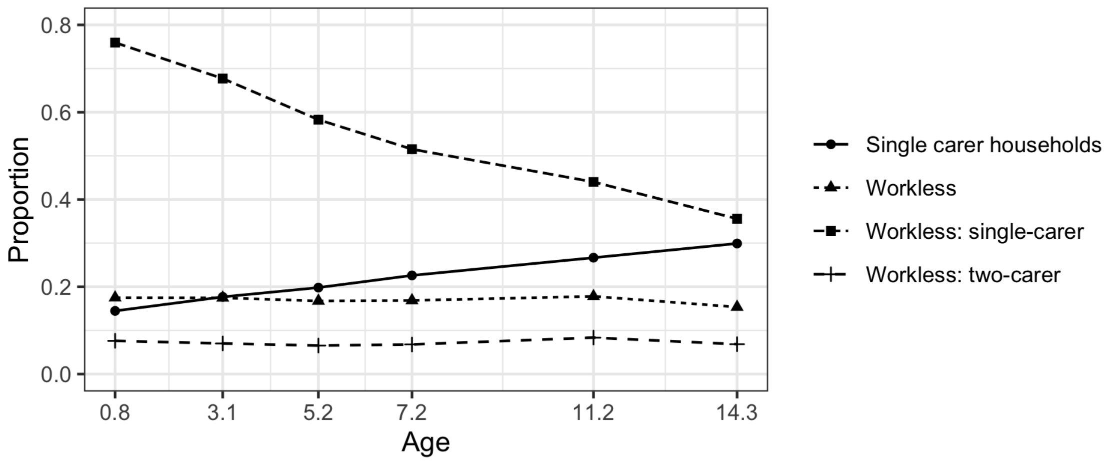
In this study, I am looking into the effect worklessness has on parental educational investments. In particular, parents can invest either their own time on their child's education or they may decide to spend their money on educational services. The MCS data contains several age-appropriate measures for investments parents make in their child's education, from a very young age until the cohort members are teenagers. In the remainder of this section, I describe the various investment variables I use for my analyses and how they are recoded in greater detail.

3.2.3.1. Time investments

Parents spend time with their child and likely use some of this time teaching their child skills and helping with school work. In this study, I look at time parents spend on their child's education at different stages of a child's life (see Table 3.1 for time investment variables recoded as binary).

First, I analyse how content parents are with the time they have to spend with their child in each of the six MCS sweeps. While not being an investment in itself, this variable indicates how much time parents have at their availability to spend with their child. When children grow older parents are more likely to report that they do not have enough time with their child. Both the main parent and their partner are asked how they assess the amount of time they have with the cohort member.

Figure 3.2.: Workless households and household composition over time.



Notes: The solid line shows the proportion of single-parent households at each sweep's average cohort member age. The three dashed lines show the proportion of workless single-parent and two-parent households as well as the overall proportion of workless households.

Table 3.1.: Overview of time investment variables

Sweep	1 (9m) N=18552	2 (3y) N=15590	3 (5y) N=15246	4 (7y) N=13857	5 (11y) N=13287	6 (14y) N=11726
Enough time with child						
Enough time	75%	72%	29%	29%	33%	26%
Just enough time or less	25%	28%	71%	71%	67%	74%
Read to child						
Once or twice a week or less		16%	12%	21%		
Several times a week or more		84%	88%	79%		
Help child with reading						
Several times a week or more			88%	48%		
Weekly or less			12%	52%		
Help child with writing						
Several times a week or more			63%	34%		
Weekly or less			37%	66%		
Help child with maths						
Several times a week or more			67%	23%		
Weekly or less			33%	77%		
Help child doing homework						
Irregularly					53%	33%
Regularly					47%	67%
Excluded	0%	1%	1%	2%	3%	3%
Missing data	0%	2%	3%	3%	4%	8%

Notes: Descriptive statistics using MCS sample weights. Percentages computed excluding missing values. Categorical outcome variables recoded to binary variables as used in the analyses. Missing data for all variables shown in one summary variable indicating the proportion of households with missing data in any of the relevant time investment variables.

In the Age 9 Months and Age 3 Sweeps (Sweeps 1 and 2), parents report in four categories: 'Nowhere near enough time', 'Not quite enough time', 'Just enough time', 'Plenty of time'. In all later sweeps, the category 'Plenty of time' is replaced with two categories: 'More than enough time' and 'Too much time'. To ensure comparability between single-parent and two-parent households, I focus on the parent that reports to be more content if more than one value is observed. When recoding the variable to become binary, I choose the cut-point to be between 'just enough time' (coded as 0) and 'plenty of time' (coded as 1).

Second, parents can spend their time reading to their child. In fact, several studies have pointed out the positive effect reading aloud can have on children's reading and writing skills (e.g. Anderson, Hiebert et al. 1985; Beck & McKeown 2001; Massaro 2017). In the MCS, this investment variable is measured when the cohort member is 3-, 5-, and 7 years old. In two-parent households, both parents are asked this question. To ensure comparability between single-parent and two-parent households, I recode this into a binary variable as follows. In single-parent households, the variable takes the value 1 if the parent reads to the cohort member 'several times per week' or 'every day or almost every day'. Otherwise I recode the variable to 0. In two-parent households, I assign the value 1 if either one of the parents reads to the child at least several times per week, or if *both* parents read to the cohort member at least 'once or twice per week'. Otherwise, I assign the value 0. Results from detailed robustness checks are presented in Appendix B.3. There, I analyse the data using varying cut-points, focussing on highest and lowest value parents, and applying ordered logistic regressions.

Third, parents can dedicate time to directly help children to learn how to read, write, and do maths. This form of time investment is measured in the MCS in Sweeps 3 and 4 when children are on average 5 and 7 years old, respectively. I recode the variable to take the value 1 if parents help their child 'several times per week' or more, and I assign the value 0 if parents help their child less frequently. For all three subjects, parents reduce the time they spend helping their child when the child gets older. While around six out of seven parents help their child with reading several times a week or more when the cohort member is around 5 years old, 2 years later only less than half of parents do so. Similarly, around two out of three parents help their child with writing and maths multiple times per week when the cohort member is 5 years old and only one in three parents does so at the age of 7.

Last, children can receive educational investments in the form of parental homework help. Many parents choose to help with their child's homework to try and benefit their child's educational attainment or because they think it is expected of them (Hoover-Dempsey et al. 2001). I recode the variable to take the value 1 if parents help their child 'usually' or 'always', and I assign the value 0 if parents help their child less frequently. Almost half of 11-year-old and more than two out of three 14-year-old cohort members are helped with their homework by their parents regularly.[8]

3.2.3.2. Monetary investments

Another key resource parents can spend on their children other than time is money. Expenses include among others food, toys, books, technology, and – the focus of this study – investments in education. These investments may take various forms. For this study, I focus on childcare, school fees, and paid-for extra lessons (see Table 3.2). These measures are observed in multiple sweeps from the age of 9 months until 14 years and allow for panel data methods (i.e. fixed effects) to be applied. Unlike with the previously discussed time investment variables, I do not need to recode these variables to be binary.

When children are young and not going to school yet, parents might decide to rely on professional childcare. Intervention studies such as the Perry Preschool Project and the Abecedarian Project have found that attending pre-school has significant and lasting benefits for their educational attainment (Campbell et al. 2002; Nores et al. 2005; Schweinhart et al. 1985). Karhula et al. (2017) study

Table 3.2.: Overview of monetary investment variables

Sweep	1 N=18552	2 N=15590	3 N=15246	4 N=13857	5 N=13287	6 N=11726
Paid-for childcare						
No	79%	69%				
Yes	21%	31%				
Fee-paying school						
No			96%	96%	96%	95%
Yes			4%	4%	4%	5%
Paid-for extra lessons						
No					86%	93%
Yes					14%	7%
Excluded	0%	1%	1%	2%	3%	3%
Missing data	0%	1%	3%	2%	4%	5%

Notes: Descriptive statistics using MCS sample weights. Percentages computed without accounting for missing values.

[8]In Sweep 5 (age 11) parents report, and in Sweep 6 (age 14) the cohort member reports on this variable.

secondary data and find a positive association between early childcare in Finland and educational attainment of young adults, although concluding that childcare does not causally impacting children's educational trajectories negatively. Furthermore, studies conducted around UK pre-schools suggest a positive association of attending pre-school with learning outcomes. longer attendance of pre-school was found to be associated with language abilities and numerical literacy (Sammons et al. 2004), with Melhuish et al. (2013) suggesting these associations being long-lasting into adulthood. However, other studies conducted in the UK-context of early childcare suggests only very limited positive impact of childcare, especially for privately run low quality providers (Blanden, Del Bono, Hansen et al. 2021). While this evidence includes predominantly free-of-charge childcare, parents in the United Kingdom may choose to pay for childcare instead.[9] The MCS data shows that 21.5% of participating households pay for childcare for their 9-months-old child and 31% do so when the child is 3 years old.

Next, children may be sent to a fee-paying school. While the biographies of highly influential people in the United Kingdom regularly include the names of infamous fee-paying 'public'[10] schools such as Eton, between 4% and 5% of pupils in the MCS attend fee-paying schools (see Table 3.2), compared to about 7% of all 5- to 15-year-olds (Henseke et al. 2021; DfE 2018).

This investment seems to pay off: controlling for a wide range of background variables, young adults who attended a fee-paying school have higher academic attainment and are significantly more likely to enter highly paid, prestigious occupations or to get a university degree, in particular from a prestigious university (Green, Anders et al. 2020; Green, Parsons et al. 2018; Macmillan, Tyler et al. 2015; Sullivan et al. 2014). However, attending a fee-paying school is strongly associated with family income and wealth (Anders, Green et al. 2020). Only between 0.5% and 2.1% (equivalent to between 11 and 34 pupils) of students attending fee-paying schools are from a workless household, compared to between 17% and 20% of workless-background students in the full MCS sample. Therefore, I exclude this variable from regression analyses due to a too-small number of observations.

[9] Since 1997, several childcare measures have been introduced in the UK (West & Noden 2016). Since 2010, every English child aged 3 or 4 is eligible to 15 hours per week of free childcare. This was extended to 2-year-olds from disadvantaged families in 2013. Additionally, since 2017, all working parents are eligible to 30 hours per week of free childcare for their 3- or 4-year-old child (UK Department for Education 2015). However, this does not negatively impact the results of this study. For a detailed analysis of the effects of free childcare in the UK on labour force participation and employment, see Brewer et al. (2020).

[10] Public schools in the UK refer to fee-paying privately run schools, as opposed to state schools which are publicly funded schools.

The third monetary investment I explore in this study is paid-for extra lessons. When pupils are around 11 years old, more than 14% of children in the MCS receive paid-for extra lessons. Parents may do so to ease their child's transition from primary to secondary education and especially parents with a higher socio-economic status tend to do so (Ireson & Rushforth 2011).

3.2.3.3. Background variables

For my analyses detailed in Section 3.3, I control for various background characteristics of the cohort member and their parents provided by the MCS data. Table 3.3 shows the full list of all background variables (and worklessness) and their distribution for all six sweeps. The most important background characteristic to take into account is the household composition: is the household a two-parent or single-parent household? As discussed before, single-parent households are much more likely to be workless households.

Furthermore, I control for two key background characteristics of the cohort member: ethnicity and exact age. Moreover, I use parents' personal characteristics (age, education, smoking behaviour, health) and economic circumstances[11] (housing situation, equivalised income[12]) as well as household size.

Over the course of the first six MCS sweeps, the (weighted) proportion of workless households ranges between 15% and 18% while single parenthood increases from 14% to 30%. The participating household's education level changes mainly in the highest category, fewer households live in their own home and the equivalised income goes up. At the same time, the proportion of smoking households goes down while overall health remains rather stable. The ethnical composition of the weighted sample shifts slightly, the proportion of white cohort members going down from 87% to 84%.

Some of these changes might be due to general changes in life: when growing older, parents that had not finished education yet may have done so now; career progress; and parents may be able to buy a home. However, some of the changes might also be due to attrition. Especially the change in ethnical composition suggests this interpretation. The longitudinal weights provided with the MCS data account

[11] Arguably, workless households change their behaviour based on their income situation. However, this is also true in other households with low income. In order to isolate the impact of household worklessness as opposed to the role poverty plays, I control for the households' economic situation.

[12] The MCS data contains the OECD equivalised income measure, adjusting overall income for household size and age of household members.

for both changes in country (England, Scotland, Wales, Northern Ireland) and stratum (disadvantaged or disadvantaged neighbourhood) as well as for changes in the composition of the observed background characteristics. I use these longitudinal weights throughout the study.

3.2.4. Missing Data

Aside from the number of observations going down with each sweep due to attrition (households dropping out of the study), participating households may have missing data as well. The weighted proportion of households having missing data in at least one of the background variables ranges from 3.6% (Sweep 3) and 6.4% (Sweep 2) (see Table 3.3). This is due to several reasons.

First, to ensure comparability between households I exclude households in which one of the main carers does not identify as (step-)parent, foster parent, or adoptive parent (row 'missing by design' in Table 3.3). Second, in some households no main or partner interview was conducted or it was stopped prior to completion, leading to missing values. Third, missing values may occur when interviewees prefer not to disclose this information or do not know the answer to a certain question such as household income.

To retain an as large as possible sample for my analysis, for all relevant households I impute missing values of all background variables other than household worklessness and single parenthood. In case of continuous variables such as equivalised household income, age, and number of household members, I perform mean imputation by sweep, employment status, single parenthood, and stratum. For all categorical variables, I impute using the mode (most common observation) within the same groups as for continuous variables. This reduces the amount of observations excluded from my analyses due to missing data in background variables to between 0.1% (Sweep 1) and 3.2% (Sweep 6).

Beyond that, the methods I use for my causal analyses (see Section 3.3) require additional information. In particular, I either use information from future sweeps or I require information about the current or previous occupation. To ensure comparability of my results across methods used, I remove those observations with missing data in either of these additional variables as well as those with missing data in any of the outcome variables. I account for this augmenting the MCS sample

Table 3.3.: Overview of background variables

Sweep	1 N=18552	2 N=15590	3 N=15246	4 N=13857	5 N=13287	6 N=11726
Workless	18%	17%	17%	17%	18%	15%
Single-carer	14%	18%	20%	23%	27%	30%
Female	49%	49%	49%	49%	48%	48%
Age (cohort member)	0.81 (0.04)	3.14 (0.21)	5.21 (0.24)	7.23 (0.25)	11.16 (0.34)	14.27 (0.35)
Ethnicity (cohort member)						
White	87%	86%	87%	85%	84%	84%
Pakistani and Bangladeshi	4%	4%	4%	5%	5%	5%
Indian	2%	2%	2%	2%	2%	2%
Black or Black British	3%	3%	3%	3%	4%	4%
Mixed	3%	3%	3%	3%	4%	4%
Other ethnic group	1%	1%	1%	1%	1%	2%
Age (younger parent)	29.06 (5.63)	31.37 (5.67)	33.46 (5.73)	35.21 (5.83)	38.95 (6.03)	41.9 (6.17)
Age (older parent)	32.45 (6.7)	34.64 (6.78)	36.61 (6.77)	38.27 (6.81)	41.49 (6.82)	44.34 (6.87)
Parental education (highest in household)						
None of these	9%	8%	7%	8%	8%	10%
Overseas qual only	2%	2%	2%	2%	2%	2%
NVQ level 1	6%	6%	5%	5%	6%	6%
NVQ level 2	25%	25%	24%	24%	23%	23%
NVQ level 3	16%	16%	15%	16%	15%	13%
NVQ level 4	36%	36%	36%	34%	33%	32%
NVQ level 5	7%	7%	10%	12%	13%	13%
Smoking household	43%	41%	39%	37%	35%	31%
Parental health (lowest in household)						
Poor	4%	4%	4%	5%	6%	7%
Fair	22%	22%	16%	15%	13%	16%
Good	59%	59%	37%	38%	34%	36%
Excellent	15%	14%	9%	10%	14%	11%
Very good			34%	33%	32%	30%
Housing situation						
Own	62%	64%	65%	63%	58%	56%
Rent	32%	32%	32%	35%	39%	42%
Living with parents	4%	2%	2%	1%	1%	1%
Shared equity	0%	0%	0%	0%	0%	0%
Other	2%	1%	1%	1%	1%	1%
Equivalised income	318.81 (206.97)	345.97 (228.58)	364.07 (225)	389.15 (231.92)	404.05 (180.31)	390.48 (178.34)
# Household members	3.97 (1.22)	4.13 (1.23)	4.28 (1.23)	4.48 (1.26)	4.45 (1.32)	4.37 (1.35)
Excluded	0%	1%	1%	2%	3%	3%
Missing data	4%	6%	4%	6%	5%	6%

Notes: Descriptive statistics using MCS sample weights. For continuous variables I show the mean (standard deviation in parentheses), for categorical variables I show the percentage of observations in each category. The row 'Excluded' shows the proportion of data missing due to households with grandparents or other carers that are not classified as parents. The 'Missing data' row shows the proportion of excluded cohort members and those having missing values in at least one of the background variables presented in this table.

weights by computing additional inverse probability weights for cohort members to be excluded from the analysis. I then combine the MCS sample weights with the inverse probability weights.[13] Robustness checks show that I obtain comparable results when analysing the largest possible dataset instead of the one ensuring comparability across methods and outcome variables (see Appendix B.3).

However, missing data may be problematic, depending on the cause. While missing data due to non-response with certain items only affects a comparably small proportion of observations which I address as described above, bias from attrition as well as missing occupational information may be the source of bias. First, consider attrition bias. While the MCS sample weights are designed to address this issue, a change in the composition of time-invariant background variables such as the cohort members' ethnicity shows the weights might deal with attrition imperfectly. More importantly, though, excluding households in which I do not observe occupation categories (see details in Section 3.3) is possibly correlated with unobserved characteristics. Parents that do not report on their current or previous occupation might do this because they never worked. Therefore, all workless households considered in the analyses in the main section of this study are households in which all present parents have held a job in the past or are currently in employment.

3.3. Methods

3.3.1. Association

In this study, I focus on the following two research questions:

1. *How do educational investments differ between workless and working households at different ages of the cohort member?*

2. *Is there a causal link between worklessness and educational investments?*

To answer the first research question, I present cross-tabulations showing the association between worklessness and outcome variables. Within each sweep, I differentiate between children in single-parent and two-parent households, without accounting for any other background characteristics besides household composition.

[13] The original MCS weights are highly correlated with my final weights: $\rho = 0.93$.

The strength of this approach is its simplicity while reliably isolating the difference between workless households and working households throughout a child's education career. Moreover, this approach provides an overview over the timing of educational investments and how they differ between workless and working households. However, the estimates I obtain from these cross-tabulations cannot be interpreted in a causal way.

3.3.2. Conditional Associations

To better understand how the estimated estimated association of household worklessness changes once control variables are included, I present conditional associations for all dependent variables. I estimate the associations using a pooled probit approach, a more detailed introduction of which follows in Section 3.3.3.1. Table 3.4 shows the order in which I include variables when estimating conditional associations. First, in

Table 3.4.: Conditional associations adding control variables

		Model			
Control		M1	M2	M3	M4
Single parenthood	S	x	x	x	x
Demographics & Health	D		x	x	x
Number of household members					
Cohort Member's age					
Cohort Member's sex					
Cohort Member's ethnicity					
Parental age (oldest)					
Parental age (youngest)					
Smoking household					
Parental health					
Parental education level	E			x	x
Economic situation	I				x
Housing situation					
Household income					

the simplest specification in Model M1, I estimate the association between household worklessness and respective outcome variables controlling only for single parenthood. Second, I include general demographic information of the cohort member and their parents as well as parental health indicators into the analysis (Model M2). Third, in Model M3 I include parental education level and last, in Model M4, I further control for the households' economic situation (housing and income).

3.3.3. Causal Effect

3.3.3.1. Overview

The methods I detail in this section aim to reduce bias due to the endogeneity of the explanatory variable of interest – household worklessness. Recall that all outcome variables are binary or recoded as binary (see Section 3.2). Consider the following model in which a binary outcome variable, D_{it}, is regressed on worklessness, wl_{it}, a set of background characteristics, X_{it}:

$$D^*_{it} = \beta_0 + \beta_1 wl_{it} + \beta_2 X_{it} + c_i + \epsilon_{it}. \tag{3.1}$$

D^* is a latent variable where

$$D^t = \begin{cases} 1 & \text{if } D^{t*} > 0, \\ 0 & \text{otherwise} \end{cases}. \tag{3.2}$$

The variable c_i denotes the unobserved time-invariant effect for each cohort member, i, e.g. parental ability, motivation, or the cohort member's innate ability. ϵ_{it} is the time-variant error term. Despite the rich set of background variables included in my regression analyses, omitted variables bias may occur resulting in the error term, ϵ_{it}, or the unobserved time invariant cohort member specific component, c_i, to be correlated with the explanatory variables, especially with the variable of interest – household worklessness.

As a benchmark, I ignore both the time dimension in the data and the potential endogeneity of household worklessness and fit a pooled probit model to estimate β_1. As Wooldridge (2010) highlights, pooling alone makes test statistics unreliable and combined with a potentially endogenous explanatory variable of interest, all estimates might be biased.

I use three different methods to reduce bias and estimate the causal relationship between household worklessness and educational investments. In the first approach, I apply an instrumental variable approach based on Macmillan (2010). Second, I focus on outcome variables observed at multiple points in time and use a fixed effects approach to measure the effect of worklessness on these educational investments.

Third, I use data on *future household worklessness* observed in a later sweep than the outcome variable of interest (see Gottschalk 1996). I do this by including two variables, one indicating if the household has a worklessness spell in the future and one indicating if the household is not workless for at least one sweep in the future.

3.3.3.2. Instrumental variables – bivariate probit

To account for potential endogeneity of household worklessness, I use an instrumental variable approach. In the literature, worklessness has been instrumented using different methods. Macmillan (2010) and Mäder, Riphahn et al. (2015) both use an instrumental variable strategy to estimate the effect of parental worklessness on children's future worklessness (intergenerational worklessness). For this, Macmillan (2010) uses a dummy indicating which industries were hard hit during the 2007 financial crisis and similarly Mäder, Riphahn et al. (2015) computes for which sectors transitioning into worklessness is more likely. Sieger (2013) introduces an instrument based on the regional composition of the labour market in terms of industry and the countrywide unemployment level in this industry. This instrument adds variation by region and over time and indicates whether the regional labour market is under strain.

I create an instrument based on the Standard Occupational Classification (SOC) categories given for current and last job in the Millennium Cohort Study. For this, I use data from the quarterly UK Labour Force Survey (LFS)[14] between April 2001 and October 2018. During this time between 55,000 and 239,000 adults[15] were surveyed for each of the 44 cycles. Of these, an average of 78,000 provided information on their current or previous job's SOC category.

For each of the resulting 102 SOC categories the LFS contains, on average, around 700 observations for each survey, ranging from as little as below 40 ('Conservation and Environmental Associate Professionals') to more than 3,000 ('Sales assistants and retail cashiers'). Especially in smaller SOC categories, the worklessness rate fluctuates in part due to measurement error as well as a changing composition of the LFS sample. However, the size of SOC categories is strongly correlated between the Labour Force Survey and the the MCS ($\rho = 0.95$), indicating that in both the MCS and LFS the distribution of occupations is comparable. Thus, small SOC categories in the Labour Force Survey affect the instrumental variable for only a few households

[14] ONS 2020.

[15] Between the age of 15 and 65.

in the MCS.

To construct the IV, I first compute the proportion of non-working adults for each SOC category. Overall, between 13% and 18% of adults with an SOC category are workless, the lowest worklessness rates observed in 2017 and 2018 and the highest worklessness rates between 2009 and 2012. On average, women are workless at higher rates than men: across sweeps, men are workless at a rate between 10% and 16% while women are not employed at a rate between 16% and 22%. This is likely due to childcare responsibilities disproportionally being taken over by women.

The rates of non-working vary substantially between occupations and over time. While employees in elementary process plant operations have the highest average worklessness rate at 32%, only 7% of architects and town planners are workless. Furthermore, within occupation the difference over time varies. Employees in caring professional services are workless at a very constant rate (around 20%) with a range of only around 2 percentage points over 17 years. Other occupations face much greater fluctuations of worklessness, e.g. the worklessness rate of assemblers and routine operatives varies around 23 percentage points over the years.

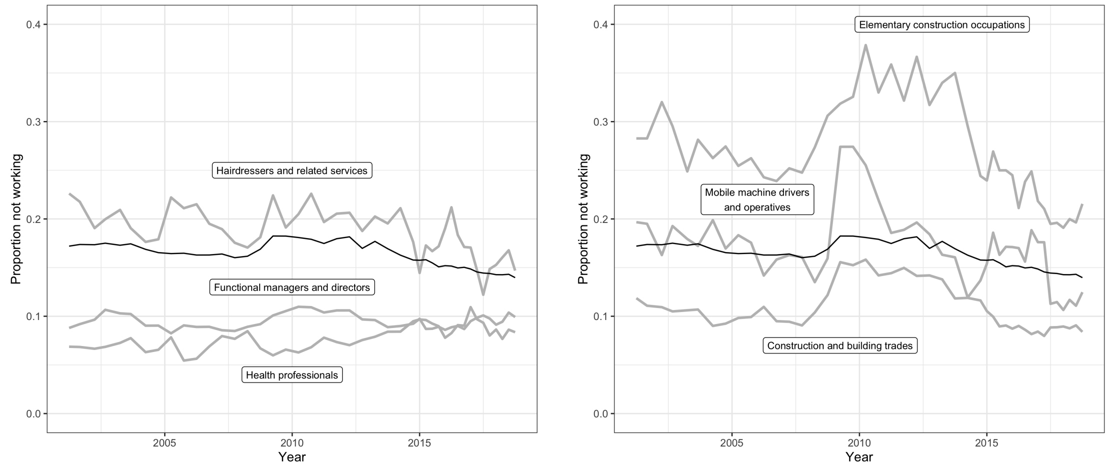
Figure 3.3 shows six occupations to illustrate the differences between them. Worklessness among health professionals, for example, is low and does not change much over time while elementary construction occupations have a high worklessness rate in all years with an increase between 2008 and 2014 during the financial crisis.

To translate these individual occupational worklessness rates into an instrument for household worklessness in two-parent households, I combine them into one household instrument according to the occupation categories of mother and father as well as the month and year of the MCS interview. Absolute levels of worklessness differ substantially between occupations resulting in very different levels of household worklessness risk. This may result in the instrument being strongly correlated with either unobserved confounders or with the outcome variables themselves. For example, low ability parents might be more likely to be workless than high ability parents. Ability is not observed directly, potentially causing bias in my estimates.[16] If low ability parents self-select into professions with high worklessness rates, this

[16] In Sweep 6 (age 14), parents are asked to complete a word recognition test which may be used as a proxy for ability. However, as this ability score is observed only for households participating in Sweep 6, this would reduce sample size considerably to around 10,600 households. Furthermore, as family compositions or parental ability might change over time, scores of primary carers at Sweep 6 do not necessarily reflect the scores they would have achieved in any of the previous sweeps. I use the word recognition scores as a robustness check and find that including them does not change my results. See Appendix B.3, Table B.18.

Figure 3.3.: Worklessness by Occupation

(a) Occupations with minor changes over time (b) Occupations with major changes over time



Notes: The left figure shows a selection of occupational categories which do not change much over time. The right figure shows occupations majorly affected by the 2008 financial crisis. The solid black line represents the average proportion of adults not working across occupations. Data from the UK Labour Force Survey (ONS 2020).

would violate the assumptions of the instrumental variable approach.

To avoid this problem, I take the difference of a household's current worklessness risk and the average worklessness risk of this household's current occupations between 2001 and 2018. For illustration purposes, consider a single parent working in elementary construction occupations (SOC 912) who never changes their job. The average worklessness rate of this occupation between 2001 and 2018 is around 27%. However, as Figure 3.3 illustrates, the worklessness rate varies substantially over time in this occupation. When the cohort members are between 5 and 7 years old, the worklessness rate measured from the LFS is lower than the average value of 27% at around 25%. In this example, the instrumental variable shows that the household's worklessness risk is lower than normal and takes the value -2%. During the following MCS sweep when cohort members are around 11 years old, the worklessness rate for people in elementary construction occupations observed in the LFS is much higher at almost 37%. So the worklessness rate is now 12 percentage points larger than the average value of 27%, resulting in the instrumental variable taking the value +12%.

Augmenting the example to a two-parent household with an elementary construction worker and a hairdresser adds an additional layer. A hairdresser's average worklessness rate is at around 19%, according to my analysis of the LFS. Combined with the average worklessness rate for construction workers, this results in an average household worklessness risk of $.19 * .27 = .0513$, thus 5.13%. In early 2008 around the time when cohort members were 7 years old, the worklessness rate for construction workers was at 27% and for hairdressers at 17%, resulting in a combined household risk of 4.59% ($.27 * .17$), 0.54 percentage points lower than average. The instrumental variable for this household takes the value -0.0054. In early 2012, however, the worklessness risk for both professions went up to 37% and 21%, respectively. This results in a combined household worklessness risk of 7.77% ($.37 * .21$), 3.18 percentage points higher than the average risk. In this example, this would result in the instrumental variable to take the value 0.0318.

Next, I introduce the estimation technique used to measure the causal link with the endogenous binary variable, household worklessness, and a binary outcome variable. This can be estimated either by a two-stage least-squares (2SLS) IV regression with a linear probability model at each stage (Hellevik 2009), or by a bivariate probit model. Following Chiburis et al. (2011) and Scott-Long (1997), I apply the bivariate probit approach as it is more suitable to estimate models with continuous covariates (such as income and age) and where the binary endogenous variable worklessness takes the value 1 (workless) only in fewer than 20% of observations. For an in-depth discussion of the estimation technique used, see Appendix B.2.

Similar to the univariate probit model introduced in Section 3.3.3.1, the bivariate probit model for the estimation of the binary outcome, D, and the binary endogenous 'worklessness' variable, wl, is constructed as follows:

$$D^* = \beta_0 + \beta_1 wl + \beta_2 X + \epsilon_D \tag{3.3}$$

$$wl^* = \gamma_0 + \gamma_1 z + \gamma_2 X + \epsilon_{wl}, \tag{3.4}$$

where z denotes the instrument and D^* and wl^* are latent variables, translating to their respective binary outcomes, D and wl:

$$D = \begin{cases} 1 & \text{if } D^* > 0, \\ 0 & \text{otherwise} \end{cases} \tag{3.5}$$

$$wl = \begin{cases} 1 & \text{if } wl^* > 0, \\ 0 & \text{otherwise} \end{cases} \tag{3.6}$$

The error terms in Equations 3.3 and 3.4 are jointly distributed with mean zero and covariance ρ, given all explanatory variables.

An instrumental variable approach comes with three assumptions: *relevance*, *exclusion restriction* and *exchangeability*. The relevance assumption states that the instrument (household worklessness risk estimated from SOC codes) must be strongly associated with the endogenous variable (household worklessness). To my knowledge there is no statistical test for this tailored to the bivariate probit approach taken. Therefore, I test this assumption using the first stage of a 2SLS approach. Table 3.5 shows the results from a weak instrument test for all relevant subsets of the data. For all combinations of sweeps used in this study the Kleinberg-Paap Wald F-statistic to test for weak instruments shows values well above the Stock-Yogo critical value of 16 as well as the critical value of 104.7 recently suggested by Lee et al. (2020) Therefore, I conclude that the instrument proposed in this section is indeed relevant.

The exclusion restriction states that there is no effect of instrument (difference between average household worklessness risk and current household worklessness risk) on the outcome variables (educational investments) through any channel other than the endogenous variable, worklessness. As this assumption cannot be tested, I discuss whether I believe this assumption to hold. Since the instrumental variable is based on a household's *difference* between the average worklessness risk based on parents' occupations and the current worklessness risk, self-selection mechanisms are unlikely to cause a violation in the exclusion restriction. However, during the years of the financial crisis some professions faced a drastic change in worklessness risk (e.g. construction workers). The instrument would reflect this by positive values during the financial crisis in the most affected professions. This is potentially problematic for the analysis of MCS data around the financial crisis if employees who self-select into affected professions have different (unobserved) attitudes towards educational investments which are not yet controlled for by included background variables. In this case, the exclusion restriction would be violated. However, for this to be an issue,

Table 3.5.: Weak identification test – F-statistics

Sweep	1 (9m)	2 (3y)	3 (5y)	4 (7y)	5 (11y)	6 (14y)
Single sweeps	1548.95	1284.55	1814.06	1486.03	3171.83	1157.97
Sweep 1-6	8571.44					
Sweep 1-2	2824.26					
Sweep 2-4	4002.40					
Sweep 3-4	2952.37					
Sweep 5-6	3525.65					

Notes: Kleibergen-Paap rk Wald F-statistic to test for weak identification with cluster robust standard errors. Stock-Yogo critical values indicate the F-statistic should take values larger than 16 to avoid a weak instrument.

strong assumptions need to be made. For one, employees in those professions hardest hit by the economic crisis would need to have certain characteristics in common. Second, these characteristics are directly correlated with educational investments. I consider these assumptions not to be very likely to hold. Furthermore, even in case the exclusion restriction was violated around the financial crisis, the instrumental variable would still be valid for the analysis of educational investments at other times.

The last assumption, exchangeability, states that the instrumental variable does not share a common cause with the outcome variables. The instrumental variable is in essence an indicator of the strain the labour market puts on certain households: in economically good times the instrument takes negative values, in bad times positive. The outcome variables, however, are unlikely to be strongly affected by the labour market as a whole. This holds especially true for all outcomes related to time investments.

One key difficulty remains regarding the interpretation of the results from an IV estimation. Under the assumption that all households in the MCS react to the instrument in the same homogenous way,[17] IV estimates would be consistent estimates of the average treatment effect (ATE). However, some households might not react to the instrument (i.e. labour market situation in their profession) the same way as other households do. If one assumes that there are two types of households – those who react to the instrument in a monotonous way and those who do not react to the instrument at all – the IV estimates are consistent estimates of the local average treatment effect (LATE) of households that react to the instrument. Therefore, as the assumption that all households are affected by the instrument homogeneously is likely violated, I interpret the IV estimates as local average treatment effects of those households that do react to the IV.[18] However, for the LATE interpretation to hold, the direction the instrument affects worklessness must be the same for all individuals. This means that a higher predicted worklessness risk cannot be the reason for a household to find work.[19]

[17] In the context of treatment assignment as instrument this can be understood as all participants are compliers.

[18] When further relaxing assumptions, the IV estimator gives greater weight to those individuals whose parents are most likely to become workless when the instrument takes high values and to get a job once the instrument takes on small values.

[19] For a detailed discussion of the LATE interpretation of the IV estimates, see Angrist & Pischke (2009).

3.3.3.3. Fixed effects

Recall the model I aim to estimate as shown in Equation 3.1:

$$D^*_{it} = \beta_0 + \beta_1 wl_{it} + \beta_2 X_{it} + \underbrace{c_i + \epsilon_{it}}_{\text{unobserved}}.$$

If there is an unobserved time-invariant element correlated with the outcome variable, i.e. $c_i \neq 0$, estimating the effect of worklessness suffers from endogeneity. If the endogeneity is caused by this time-invariant confounding factor alone, a fixed effects approach removes this endogeneity and the bias it may cause.

The fixed effects approach possibly suffers from low power to detect the causal relationship between household worklessness, wl, and the binary outcome variable of interest, D. The effect size is only computed based on with-individual variation in household variation, meaning that households that are never workless or that never work for the time frame of the regression do not contribute to the estimation of the parameter of interest. While sample sizes and variation are sufficient for outcome variables such as parents having enough time with their child, the analysis of the relationship of household worklessness with paid-for extra lessons might suffer from a small number of observations: only for a total of 75 cohort members do household worklessness *and* paid-for extra lessons change.

To estimate the fixed effects coefficients, one can use a linear probability model with fixed effects or a conditional logistic model. While both approaches can be expected to result in a consistent estimate of the effect size (see Appendix B.2 for a detailed discussion), only the linear probability model's regression coefficients are directly interpretable and can be compared to the marginal effects from my other regression analyses. Therefore, I report the results of the linear probability fixed effects approach and use the conditional logit approach as a robustness check.

In the context of this study, the fixed effects estimator relies on variation household worklessness. Moreover, only educational investments by households that are workless for at least one relevant period affect the fixed effects estimates. As only a subset of households are workless for one or more periods, the fixed effects approach estimates the average treatment effect among the treated (ATT). This is different from the (weighted) LATE interpretation of the IV estimator discussed above.

Note that the assumptions of an alternative *random effects* model are not met and are rejected by the Hausmann test.

3.3.3.4. Future worklessness

One of the methods introduced by Gottschalk (1996) for causal analysis of worklessness is to use future worklessness spells to control for variation in the data caused by unobservable factors. In the context of this study, the idea is that – while a regression of current worklessness on current educational investments may result in biased estimates because of unobserved factors – including future household worklessness as a control variable accounts for unobserved effects and reduces bias in the estimate for the causal effect of worklessness on educational investments. Since household worklessness is closely related to household composition with single-parent households being more likely to become workless, I also include future household composition as a covariate, resulting in the following regression models:

$$D^*_{it} = \beta_0 + \beta_1 wl_{it} + \beta_2 X_{it} + \underbrace{\gamma_1 wl_{it,F} + \gamma_2 wk_{it,F}}_{\text{future employment status}} + \overbrace{\delta_1 sp_{it,F} + \delta_2 tp_{it,F}}^{\text{future household composition}} + c_i + \epsilon_{it}. \quad (3.7)$$

The subscript F indicates variables containing information about future worklessness/non-worklessness and future single-parent/two-parent status. I construct the variables about future employment status, $wl_{it,F}$ and $wk_{it,F}$, as follows. For household i in period t, $wl_{it,F}$ takes the value 1 if this household is workless in any period $f > t$ and it takes the value 0 otherwise. The variable $wk_{it,F}$ indicates future non-worklessness in the same way and variables sp and tp indicate spells of future single parenthood and two-parenthood, respectively.

While emphasising this method's potential for bias reduction, Elwert & Pfeffer (2019) highlight some limitations. First, the better current worklessness causally predicts future worklessness (true state dependence), the worse the properties for bias reduction. This is a potential issue for my analyses. For workless households to become working, at least one parent needs to find a job. Conversely, in a working household *all* working parents need to lose their job in order to turn this household workless.[20] Moreover, Elwert & Pfeffer (2019) show that a very strong link between occupation status in $t_{present}$ and t_{future} might even exacerbate bias instead of reducing it.

[20] Alternatively, a household can transition from two-parent to single-parent and become workless due to that.

In the context of the problems detailed in this section, future worklessness is likely to perform better for earlier sweeps as later sweeps are more likely to contain independent information than adjacent sweeps. For example, future worklessness when the cohort member is only 9 months old contains information about the household's occupation status for the following 17 years over six sweeps as I use employment data and household composition from the recently published seventh sweep (age 17).

I observe that households that were workless in the Age 9 Months Sweep have a 79% chance of having at least one future worklessness spell, compared to only 17% among households who were not workless at the Age 9 Months Sweep. The correlation between household worklessness and future worklessness spells intensifies in later sweeps (68% compared to 3% in the Age 14 Sweep) as fewer future periods are observed. Similarly, 70% workless households at the Age 9 Months Sweep have at least one future period in which the household is not workless compared to 98% among working households.

Again, this difference between workless and working households becomes more pronounced in later sweeps: at age 14, only 32% of workless households have a future working sweep compared to 97% of working households. Whether the link between current household worklessness and future occupation is strong enough to potentially exacerbate bias is unclear. However, as I include both information on future worklessness spells and future working spells as well as information on future household composition, this estimation method might help reduce bias, in particular when used in comparison with other estimation techniques.[21]

Note that a disadvantage of this approach is a reduced sample size because of households dropping out in the following sweep. For example, a household participating up until the Age 7 Sweep does not contain any information about future worklessness and future household composition from subsequent sweeps. Therefore, this household cannot be analysed in the Age 7 Sweep either.

[21]The results from my estimations presented in Section 3.4 suggest that including future worklessness spells as a control variable does not meaningfully change my estimates as compared to the benchmark pooled probit case.

3.4. Results

3.4.1. Associations

Table 3.6.: Descriptive results – time investments

	Two-parent		Single-parent	
Variable	working	workless	working	workless
Enough time with child				
Sweep 1	72%	95%	55%	91%
Sweep 2	70%	94%	43%	87%
Sweep 3	26%	52%	21%	42%
Sweep 4	28%	50%	17%	40%
Sweep 5	32%	55%	23%	37%
Sweep 6	24%	42%	20%	36%
Reading to child (several times per week or more)				
Sweep 2	90%	70%	76%	66%
Sweep 3	92%	83%	79%	76%
Sweep 4	85%	73%	67%	64%
Help child with reading (several times per week or more)				
Sweep 3	90%	81%	86%	81%
Sweep 4	48%	47%	45%	51%
Help child with writing (several times per week or more)				
Sweep 3	62%	65%	63%	63%
Sweep 4	33%	35%	35%	39%
Help child with maths (several times per week or more)				
Sweep 3	66%	72%	69%	69%
Sweep 4	22%	23%	21%	25%
Help child with homework regularly				
Sweep 5	48%	49%	45%	46%
Sweep 6	71%	66%	62%	60%

Notes: Total number of households: 15,640. Sample weights and inverse probability weights applied.

The first result I present in this section focusses on the pure association between worklessness and educational investments without accounting for any background characteristics. Tables 3.6 and 3.7 show time and money investments and how they differ in workless and working households. The left side of the tables shows the difference within two-parent households, the right side for single-parent households.

The first observation from these descriptive results is that workless parents are much more likely to report that they have enough time available with their child than parents in working households. This is true both in single-parent and two-parent households. However, the additional time available is not reflected in higher time investments. Workless parents are less likely to regularly read to their child. They help their child with reading, writing, maths, and homework at about the same rate as parents in working households.

Furthermore, children in workless households are less likely to receive monetary investments in their education. Workless parents are less likely to pay for childcare, with less than one in 10 workless households paying for childcare compared to up to half of working households. Children in workless households are very unlikely to attend a fee-paying school.[22] Futhermore, working households pay for extra lessons at much higher rates than workless households. Especially around the time at which pupils transition from primary to secondary school between 12% (single-parent) and 18% (two-parent) of children from a working background take paid-for extra lessons, compared to only 4% of children from workless households.

Overall, this suggests that the average child growing up in a workless household does not receive more time investments in their education while having fewer monetary resources invested in them, compared to the average child in a working household – regardless of household composition. However, these estimates do not take into account any background characteristics such as parental education. The remainder of this section explores the causal link between worklessness and educational investments.

Table 3.7.: Descriptive results – monetary investments

	Two-parent		Single-parent	
Variable	working	workless	working	workless
Pay for childcare				
Sweep 1	26%	2%	37%	2%
Sweep 2	36%	4%	50%	10%
Fee-paying school				
Sweep 3	5%	0%	3%	1%
Sweep 4	5%	0%	2%	0%
Sweep 5	6%	2%	2%	1%
Sweep 6	8%	2%	2%	2%
Pay for extra lessons				
Sweep 5	18%	4%	12%	4%
Sweep 6	8%	4%	6%	3%

Notes: Total number of households: 15,640. Sample weights and inverse probability weights applied.

[22] Only between 11 and 32 students in fee-paying schools are workless, depending on MCS sweep.

3.4.2. Conditional Associations

In this paragraph, I present the estimated associations between household worklessness and the outcome variables, conditional on an increasingly large set of background characteristics as described in Section 3.3.2. From loading more variables into the analysis, a few observations can be made. First, for variables such as 'enough time with child', 'paid-for childcare', and 'paid-for extra lessons', including more background characteristics reduces the magnitude of the point estimate. In case of paid-for extra lessons, including parental income and home-ownership results in no association at all. With fewer control variables, estimates indicate a stronger association than when controlling for background information such as demographics,

Table 3.8.: Conditional associations of household worklessness with respective outcome variables

	Model				
Outcome Variable	M1	M2	M3	M4	N
Time investments					
Enough time with child	0.302***	0.214***	0.191***	0.143***	67,550
	(0.00857)	(0.00817)	(0.00840)	(0.00886)	
Reading to child	-0.0693***	-0.0154*	0.0118	0.0284***	35,680
	(0.00805)	(0.00781)	(0.00791)	(0.00824)	
Help child with...					23,210
Reading	-0.00798	-0.0144	-0.00279	0.00214	
	(0.0128)	(0.0124)	(0.0128)	(0.0135)	
Writing	0.0306*	0.00943	0.00661	0.00464	
	(0.0137)	(0.0139)	(0.0144)	(0.0152)	
Maths	0.0391**	0.0164	0.0146	0.0153	
	(0.0129)	(0.0127)	(0.0130)	(0.0138)	
Homework Help	-0.0201	0.0250	0.0329	0.0435*	18,261
	(0.0185)	(0.0190)	(0.0191)	(0.0205)	
Monetary investments					
Paid-for Childcare	-0.441***	-0.349***	-0.308***	-0.202***	26,079
	(0.0147)	(0.0161)	(0.0159)	(0.0166)	
Paid-for Extra Lessons	-0.0979***	-0.0723***	-0.0590***	-0.0200	18,261
	(0.0122)	(0.0127)	(0.0128)	(0.0136)	
Single parenthood	x	x	x	x	
Demographics & Health		x	x	x	
Parental education level			x	x	
Economic situation				x	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Data from age-1-sweep until age-14-sweep. All results are average marginal effects from a pooled probit model with different sets of background variables included (see Section 3.3.2).

parental education and – in particular – parental income and housing situation.

Second, For variables such as ‘reading to child’ and ‘homework help’, I observe a reversal of the sign of the association. For example, while Model M1 suggests that workless parents are less likely to read to their child on a regular basis, including more parental background information reverses the sign: workless parents with comparable demographics, similar education background and income are *more* likely to regularly read to their child.

Third, in outcome variables related to helping children with reading, writing, and maths, including more background characteristics does not change my estimated associations by much. Overall, I do not observe an association between household worklessness and any of these outcome variables.

In summary, depending on the outcome variable of interest, including more background characteristics has a different impact on the measured conditional association. Estimated associations between household worklessness and monetary investments are particularly impacted by including household income as a control variable. While unsurprising – income determines how much money a household is able to spend on a child’s education – this is important to bear in mind when interpreting the results of the following sections.

3.4.3. Time Investments

3.4.3.1. Enough time with child

In all six sweeps of the MCS, both parents report on whether they consider the time they have with their child as enough. Table 3.9 shows the estimated effect size of household worklessness on parents' reports on their time with their child. The estimates from all regressions are positive and significant at the 0.1% level. As my results are robust across several different approaches, this is strong evidence for the causal positive impact household worklessness has on parents having enough time with their child.

I estimate parents in workless households to be between 9 and 14 percentage points more likely to report having ample time with their child as compared with parents in working households.[23] These results are also in line with the associations discussed in Section 3.4.1. Furthermore, all robustness checks support the results discussed in this section. Overall, these results support the hypothesis that workless parents have more time to spare and could potentially spend it investing in their child. Next, I analyse how parents use this additional time to assist their child's education.

3.4.3.2. Reading to child

Table 3.10 shows the result of my regression analyses estimating the causal link between household worklessness and the frequency parents read to their child. The pooled probit, bivariate probit, and future worklessness estimates are statistically significant at between the 1% and 0.1% level. However, the fixed effects estimate has a point estimate close to zero and is statistically not significant.[24]

The statistically significant regressions estimate that parents in workless households are between 3 and 9 percentage points more likely to read to their child multiple times per week than parents in working households.

When regressing on each cross-section separately as a robustness check, I find that the link between worklessness and the frequency with which parents read to their

[23]Children growing up in single-parent households are between 12 and 15 percentage points less likely to have a parent that reports to have plenty of time with the child. This highlights the importance of controlling for household composition when looking at household worklessness.

[24]The conditional logistic regression fixed effects approach supports this result and also does not show a significant effect of worklessness on the frequency parents read to their child.

Table 3.9.: Enough time with child

	(1) Pooled probit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Workless	0.143***	0.0914***	0.100***	0.122***
	(0.00886)	(0.0228)	(0.00875)	(0.00944)
Single-carer	-0.153***	-0.138***	-0.121***	-0.147***
	(0.00837)	(0.0105)	(0.0104)	(0.00922)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Data from Age 9 Months until Age 14 Sweeps. Number of households: 15,640. Number of household-sweep observations: 67,550. Categorical outcome variable recoded as binary categories. Households in which at least one parent has 'plenty of time', 'more than enough time' or 'too much time' are coded as 1, households in which parents have 'just enough time' or less are coded as 0. Regression 3 shows results from a fixed effects linear probability model. All other results are average marginal effects. Cluster robust standard errors. Sample weights and inverse probability weights applied.

Table 3.10.: Reading to child

	(1) Pooled probit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Workless	0.0284***	0.0936***	-0.00264	0.0267**
	(0.00823)	(0.0187)	(0.0132)	(0.00873)
Single-carer	-0.153***	-0.185***	-0.107***	-0.140***
	(0.0119)	(0.0141)	(0.0187)	(0.0128)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Data from Age 3, Age 5, and Age 7 Sweeps. Number of households: 14,104. Number of household-sweep observations: 35,680. Categorical outcome variable recoded as binary categories. Households in which two parents read to their child 'once or twice a week' and households in which at least one parent reads to their child 'several times a week' are coded as '1', households in which parents read to their child less frequently are coded as '0'. Regression 3 shows results from a fixed effects linear probability model; a conditional logit model supports the result from the linear probability model. All other results are average marginal effects. Cluster robust standard errors. Sample weights and inverse probability weights applied.

child is strongest for the Age 5 and Age 7 Sweeps and I find no significant link at age 3 (see Table B.13). Furthermore, robustness checks changing the cut-point when creating the binary variable and using an ordered logistic regression confirm my results presented above: pooled probit, bivariate probit, and future worklessness approaches all result in significant point estimates while the fixed effects estimates are insignificant. Again, point estimates for pooled probit and future worklessness approaches are substantially lower than for those obtained from the bivariate probit.

Overall, these results are mixed. The fixed effects regression shows no significant effect while all other approaches estimate a significant association between household worklessness and the regularity with which parents read to their child. As the results are sensitive to the analytic approach, I conclude that the evidence is tentative, showing evidence for a positive association but not for causality.[25] This is a stark contrast to the descriptive results discussed in Section 3.4.1 which showed that parents in workless households were *less* likely to read to their child regularly, not controlling for any background characteristics.

3.4.3.3. Helping child with reading, writing, and maths

Parents can invest their time by helping their child learn how to read, write, and do maths. In MCS Sweeps 3 and 4, the main carer reports on the frequency with which someone in the household helps the child (aged 5 and 7) with reading, writing, and maths.

Table 3.11 shows the results from my regression analyses. For all three outcome variables, none of the estimates are statistically significant, the only exception being the fixed effects estimate for parents helping their child with writing (five percent level).[26] Moreover, most point estimates for the effect size fall very close to zero. Overall, this suggests that there is no causal link between household worklessness and the amount of time parents spend helping their child with homework. This result is supported by all robustness checks (Appendix B.3). The associations discussed in Section 3.4.1 show a mixed relationship between household worklessness and parents helping their children with reading, writing, and maths, largely depending on the MCS sweep and subject. Therefore, finding there to be no causal relationship nor

[25] As discussed in Section B.2, the fixed effects approach estimates the average treatment effect among the treated (ATT) whereas an instrumental variable approach estimates a local average treatment effect (LATE). This can help explain part of the difference in my results.

[26] The conditional logit regression fixed effects approach results in a non-significant estimate for parents helping their child with writing.

Table 3.11.: Helping child with reading, writing, and maths

(a) Dependent variable: help with reading

	(1) Pooled probit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Workless	0.00216	0.0156	0.0464	0.00419
	(0.0135)	(0.0230)	(0.0246)	(0.0147)
Single-carer	-0.0191	-0.0234	0.0283	-0.0178
	(0.0129)	(0.0140)	(0.0332)	(0.0144)

(b) Dependent variable: help with writing

	(1) Pooled probit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Workless	0.00459	-0.00774	0.0596*	0.00119
	(0.0152)	(0.0323)	(0.0244)	(0.0165)
Single-carer	-0.0143	-0.0103	-0.0559	-0.00994
	(0.0147)	(0.0172)	(0.0349)	(0.0166)

(c) Dependent variable: help with maths

	(1) Pooled probit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Workless	0.0153	-0.0112	0.0287	0.00837
	(0.0138)	(0.0312)	(0.0234)	(0.0149)
Single-carer	-0.0224	-0.0139	0.000111	-0.0170
	(0.0134)	(0.0161)	(0.0339)	(0.0155)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Data from Age 5 and Age 7 Sweeps. Number of households: 12,897. Number of household-sweep observations: 23,210. Categorical outcome variable recoded as binary categories. Helping child with the respective subject at most 'once or twice a week' to the child is coded as '0' and helping child at least 'several times a week' is coded as '1'. Regression 3 shows results from a fixed effects linear probability model; all corresponding conditional logit models are not significant. All other results are average marginal effects. Cluster robust standard errors. Sample weights and inverse probability weights applied.

strong association once controlling for background characteristics is in line with the unconditional associations presented above.

3.4.3.4. Homework help

Similar to parents helping their child with reading, writing, and maths, MCS Sweeps 5 and 6 contain information on parental homework help for cohort members aged 11 and 14.

Table 3.12 shows the estimates for the effect of household worklessess on parental homework help. The estimates from the pooled probit regression and the model using future worklessness to remove bias are statistically significant at the 5% level. Both the IV and fixed effects approach are statistically not significant. This suggests that there might be a weak positive association between household worklessness and the frequency with which parents help their child with homework. However, this finding is not supported by any of the robustness checks, which all show no significant association. Overall, I conclude that there is no clear evidence for a causal effect of worklessness on the frequency with which parents help their child doing homework. This is also in line with the associations presented in Section 3.4.1.

Table 3.12.: Homework help

	(1) Pooled probit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Workless	0.0435*	0.0237	0.0291	0.0590*
	(0.0205)	(0.0360)	(0.0338)	(0.0232)
Single-carer	-0.0682***	-0.0664***	-0.0216	-0.0559*
	(0.0184)	(0.0186)	(0.0371)	(0.0223)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Data from Age 11 and Age 14 Sweeps. Number of households: 10,387. Number of household-sweep observations: 18,261. Categorical outcome variable recoded as binary categories. Homework help 'Never' or 'Sometimes' is coded as '0' and homework help 'Usually' or 'Always' is coded as '1'. Regression 3 shows results from a fixed effects linear probability model, conditional logit fixed effects estimates supporting the results. All other results are average marginal effects. Cluster robust standard errors. Sample weights and inverse probability weights applied.

3.4.4. Monetary Investments

3.4.4.1. Pay for childcare

When children are young, parents may decide on paying for professional childcare to reduce their own childcare obligations. While this decision is often made for pragmatic reasons to lower the childcare burden for parents, it is also an important investment in the generation of children's human capital (Campbell et al. 2002; Karhula et al. 2017; Nores et al. 2005; Schweinhart et al. 1985). In the first two sweeps of the MCS, parents report whether or not they pay for childcare for their child aged around 9 months to 3 years. Overall, around 24% of parents do pay for childcare.

As discussed in Section 3.4.1, workless households are less likely to pay for childcare compared to working households. Table 3.13 shows the results of several approaches to measure the *causal effect* of household worklessness on childcare.

All approaches indicate that the likelihood of workless parents paying for their children's childcare is significantly (0.1% level) lower than for working parents. My estimates suggest household worklessness causes these households to be between 7 percentage points (fixed effects model) and 20 percentage points (pooled probit) less likely to pay for childcare. As the estimates from the instrumental variable approach, fixed effects regression, and using future worklessness all suggest a smaller link between worklessness and paid-for childcare, this suggests that the causal effect is strictly smaller than 20 percentage points.

Table 3.13.: Paying for childcare

	(1) Pooled probit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Workless	-0.202***	-0.0944***	-0.0685***	-0.177***
	(0.0166)	(0.0277)	(0.0138)	(0.0176)
Single-carer	0.196***	0.149***	0.0837***	0.193***
	(0.0162)	(0.0187)	(0.0212)	(0.0172)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Data from Age 9 Months and Age 3 Years Sweeps. Number of households: 14,840. Number of household-sweep observations: 26,079. Regression 3 shows results from a fixed effects linear probability model with a conditional logit fixed effects model confirming the estimated significance level (not in table). All results are average marginal effects. Cluster robust standard errors. Sample weights and inverse probability weights applied.

This reflects the associations discussed in Section 3.4.1: between 2% and 10% of workless parents pay for childcare, compared to between 26% and 50% when at least one parent has work. However, my estimates suggest that household worklessness is causally related to not using childcare, controlling for background characteristics such as household income. Together with workless parents reporting having enough time with their child, this suggests that workless parents spend their time rather than their money on childcare.

This finding is of particular interest in the context of UK childcare policy. Since 2017, every *working*[27] family is entitled to 30 hours per week free childcare, compared to 15 hours per week for all other families. As my estimates control for household income and other related factors such as single-parent status, my findings suggest that worklessness causes parents to have substantially lower demand for childcare. This could mean that after the introduction of free childcare, workless parents might not take up this offer as frequently as working parents – *additionally* to the difference in eligibility. In the context of the benefits of childcare for child development discussed in Sections 1.2 and 3.1, this finding could mean that household worklessness leads to adverse outcomes through lower childcare uptake. If the difference in childcare uptake were to persist after 2017, this could be a reason to reevaluate differentiating between working and workless families in free childcare policies. Furthermore, it could be possible to actively encourage workless parents to take up free childcare offers, which might positively affect their child's development.

3.4.4.2. Extra lessons

When parents want to help their children improve their marks they might decide to pay for extra lessons. In the UK context, this appears to be particularly common around the age of 11 shortly before children move on from primary to secondary schools and potentially take entry exams to get into selective school forms such as grammar schools. Around 17% of pupils in the MCS sample sit such entrance exams. While at age 7, less than 5% of pupils receive extra lessons, paid for or not, at age 11, 15% of households pay for extra lessons and 8% do so at age 14.[28]

Table 3.14 shows the effect of worklessness on paid extra lessons for MCS Sweeps 5 and 6 (age 11 and 14). None of my estimates show a statistically significant link

[27] Both carers need to be in work in two-carer households.

[28] As discussed in Appendix B.2, linear probability models might be biased in this context. This affects the effect sizes measured by the fixed effects linear probability model.

Table 3.14.: Extra lessons

	(1) Pooled probit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Workless	-0.0200	-0.0374	-0.0238	-0.0212
	(0.0136)	(0.0238)	(0.0150)	(0.0154)
Single-carer	0.00270	0.00419	-0.0293	0.00373
	(0.0113)	(0.0114)	(0.0202)	(0.0129)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Data from Age 11 and Age 14 Sweeps. Number of households: 10,387. Number of household-sweep observations: 18,261. Regression 3 shows results from a fixed effects linear probability model, a conditional logit fixed effects model results in a non-significant estimate. All results are average marginal effects. Cluster robust standard errors. Sample weights and inverse probability weights applied.

between household worklessness and whether or not parents pay for extra lessons. Therefore, I do not observe a causal link between household worklessness and whether or not children receive paid-for extra lessons.

While the associations discussed in Section 3.4.1 showed that children in workless households are substantially less likely to receive extra lessons, this association is not causal. This means that – when accounting for background characteristics such as household income and parental education and using methods to account for potential endogeneity of the worklessness variable – the estimates are not significant and point estimates are close to zero.

This result is particularly interesting when comparing the causal link between worklessness and homework help as both outcome variables cover the age range from 11 to 14. Parental worklessness does not cause parents to spend more time helping their child doing homework, nor do workless parents spend less money on extra lessons. Similarly, results for the Age 5 and Age 7 Sweeps indicate that workless parents do not help their child with reading, writing, or maths significantly more often than parents in working households.

3.5. Conclusion

The results of my analyses are mixed. While workless parents report to be more satisfied with the time they can spend with their child, they do not necessarily use it for educational purposes.

My estimates suggest that workless parents might read to their child more regularly. However, as the results are very sensitive to the methods used, my estimates do not allow for any causal claims. When looking at more school-related tasks such as helping to read, write, do maths, or do homework, workless parents seem to help their child just as frequently as parents in working households. One explanation for this is that working households include those in which at least one parent does not work full-time. In case of two-carer households, one parent might stay at home explicitly to care for the children while the other may work. Furthermore, as Balli et al. (1997) highlights, many parents might struggle to help with their child's homework.

Focussing on monetary investments, workless parents are up to 18 percentage points less likely to pay for childcare when children are between 1 and 3 years old. As childcare is often used by parents to lower the burden of their own childcare obligations in the face of other commitments, workless parents – having more time at their disposal – take care of their child themselves. However, I do not find a causal link between household worklessness and whether parents pay for extra lessons when the child is around 11 and 14. Possibly, this is because low-income working parents most comparable to workless parents have similar resources or preferences.

Overall, my results suggest that there is only a limited causal link between worklessness and educational investments. While I still find an effect of worklessness on investments into very young children, differences are not significant for older pupils going to school. In the context of the literature investigating intergenerational effects of worklessness such as Barnes et al. (2012), Macmillan (2014) and Mäder, Müller et al. (2014), my results indicate that educational investments have a small potential impact on disadvantage passed on from workless parents to their children – mainly through lower rates of childcare.

This has several implications for education policy in times of economic crises, such as the 2008 financial crisis or the 2020 Covid-19-related related crisis. When more households become workless, educational policy might need to adjust to ensure pupils' education does not suffer due to their parents' employment situation. Particularly, benefits from early childcare for child development might be reduced if parents who become workless stop demanding (free) childcare.

First, since I find that workless parents do not necessarily spend their additional time supporting their child's education, workless parents are unlikely to be able to compensate for potential reduced spending due to an income reduction. Therefore, during times of rising unemployment, education policy might benefit from instruments to ensure parental spending is not reduced. While I do not find a causal link between household worklessness and paid-for extra lessons, parental investments into other resources outside the scope of my research might still be lower in workless households than other households.

Second, my results show a very clear causal effect of household worklessness on early childcare. While the UK has introduced several policies in recent years to make childcare more accessible, the government's focus has been on enabling working parents to benefit from free full-time childcare. As working parents previously regularly paid for childcare themselves, the effects of this policy on average attainment is found to be minimal (Blanden, Del Bono, McNally et al. 2016). However, my results show that workless parents are significantly less likely to pay for childcare in the first place. Additionally, as my results indicate, workless parents on average do not spend more time helping their child learning, thus possibly not compensating for the disadvantage from not attending childcare. Therefore, easing access to full-time early childcare for workless households might ensure these children do not fall behind prior to entering primary school. This is also in line with Sutton Trust (2021), finding that the current UK childcare policy keeps children from workless households from attending childcare at similar rates as children from working households.

This study comes with several limitations. First, while I look at a variety of investments parents can make in their children, there are many other ways parents may use their resources to benefit their child's education. Especially monetary investments in technical equipment such as laptops are not covered in this study but might have a strong impact on a child's education. Second, in using two different main identification strategies – instrumental variables and fixed effects – I also find that for some outcomes the resulting estimates are substantially different. This can be interpreted in the context of different techniques estimating different treatment effects: LATE and ATT. But this might also point to a deeper issue with one or both estimation methods. Especially instrumental variable estimators are sensitive to violated assumptions. Even if assumptions are met, small sample properties might still result in bias, especially in the case of weaker instruments. Third, in my study I focus on the quantity of educational investments, not quality. For example, while my results suggest that workless parents are less likely to pay for childcare, I can not make claims about the quality of childcare services. As Blanden, Del Bono, Hansen et al. (2021) point out, the educational benefits of additional childcare are larger for higher quality childcare. Last, measuring the impact of household worklessness in general is conceptually challenging. In this study, I control for income to disentangle the two effects. This provides me with a clearer picture of which changes in behaviour could be expected after finding work as opposed to after a pay rise. However, changes in employment usually coincide with changes in the financial situation. Arguably, one channel through which the disadvantage of worklessness manifests is through lower income.

Despite these limitations, this chapter contributes to the literature in the following ways. First, this study adds to the understanding of the mechanisms household worklessness may or may not affect children's development. While I detect robust differences in the time parents have with their child and in whether parents pay for early childcare, I find no link between worklessness and helping with learning how to read, write or do maths nor between worklessness and investments made in children age 11 and 14. Second, I add to the literature in introducing a new instrumental variable to research the causal impact of household worklessness. Future research might be able to build on this and expand on the evidence around the causal impact of household worklessness.

As this study is – to my knowledge – the first to examine the causal effect of household worklessness on educational investments, there is great potential for more research to be done in this field. Especially, with the current global recession and rising unemployment in many countries, exploring the impact worklessness, furlough, and reduced pay have on educational investments are potential future approaches to this topic.

4. Educational Expectations of Socio-Economically Disadvantaged Teenagers and the Role of Economic Preferences

4.1. Introduction

From educational attainment to lifetime earnings, coming from a family with a low socio-economic status (SES) is often expected to profoundly affect people's lives (Bradley & Corwyn 2002). In the UK, between 20% and 30%[1] of children lived in relative poverty in 2019 (UK Department for Work and Pensions 2020), and more than 15% of children were eligible for free school meals – a programme aimed at families with low incomes (Office for National Statistics 2020). Furthermore, British children are much more likely to live in a poor household than those in other European countries. According to Eurostat (2020a), in 2019 almost 30% of children lived in relative poverty in the UK, compared to only 15% and 23% in Germany and France, respectively. Where and how we grow up shapes the way we perceive the world around us, what we deem possible goals worth pursuing, and what we expect to remain dreams. In the UK, education is often seen as a key part in social mobility: more equality in education outcomes is expected to lead to a more equal society (Great Britain. HM Government 2011). Therefore, the impact socio-economic status has on educational decisions is of great importance in understanding social mobility.

Using the most recent UK specific panel data, I study the relationship between

[1] Depending on measure used.

socio-economic background during childhood and adolescence and how this affects young adults' educational expectations. Moreover, I focus on the role economic preferences (risk and time preferences) play in the formation of adolescents' educational expectations. Among adolescent cohort members expecting not to go to university, I analyse the role the cost of higher education plays in decision-making and how this differs between higher and lower SES pupils.

Economic preferences, i.e. risk and time preferences, are the subject of a wide variety of economic research. Assumptions about risk attitudes are often made in theoretical models (e.g. Eeckhoudt et al. 2011; Gollier 2001) and time preferences are regularly embedded in inter-temporal models (e.g. Blackorby et al. 1973; Chamberlain & Wilson 2000). The mechanics of how these preferences are formed and what makes some people more risk-loving and impatient than others is subject to both experimental and observational studies (Becker, Enke et al. 2020; Deckers, Falk, Kosse & Schildberg-Hörisch 2015; Neyse et al. 2021). Some studies examine the link between socio-economic status and the formation of economic preferences. For example, Deckers, Falk, Kosse, Pinger et al. (2017) show that 7- to 9-year-old children from lower socio-economic status households are more impatient and more risk-taking compared to their high-SES peers. However, Chowdhury et al. (2018) find no effect of household SES in the preference formation of children once accounting for parental economic preferences.

Furthermore, economic preferences are considered important factors for decision-making. Both risk preferences and time preferences have been shown to be linked to decisions such as smoking and drinking (Anderson & Mellor 2008; Dohmen, Falk, Huffman, Sunde et al. 2011) as well as criminal behaviour (Becker & Landes 1974; McCarthy & Hagan 2001; Mesquita & Cohen 1995).

Risk attitudes may be linked to educational decisions in the UK in the following ways. First, going to university requires most young people to take up a loan of tens of thousands of pounds with uncertain returns on that investment. The repayment of these loans is income contingent: repayments only need to be made if a certain salary threshold is met and the amount due every month is a fraction of the salary exceeding the threshold. However, strongly risk-averse people may be put off by this, especially as the terms and conditions of the repayment might not be clear to every prospective student. Empirically, Belzil & Leonardi (2013) find that in Italy higher risk aversion functions as a deterrent to going to university. Similarly, in a review of the economic literature, Outreville (2015) concludes that more-risk-averse individuals have lower educational attainment. Following these studies, I would expect more-risk-averse individuals to have *lower* educational expectations. Conversely, a university education can be viewed as 'insurance' against unemployment and poverty – causing more-risk-averse individuals to pursue university degrees. Hanushek, Kinne et al. (2020) and Sunde et al. (2020) find that on average more-risk-averse societies have higher student achievement, supporting this hypothesis. According to these studies, I would expect risk-averse students to think it *more likely* they would go to university. Thus, the direction of the impact of risk attitudes on education decisions is debated. This study will give insights into which of these two channels might dominate in UK teenagers.

The case for the potential impact of time preferences is clearer. The more patient an individual is, the more willing they are to postpone monetary pay-offs to a later date. Monetary pay-offs from a university degree lie in the future, with upfront costs of obtaining a degree in the present. Part of the reasoning why young people choose to go to university is likely the prospect of higher salaries in their career. This may lead to more patient individuals being more likely to go to university (Hanushek, Kinne et al. 2020) resulting in higher human capital (Sunde et al. 2020). Furthermore, Golsteyn et al. (2014) find that more impatient individuals perform worse in school and have lower earnings later in life. Thus, I expect that more patient individuals show higher educational expectations compared to their impatient peers.

The studies detailed above link SES, risk attitudes and time preferences to different outcomes such as educational attainment. In my study, I focus on educational expectations: in particular, how likely it is 17-year-olds think they will go to university after finishing school. Educational expectations in teenagers are found to have a strong association with actual education decisions later in life (Anders & Micklewright 2015; Jerrim 2011). Some evidence suggests there might even be a *causal* link between educational expectations and outcomes, meaning that increasing educational expectations directly affects educational outcomes (Morgan 2004). The level of education young people obtain is an important contributor to their opportunities later in life. For instance, lifetime earnings of university graduates in the UK are on average significantly higher than for non-graduates (Belfield et al. 2018; Blundell et al. 2000; Green, Jin et al. 2016; Walker & Zhu 2011; Walker & Zhu 2013). Higher education further affects health outcomes (Davies et al. 2018) and is considered an important contributor to social mobility both by academics (Gregg et al. 2013; Jerrim & Macmillan 2015) and policy-makers (Great Britain. HM Government 2011; Milburn 2012).

As socio-economic status may be linked to the formation of economic preferences, so may educational decisions be influenced by socio-economic status. While parts of the literature focus on the link between SES and educational outcomes, such as going to university (Crawford et al. 2016; Declercq & Verboven 2015), others have focussed more on educational expectations – a good predictor of subsequent decisions (Anders & Micklewright 2015; Jerrim 2011; Morgan 2004). Children growing up in low-SES households in the UK are found to have lower educational expectations when controlling for rich background characteristics including prior attainment (Anders & Micklewright 2015; Jerrim 2011). Moreover, low-SES students are much more likely to lower their expectations after receiving discouraging GCSE results and are less likely to level their expectations up after good results (Anders 2017). While overall educational expectations have been on the rise in the UK over the past decades, the SES gap remains rather stable (Schoon 2021).

In this study, I explore how socio-economic household characteristics during childhood and young people's economic preferences (i.e. risk and time preferences) are associated with educational expectations. In the UK, schooling is compulsory until the age of 16. At age 17 – the age group subject of this study – can either continue full-time education in school leading to qualifications such as A-levels, or they can leave school and choose another form of education such as an apprenticeship or further education (FE) colleges. Therefore, at this point, the MCS cohort members have already decided whether to stay in school or not and possibly have informed expectations on how likely they are to continue their education at a university. As discussed before, there is strong evidence that educational expectations formed at the age of 14 and 17 are good predictors of future university enrolment (Anders 2017; Anders & Micklewright 2015; Jerrim 2011). Therefore, they are a good indicator of the educational careers taken a few years later.

My research contributes to the existing literature in the following ways. First, I use the most recent data from the Millennium Cohort Study (MCS), published in 2020 to research the link between educational expectations and socio-economic status. This adds to evidence from studies such as Anders (2017) and Anders & Micklewright (2015) who use data for teenagers and young adults born in England around 1990, more than 10 years prior to when MCS cohort members were born. In the meantime, student fees increased steeply from around £3,000 per year to more than £9,000 per year for an undergraduate degree. This step was discussed extensively by the wider public. Many argued the increase in student fees may deter young people from low-income backgrounds from going to university (BBC 2010; Coughlan 2010;

Wintour et al. 2010). However, the UK government at the time, alongside others, argued that the way the student fee system is structured – no upfront payments with loans repaid proportional to earnings – would even reduce the burden on many students (The Independent 2010). This and other factors such as the financial crisis of 2007 may have changed the way socio-economic status is linked to educational expectations. Therefore, adding an updated view on the link between SES and educational expectations contributes to the understanding of educational choices in the UK context.

Second, I analyse the influence that economic preferences have on educational expectations. In the UK, going to university is a commitment of at least three years, costing close to £30,000 in student fees alone. The potential return on the investment lies in the future and is not immediately available. It may not be until university graduates' 30s that an advantage in earnings becomes sizeable. Moreover, even though studies consistently find that getting a university degree increases average lifetime earnings in the UK, especially for women (Belfield et al. 2018; Blundell et al. 2000; Walker & Zhu 2011; Walker & Zhu 2013; Waltmann et al. 2020), any university premium heavily relies on career choices (Belfield et al. 2018; Walker & Zhu 2011; Waltmann et al. 2020) and is distributed unevenly within subject (Waltmann et al. 2020). Risk-averse individuals might see this as too much of a gamble and might shy away from university education. On the other hand, higher education serving as insurance against unemployment and poverty might attract more-risk-averse individuals. Risk aversion may contribute to higher educational achievements (Hanushek, Kinne et al. 2020; Sunde et al. 2020). However, the link between risk aversion and educational expectations in the UK context of recently increased student fees remains unclear. The narrative for the role time preferences play in the formation of educational expectations is clearer. Impatient people might not want to wait more than 10 years after graduating to see their investment pay off. Hence, I hypothesise that more-patient individuals are more likely to expect to go to university.

In this study, I look at the unconditional associations of socio-economic status, risk attitudes, and time preferences on educational expectations as well as the associations conditional on a rich set of background variables. Throughout all methods applied in my analyses, I find that both long-term socio-economic status and time preferences at age 17 matter in the formation of educational expectations: more-patient cohort members with a higher SES are more likely to expect to go to university than impatient cohort members with a lower SES. Risk attitudes, on the other hand, are not associated with the expectation of going to university. Including control variables such as cognitive scores reduces the size of my estimates. While controlling for cognitive scores[2] reduces the size of my estimates, regardless of model choice I find a very robust and substantial influence both SES and patience have on the expectations to go to university.

The remainder of this chapter is structured as follows. In Section 4.2, I introduce the data and describe how I recoded variables of interest. This includes a discussion of attrition bias and missing data as issues for the representativeness of the MCS cohort for the generation of young adults in the UK. Section 4.3 introduces the methods I use to analyse the data. In Section 4.4, I discuss the results of these analyses. Last, in Section 4.5, I summarise the findings of this paper, arising questions for future research, and potential implications of my findings for policy-making.

4.2. Data

To answer the research questions, I conduct secondary data analysis of the Millennium Cohort Study (University of London 2017a; University of London 2017b; University of London 2017c; University of London 2017d; University of London 2017e; University of London 2019; University of London 2020), a longitudinal survey following a representative sample of approximately 19,000 children born in the UK around 2001. At the time of writing this chapter, MCS data has been collected and published in seven sweeps at age 1, 3, 5, 7, 11, 14 and 17. The data contains rich information provided by parents, teachers, and cohort members themselves.

4.2.1. Educational Expectations

Of greatest interest for this study are educational expectations reported by cohort members at age 17. Cohort members are asked to report on the likelihood of them going to university on a percentage scale from 0% (not at all likely) to 100% (sure to go to university). The probability scale might be preferable to the verbal scales often used in these types of questionnaires: the interpretation of what is likely and what is not might vary between individuals and between questions and is at the same time unnecessarily coarse, not allowing for more nuanced expressions of expectations

[2] And GCSE grades for England.

(Manski 2004).

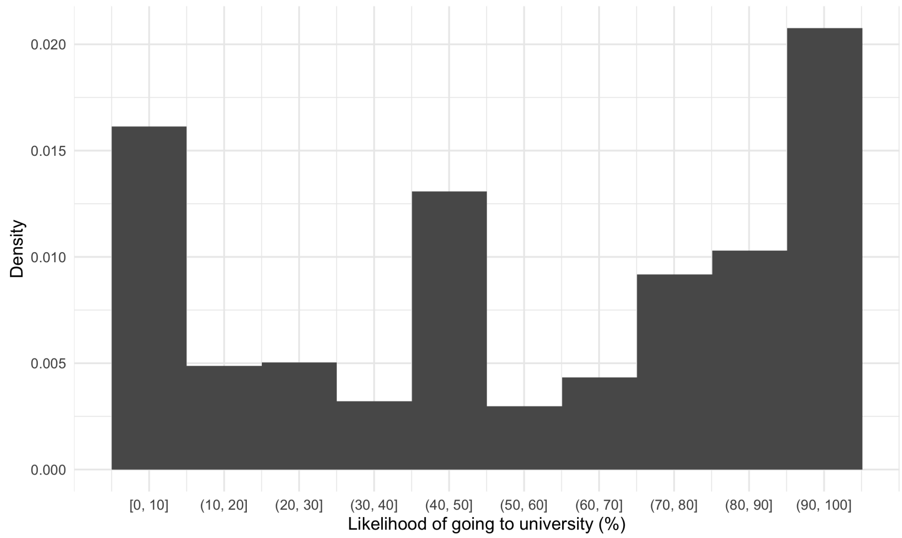
Figure 4.1 shows the distribution of cohort members' educational expectations. The histogram shows the expectation of going to university in 10 bins. One can see a concentration at the bottom of the distribution close to 0%. This is likely the group of 17-year-olds who are very certain that they will not be going to university and that have potentially made alternative plans already. Unsurprisingly, at around 50% there is another spike in observations. The third spike is in the 90-100% bin, consisting of those adolescents who are very sure that they will go to university.

Additionally, cohort members reporting a value below 100% are asked what would be the main reason not to go to university, such as, for example, that their family can not afford it. In this study, I use this information to better understand why cohort members are not sure they will or are certain they will not go to university. Figure 4.2 shows the distribution of educational expectations in those cohort members who say money would be the main reason for them not to attend university and those who mention other reasons. Educational expectations are very similar between 17-year-olds who report financial constraints as a reason not to go to university and those who do not. However, financially constrained pupils are less likely to have very low educational expectations. This is possibly because low-ability pupils might list poor grades and no interest in further education as the main reason not to go to university, whereas higher ability pupils' primary rationale for not attending might be more likely for money reasons.

4.2.2. Economic Preferences

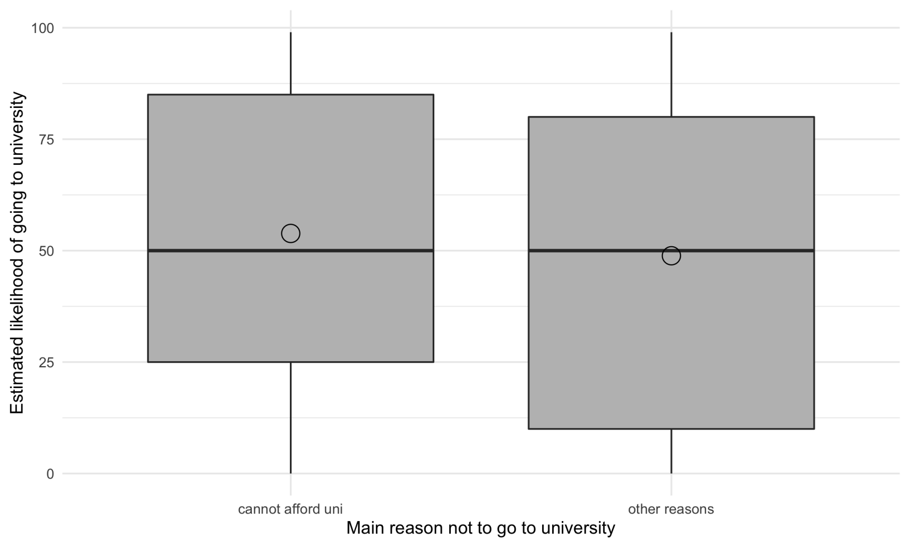
Risk preferences are measured at the Age 17 Sweep by asking cohort members to choose between a hypothetical game in which they would win £240 with a 50% chance or nothing, and a hypothetical payout between £132 and £24. The lower the safe payout cohort members choose over the bet, the more risk averse they are. This is in line with how risk preferences are regularly measured in economics literature: test subjects are asked for their preferences between two more or less risky choices (e.g. Dohmen, Falk, Huffman, Sunde et al. 2011; Galizzi & Miniaci 2016; Holt & Laury 2002). Time preferences at age 17 are measured in a similar way by giving the alternative between a certain hypothetical payout of £50 in 2 months' time and a hypothetical payout between £50 and £150 in 4 months' time (Cohen et al. 2020). This measures the level of *impatience* the cohort member shows. If the cohort

Figure 4.1.: Histogram of educational expectations at age 17



Notes: Number of observations: 6,382. Average educational expectation (weighted): 56%. Educational expectations as observed in MCS Age 17 Sweep. A total of 10 bins closed to the right, hence the estimated chance of 50% falls in the 40-50% bin. Inverse probability weights applied.

Figure 4.2.: Boxplot of educational expectations by main reason not to go to university



Notes: Number of observations: 5,307. Inverse probability weights applied.

member is very patient and does not mind waiting for the money and additional 2 months, they might choose £50 or £52 in 4 months over £50 in 2 months. The higher the amount that needs to be offered such that the cohort member prefers to wait another 2 months, the more impatient they are.

The obvious caveat of measuring economic preferences without actual payouts is that people might report a certain (potentially more risk-loving, more patient) preference than if they were actually confronted with a question such as the ones described above in real life with real money. However, in a literature review Camerer et al. (1999) find that monetary incentives barely change economic preferences, mainly reducing the variance of the measurements, not the mean. In the context of the MCS measures, this likely results in additional measurement error. In the case of risk attitudes, some of the reviewed studies suggest subjects becoming more risk averse when real money is involved. Similarly, the measurement of time preferences appears not to be affected by monetary rewards (Madden et al. 2004).

Another shortcoming of the way economic preferences are measured in the MCS is that the measure for risk aversions is less sophisticated than the widely applied one proposed by Holt & Laury (2002), although similar to Eckel & Grossman (2008). While risk attitudes and time preferences are measured in line with the wider economic literature, it is common in other studies to measure economic preferences by asking subjects for their preferences in a set of different risky choices or time-dependent payouts. As the MCS only uses one question each to measure risk attitudes and time preferences, this likely contributes to measurement error and might therefore bias estimates towards zero, i.e. attenuation bias (Wooldridge 2010). Moreover, risk and time preferences are only observed at one point in time while studies such as Deckers, Falk, Kosse, Pinger et al. (2017) use an average of multiple measures further increasing the accuracy of the measure.[3] Lastly, the external validity of economic preferences measured in survey or laboratory settings appears to be limited and, at best, weakly linked to outcomes hypothesised to correlate with risk or time preferences such as smoking (Galizzi & Miniaci 2016).

The following paragraphs describe how I create a measure for risk and time preferences from the survey data of the MCS.

[3]Note that the measure by Deckers, Falk, Kosse, Pinger et al. (2017) is based on a simplified risk attitudes measure as they interview 7-year-old children in their study.

4.2.2.1. Risk preferences

The MCS variable measuring risk attitudes is designed as follows. Cohort members are asked to state their preference between a bet – winning £240 with a 50% chance and nothing in the remaining 50% of cases – and a safe payout between £132 and £24, decreasing by steps of 12. Once a cohort member prefers the bet over the safe payout, this value measures their attitudes towards risk.

To clarify this, it is important to understand the concept of risk aversion frequently used by economists. If one were to repeat the above-described bet (50% chance to win £240) many times, one would expect to win on average £120 each round. This is the so-called *expected value* of the bet. This can be more formally expressed as the expected value of a bet, b, in which one gains a high prize, g, with probability p_g and one loses gaining the low prize, l, with probability p_l:

$$E(b) = p_g \cdot g + \underbrace{(1 - p_g)}_{p_l} \cdot l. \tag{4.1}$$

While this is a useful concept in general, it does not describe human preferences in a single-round bet very well. As a solution, I use the Von Neumann–Morgenstern expected utility framework, in which individuals maximise their expected utility rather than the expected value. In the case of a concave utility function, this means that the difference between a prize of £10 and a prize of £110 results in a larger difference in utility from the prizes than the difference between prizes of £1,000 and £1,100.

In the context of the question being asked to cohort members to state their preference between a bet and a safe payment, they reveal something about their risk attitudes. This can be formalised as follows. Each cohort member i with utility function u_i can decide between a 50% chance to gain £240 or to take the safe payout s. If the expected utility of the bet is higher than the utility of the safe payout, the cohort member would choose the bet, otherwise the safe payout:[4]

$$u_i(s) \lesseqgtr 0.5 \cdot u_i(\text{£}240) + 0.5 \cdot u_i(0). \tag{4.2}$$

The more risk averse an individual is, the smaller the safe payout, s, they would

[4]Often this representation includes the individual's wealth level, w_i, as part of the utility function. For reasons of simplicity and as this wealth level is often assumed to be 0 in applied research, I do not include it in the equation.

accept. Hence, I use information from this question asked to cohort members in the Age 17 Sweep to measure the degree of risk aversion. The lower the safe payout they would prefer over the 50-50 bet, the more risk averse the cohort member.

To create a meaningful variable from this survey data in order to conduct regression analyses, I quantify the level of risk aversion an individual expresses. Galizzi & Miniaci (2016) highlight that risk aversion is unlikely to linearly follow the value of the safe payout an individual chooses. Therefore, based on Galizzi & Miniaci (2016), I assume each expected utility-maximising individual to have constant relative risk aversion (CRRA), with isoelastic utility function

$$u_i(M) = \begin{cases} \frac{M^{(1-r_i)}-1}{1-r_i} & \text{for } r_i \neq 1 \\ \ln(M) & \text{for } r_i = 1, \end{cases} \tag{4.3}$$

where M represents a monetary prize and r_i represents the individual risk attitudes. An individual is risk averse for $r_i > 0$ and risk-taking for $r_i < 0$.

Using this utility function, I compute lower and upper bounds of r for each choice between the lottery and a safe payout. Table 4.1 shows the lower and upper bounds of r, r_l and r_u, for which an individual would choose the lottery of a 50% chance of £240 and a 50% chance of £0 over the safe payout as presented in the first column.

Table 4.1.: Risk attitudes measured in the MCS

Smallest safe payout preferred over lottery	r_l	r_u
£132 $\prec$ lottery	$-\infty$	-0.16
£120 $\prec$ lottery $\prec$ £132	-0.16	0
£108 $\prec$ lottery $\prec$ £120	0	0.13
£96 $\prec$ lottery $\prec$ £108	0.13	0.24
£84 $\prec$ lottery $\prec$ £96	0.24	0.33
£72 $\prec$ lottery $\prec$ £84	0.33	0.42
£60 $\prec$ lottery $\prec$ £72	0.42	0.49
£48 $\prec$ lottery $\prec$ £60	0.49	0.56
£36 $\prec$ lottery $\prec$ £48	0.56	0.63
£24 $\prec$ lottery $\prec$ £36	0.63	0.69
lottery $\prec$ £24	0.69	∞

Notes: Each row represents the choice between a safe payout and the bet of winning £240 with a 50% chance and £0 otherwise. Individuals with $r_l \leq r_i \leq r_u$ choose the lottery over the safe bet presented in the respective row.

In order to obtain a single value r_i for each cohort member rather than only assigning them to the intervals $[r_l, r_u]$, I run an interval regression. For this, I use a set of background variables X_i and restrict predicted values to fall into the interval $[r_l, r_u]$. For the distribution of resulting r values, see Figure 4.4.

As a robustness check I construct a simple binary risk attitudes variable directly from MCS responses. This binary variable splits the sample in two roughly equally sized 'low risk aversion' and 'high risk aversion' groups. See Appendix C.2 for more details on this robustness check.

4.2.2.2. Time preferences

The MCS also contains information about cohort members' time preferences, i.e. how much the cohort member prefers a payout to be sooner rather than later. The time preference measure is constructed as follows. Each cohort member is asked whether they would prefer a safe payout of £50 in 2 months' time or a safe payout in 4 months' time of £$(50 + x)$, where $x \in \{0, 2, 5, 10, 20, 30, 40, 50, 70, 100\}$. The higher the extra payout necessary for the cohort member to prefer the payout in 4 months over the payout in 2 months, the stronger the *present bias* or *impatience*. Note that both payouts being set in the future avoids methodological difficulties around time-inconsistent preferences (for an in-depth discussion of different measures for time preferences, see Cohen et al. 2020).

To translate each cohort member's survey answers into a measure of time preferences, I choose a framework based on Samuelson's classical discounted utility model (Samuelson 1937). In this framework, each individual has a *discount rate*, δ_i, with which they discount their utility of future monetary payouts. More formally, the cohort member prefers a payout in 2 months of £50 over a payout in 4 months of £$(50 + x)$ if the following holds:

$$\begin{aligned} & \delta_i u_i(\text{£}50) > \delta_i^2 u_i(\text{£}50 + x) \\ \Leftrightarrow \quad & u_i(\text{£}50) > \delta_i u_i(\text{£}50 + x). \end{aligned} \tag{4.4}$$

In order to estimate an individual's inter-temporal discount rate, δ_i, additional assumptions about the utility function, u_i, are needed. It is common in the literature to assume utility to be linear in the monetary payout (Cohen et al. 2020; Lawyer et al. 2010). However, this would not be in line with the concave utility function assumed to estimate risk attitudes as discussed in Section 4.2.2.1.

Therefore, in line with Ubfal (2016), I use the previously estimated cohort members' risk attitudes, r_i, which constitutes the curvature of the individual's utility function. Based on the estimated utility function, u_i, I estimate the individual inter-temporal discount factor, δ_i.

Similar to the MCS measurement of risk preferences detailed in Section 4.2.2.1, time preferences are measured in 10 categories. For each cohort member, i, I calculate the range of plausible discount factors, $\delta_i \in [\delta_{i,l}, \delta_{i,u}]$, that would result in the observed choice of x. Based on these estimated intervals, I estimate a single individual discount factor, δ_i, using the interval regression approach described above. For additional information on the distribution of δ, see Figure 4.4.

As for risk attitudes, I construct a simple binary time preference variable from the MCS responses directly. Thus, for this variable I do not take into account the estimated shape of each individual's utility function but directly use their questionnaire responses. For more information on the construction of this variable and results from regression analyses, see Appendix C.2.

4.2.3. Socio-Economic Status

Household SES is a central component of many studies in educational economics (Boneva & Rauh 2017; Croll 2008; Declercq & Verboven 2015; Duarte et al. 2018; Kajonius & Carlander 2017; Polidano et al. 2013; Ratshivhanda & Guvuriro 2018; Taylor & Yu 2009). Often researchers have to rely on available proxy measures for SES such as the number of books at home (Quintelier & Hooghe 2013; Wößmann 2005; Yang Hansen et al. 2011). However, the MCS data I use for this study is rich in background variables and contains all the main measures of SES discussed by Galobardes et al. (2007): parental education, (last-held) occupation, permanent income, and wealth. Moreover, additional indicators (e.g. eligibility for free school meals) are available (see Jerrim 2020 for a detailed discussion on the relationship between different proxymeasures of socio-economic status and Hobbs & Vignoles 2010 for a discussion of free school meals and family income).

For this study, I measure socio-economic status in two different ways. First, I use a set of variables capturing different aspects of a household's socio-economic status. This includes a household's permanent income, income volatility, housing situation, number of worklessness spills, single parenthood, and highest parental education. Using this approach, the individual contribution of each SES dimension to the outcomes of interest can be measured. However, multicollinearity between the different SES indicators as well as with control variables might make it difficult to disentangle the effect sizes of each variable, thwarting a clear interpretation of the results.

In a second approach, I combine all of the aforementioned relevant measures for socio-economic status into a single index. While now I cannot distinguish between the different contributors of SES, having a single indicator allows for a more direct interpretation of the results. The method I use to construct this index is principal component analysis. This technique is fully data driven and identifies the dimension in the dataset which explains most of the variance (and subsequently dimensions with smaller contributions to overall variance). I then use the dimension explaining the largest amount of variance, i.e. around 56%, in the above-mentioned variables.

4.2.4. Background Variables

The Millennium Cohort Study is a rich survey dataset with hundreds of data points measuring different aspects of the household cohort members grow up in. By including this information, I aim at reducing any potential bias in my estimates as well as possible. In the following paragraphs, I discuss which household characteristics I use as control variables and how I include them in my subsequent analyses.

Demographics As demographic variables, D, I consider a set of background variables. For one, I use the region which the cohort member lives in. In case this changes over the course of the MCS, I choose the region in which the cohort member has lived for the majority of MCS sweeps. Next, the MCS consists of a sampling stratum – advantaged or disadvantaged neighbourhood and ethnic minority neighbourhood (England only). While every cohort member I include in my analysis has to participate in the Age 17 Sweep, I control for the number of sweeps missed up until that point. Furthermore, I include some cohort-member-specific characteristics about their gender or sex and their ethnicity.

Parental health Whether or not cohort members think they will go to university may be influenced by household environment other than SES. For example, if parents have health issues, this affects the decision-making process and, therefore, educational expectations. When controlling for parental health, I construct two variables. First, each carer is asked to assess their personal health level, ranging from 'poor' to 'excellent'. In the first two sweeps, health is measured in four categories, and the remaining sweeps provide five parental-health categories. To ensure comparability across sweeps, I assign value 1 for the lowest category (poor) and 5 for the highest category (excellent) and fit the additional categories in between spaced equally. More formally, I construct the parental health measure as follows. To account for parental health in household i, I create the long-term health score, $\mathcal{H}_i$, from the health levels all carers in the household report, $h^j_{i,t}$, where $j \in \{m, p\}$ denotes main carer and their partner, respectively, and $t \in \{1, 2, \ldots, 7\}$ denotes the sweep. I divide the household's total health score by the total number of household observations, i.e. $\mathcal{I}(i, j, t)$ takes the value 1 if for household i, carer j and sweep t the health level is observed, and 0 otherwise. Hence:

$$\mathcal{H}_i = \frac{\sum_t \sum_j h^j_{i,t}}{\sum_t \sum_j \mathcal{I}(i, j, t)}. \tag{4.5}$$

Therefore, the highest household health level in this measure is 5 and the lowest possible value is 1. The second health variable is smoking behaviour which indicates whether or not the household ever was a smoking household during the course of the MCS.

Educational investments Parents can invest their time and money in their child's education. These investments vary substantially depending on age, ranging from childcare and reading to the child for young children, to homework help and fee-paying schools for older kids. To account for these investments, I use the set of variables from across sweeps as introduced in Chapter 3 and conduct a principal component analysis to create a separate time investments and monetary investments variable.

Cohort member's cognitive ability Throughout the MCS, cohort members are assessed in terms of their cognitive ability. In the MCS, these scores are collected from the age of 3 onwards with every sweep containing age-appropriate cognitive measures. Furthermore, they cover a wide range of abilities ranging from vocabulary to pattern recognition and numeric skills. In order to create a single overall cognitive ability score for cohort members, A_i^{CM}, I proceed as follows. First, I take the so-called standard scores or T-scores which take into account the individual cohort member's age at the time of testing, as age varies considerably within each MCS sweep. Second, I standardise each of the 10 scores to have mean 0 and standard deviation 1, which ensures that in creating a composite score I do treat the information provided by each score equally. Third, I impute missing values. Some cohort members do not participate in all of the cognitive assessments. I compute the quantile a cohort member falls into in those cognitive assessments observed. For each cohort member with missing values, I then impute the score consistent with the observed quantile. In a final step, I use the standardised and imputed scores and perform a principal component analysis. As composite cognitive score, A_i^{CM}, I use the first principal component which alone explains around 50% of the variance in the 10 cognitive measures.[5]

Strengths and difficulties Each MCS sweep from age 3 onwards contains the Strengths and Difficulties Questionnaire (SDQ). In these questionnaires, four categories are assessed: emotional symptoms, conduct problems, hyperactivity, and peer relationship problems. In each of these four categories, 10 points can be scored with higher scores indicating more difficulties. The sum of these four categories is reported as total difficulties. I construct my SDQ score to be the average of total difficulties scored over the course of the MCS.

4.2.5. Missing Data

The Age 17 Sweep of the MCS takes place approximately 16 years after the interviews for the first sweep. During this time, a considerable proportion of cohort members have dropped out of the MCS, so-called ‘attrition’ or ‘mortality’. Therefore, while the MCS was originally designed to be representative of the population of children born in the UK in the year 2001, this does not naturally hold for those cohort members still participating in the study in 2018. In previous cycles up until the Age 14 Sweep, the MCS data contained weights accounting for both survey design (some demographics were ‘oversampled’) and attrition. These weights, however, are not available for the Age 17 Sweep.

Another source of missing data at age 17 is due to multiple questionnaires being administered to both the household (e.g. parents) and the cohort member. While a

[5] Further principal components explain only less than 10% of variance each. Including additional principal components in the analysis does not meaningfully change point estimates for any of the variables of interest.

household can be responsive in general, the cohort member may have decided not to take part in the questionnaire themselves or to skip certain questions, resulting in missing data for educational expectations or economic preferences.

Last, some households may skip one or more sweeps before being responsive again at the Age 17 Sweep. This does not affect my analyses in principle, but this requires me to exclude these sweeps for the computation of aggregate measures for SES, parental health, cohort members' cognitive ability, and more.

I address these sources of missing data in different ways. The last mentioned missing data in sweeps prior to the Age 17 Sweep is least problematic. As described previously, I can often simply exclude these measures from the calculation of average measures such as health or permanent income. For composite measures based on the principal components of multiple variables, missing values need to be imputed. Depending on variables, I either use the mean, mode (i.e. most commonly observed category), or – in the case of cognitive scores – my imputing based on the relative performance in observed sweeps.

I address missing values from attrition and non-response to questions the same way using inverse probability weights (IPWs). To construct these IPWs, I indicate whether a cohort member present at a previous sweep is used in my final analysis or not. Then, I calculate the propensity with which an MCS cohort member is part of my final sample, given observed background characteristics. This is done using the predicted values from a logistic regression. I then take the inverse of these predicted probabilities. Finally, to ensure my final sample is as representative as possible of children born in the UK in 2001, I combine the inverse probability weights with the original sampling weights provided with the MCS. If not stated otherwise, I use these weights in all descriptive statistics as well as regression analyses, ensuring my results are representative of young people in the UK.

4.2.6. Descriptive Statistics

After removing all cohort members that are not present at the Age 17 Sweep or have missing values in either socio-economic status, risk attitudes, time preferences, or educational expectations, a total of 6,382 observations remain for further analysis.

First, I look at the outcome variables of interest. The main outcome variable is educational expectations in the MCS Age 17 Sweep. Recall that 'educational expectations' refers to cohort members reporting their estimate of how likely they think it is that they will go to university on a 0 to 100 percentage scale. As previously shown in Figure 4.1, the distribution of educational expectations is particularly heavy around 0%, 50%, and 100%.

A total of 5,307 cohort members reporting educational expectations below 100% answered questions about the possible reasons for them not to attend university. Of these cohort members, around 13% report the *main* reason for them not to go to university would be that they or their family cannot afford it. The distribution of educational expectations among financially constrained pupils is very similar to the distribution among pupils who name other reasons as their main reason not to go to university. For more details, see Figure 4.2.

Table 4.2 shows descriptive statistics for all variables included in my analysis as explanatory variables of interest or control variables. In creating this table, I apply the combined sampling and inverse probability weights (see above and Appendix C.1 for a detailed discussion on the construction of weights). As the variables measuring SES, educational investments, and cognitive aptitude are constructed using a principal component analysis, the distribution of these variables, including their mean, do not allow for any meaningful interpretation. These variables are included in the descriptive table in their original form but are being standardised (mean 0, standard deviation 1) for further analysis.

The economic preferences variables – risk attitude and time preferences – need to be interpreted in the context of their economic meaning. Recall that from Equation 4.3, r is defined as follows:

$$u_i(M) = \begin{cases} \frac{M^{(1-r_i)}-1}{1-r_i} & \text{for } r_i \neq 1 \\ \ln(M) & \text{for } r_i = 1. \end{cases}$$

Negative values of r result in a convex function resulting in risk-seeking behaviour. Conversely, positive r corresponds with a concave utility function causing risk aversion. Hence, the average value of r measured in the MCS of 0.22 corresponds to moderate risk aversion. In the context of the lottery choice given in the questionnaire, this level of risk aversion would make the average cohort member indifferent between a 50% chance of £240 or a safe payout of £98.

Panel (a) of Figure 4.3 shows the relationship between r (x-axis) and the safe payout necessary to make a cohort member indifferent (y-axis). As explained before, the

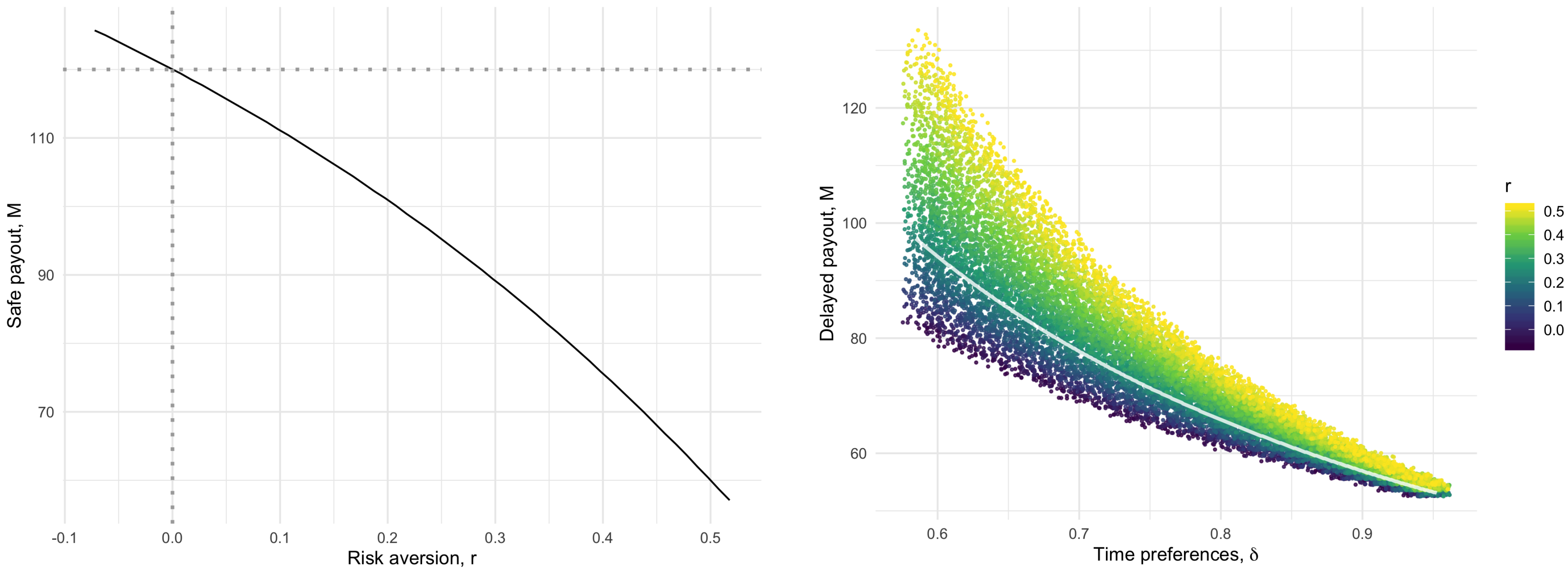
Table 4.2.: Descriptive statistics

Variable	mean	sd	min	max
SES[a]	0.328	1.758	-4.7	3.784
r (risk preference)	0.224	0.313	-0.344	0.853
δ (impatience)	0.75	0.207	0.168	1.12
Region				
South East	14.7%			
London	11%			
North West	10.9%			
East of England	10.4%			
Yorkshire and the Humber	8.5%			
South West	8.4%			
West Midlands	8%			
East Midlands	7.3%			
North East	3.5%			
Scotland	8.8%			
Wales	5.1%			
Northern Ireland	3.5%			
Sex (cohort member)				
Male	51.1%			
Female	48.9%			
Ethnicity (cohort member)				
White	87.4%			
Pakistani & Bangladeshi	4%			
Indian	1.9%			
Black	2.5%			
Mixed	3.1%			
Other	1.2%			
Number of sweeps (until age 14)	5.729	0.591	2	6
Parental health score	3.722	0.656	1.19	5
Ever a smoking household				
Yes	53%			
No	47%			
Monetary investments[a]	0.132	1.451	-0.901	8.081
Time investments[a]	0.017	1.518	-5.623	3.211
Strengths and Difficulties	8.148	4.683	0	31.5
Cognitive aptitude score[a]	0.199	2.157	-9.376	6.857

[a]Composite variables created by principle component analysis.

Notes: Number of observations: 6,382. Inverse probability weights and sample weights applied.

Figure 4.3.: Parameters of economic preferences and their relationship with monetary values in the MCS questionnaire



(a) Risk attitudes

(b) Time preferences

Notes: Panel (a) shows the relationship between the parameter for risk attitudes, r, and the safe payout resulting in indifference with a 50−50 gamble of £0 or £240. The dashed lines show the safe payout of £240 that makes a risk-neutral individual ($r = 0$) indifferent. $r > 0$ represents risk aversion, $r < 0$ represents risk-taking. Panel (b) shows how time preferences, δ, are related to the payout in 4 months resulting in indifference to a payout of £50 in 2 months. Large values of δ represent patience and small values represent impatience. Point colour shows risk attitudes range from risk-taking (purple), average risk aversion (blue/green), to strong risk aversion (yellow). The white line shows the relationship between δ and the delayed payout for an individual with average risk attitudes, $r = 0.22f$.

figure shows that individuals with stronger risk aversion require a smaller safe payout to be indifferent. However, this relationship is not linear: the slope is steeper at higher values of risk aversion and flatter at risk neutrality.

Further, recall that the time preference measure, δ, was introduced in Equation 4.4 as follows:

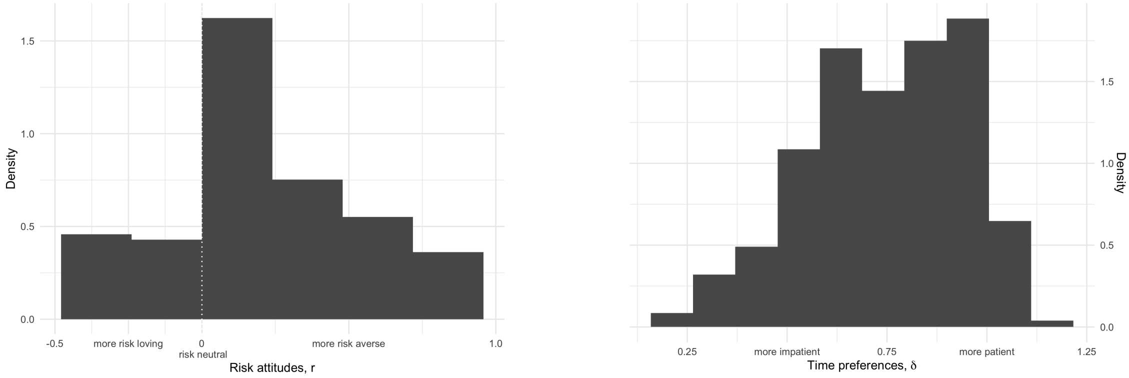
$$\delta_i = \frac{u_i(£50)}{u_i(£50 + x)},$$

where x is the amount needed to make a cohort member with discount factor δ_i indifferent between receiving £50 in 2 months' time or £50 plus x in 4 months' time. For the average cohort member, this discount factor is 0.75. Also using the average r of 0.22, this means that such an individual is indifferent between £50 in 2 months and £71 in 4 months.

Panel (b) of Figure 4.3 shows the interaction between δ, r, and the payout in 4 months required to make an individual indifferent to a payout of £50 in 2 months. The white line shows this relationship for an individual with average risk aversion of $r = 0.22$. The larger δ is (i.e. higher patience), the smaller the extra payout necessary resulting in indifference. The purple dots show this relationship for risk-neutral individuals and the green and yellow dots represent increasing levels of risk aversion. Generally, more-risk-averse individuals also require a higher additional payout in 4 months to be indifferent to £50 in 2 months – time preferences, δ, held equal. Conversely, more-risk-neutral individuals require a lower additional payout. This difference is larger for more impatient individuals and becomes smaller with higher patience.

Finally, Figure 4.4 shows the distribution of the risk attitudes and time preference variables. Panel (a) shows the distribution of risk attitudes measured in the coefficient r. Values below 0 indicate risk-loving attitudes, values around 0 indicate risk neutrality, and more positive values indicate more-risk-averse attitudes. Only a small subgroup of observations falls in the 'risk-loving' category. Similarly, very few observations correspond with highly risk-averse preferences. The vast majority of observations fall in moderately risk-averse categories. Panel (b) of Figure 4.4 shows the distribution of the inter-temporal discount factor, δ, measuring time preferences. Smaller values mean future payouts are discounted strongly and present payouts are preferred – i.e. impatience. Larger values indicate more-patient preferences. The histogram indicates that very few cohort members are very impatient at the left tail of the distribution. Most observations correspond with moderate to low impatience.

Figure 4.4.: Distribution of risk attitudes and time preferences



(a) Risk attitudes (b) Time preferences

Notes: Number of observations: 6,382. Panel (a): Risk attitudes as utility function coefficient, r*. Negative values indicate risk-loving;* $r = 0$ *indicates risk neutrality; positive values indicate risk aversion. Panel (b): Time preferences as discount factor,* δ*. Smaller values represent higher impatience, larger values represent more-patient attitudes. Sampling weights and inverse probability weights applied.*

4.3. Methods

In this section, I introduce the methods I use to understand the associations between socio-economic status and economic preferences with educational expectations.

The key variable of interest, long-term socio-economic status, is essentially a time-invariant construct: as I am interested in the association between SES during childhood on educational expectations at age 17, this variable does not change over time. The other key explanatory variables, risk attitudes and time preferences, are measured at age 17. Therefore, the methods I apply to understand the formation of educational expectations reflect the nature of socio-economic status and isolate the role SES and economic preferences play conditional on a rich set of control variables.

Thanks to the detailed information provided in the MCS, my estimates account for many often unobserved factors, including parental health, education, income, home ownership, the cohort members' cognitive performance, sex, ethnicity, and more. In the remainder of this section, I introduce the methods I apply to measure the association between socio-economic status, economic preferences, and educational expectations.

4.3.1. Unconditional Associations

The methods detailed below aim to measure the association between socio-economic status, risk attitudes, and time preferences on the one hand, and educational expectations on the other hand. To do so, I start by focussing on each of the three explanatory variables of interest at a time, not yet including any background characteristics. These correlations serve as a benchmark.

I estimate these correlations using a linear regression with educational expectations as the dependent variable and SES, risk attitudes, r, and time preferences, δ, respectively, as sole explanatory variables:

$$EduExp_i = \beta_0^{SES} + \beta_1\ SES_i + \epsilon_i^{SES} \tag{C1}$$
$$EduExp_i = \beta_0^{r} + \beta_2\ r_i + \epsilon_i^{r} \tag{C2}$$
$$EduExp_i = \beta_0^{\delta} + \beta_3\ \delta_i + \epsilon_i^{\delta} \tag{C3}$$

Next, I aim to better understand how these three explanatory variables interact in their association with educational expectations. I do so by using linear regressions combining pairs of two explanatory variables as well as all three explanatory variables and examining how the associations are impacted by different combinations.

$$EduExp_i = \beta_0 + \beta_1\ SES_i + \beta_2 r_i + \epsilon_i \tag{C4}$$
$$EduExp_i = \beta_0 + \beta_1\ SES_i + \beta_3 \delta_i + \epsilon_i \tag{C5}$$
$$EduExp_i = \beta_0 + \beta_2 r_i + \beta_3 \delta_i + \epsilon_i \tag{C6}$$
$$EduExp_i = \beta_0 + \beta_1\ SES_i + \beta_2 r_i + \beta_3 \delta_i + \epsilon_i \tag{C7}$$

4.3.2. Conditional Associations

From the correlation analysis, I move on to include further background variables to control for various individual and household characteristics. This is to measure the association between the three explanatory variables of interest – socio-economic status, risk attitudes, and time preferences – and the cohort members' educational expectations as accurately as possible, eliminating all observable confounders.

Table 4.3 shows which groups of variables are included in each model. There are three groups of control variables I consider. The first group of control variables, demographic information, contains country, deprivation, region, and the cohort members' sex and ethnicity. Additionally, I control for long-term parental health. The second group, educational investments, consists of two composite measures, one for monetary and one for time investments. The final group includes a behavioural score based on the Strength and Difficulties Questionnaire and a cognitive score based on a combination of all cognitive assessments – both between age 3 and 14.

By including additional control variables with each model, I show how my estimates change once I account for more background characteristics. Including general demographic and household characteristics controls for the general situation the adolescents grew up in, accounting for household characteristics not captured by SES. In controlling for parental educational investments, I see how these affect young people's educational expectations. By adding behavioural and cognitive scores to my analysis, I control for individual characteristics relevant for education choices and see how my estimates change.

Table 4.3.: Overview of regression analyses

				Model		
Control		M1	M2	M3	M4	M5
Demographics	D	x	x	x	x	x
Region						
Stratum						
Sex						
Ethnicity						
MCS sweeps missed						
Parental Health	H	x	x	x	x	x
Average health score						
Smoking habits						
Educational Investments	I	–	x	x	x	x
Time investments						
Monetary investments						
Behavioural and cognitive scores	C	–	–	x	x	x
SDQ score						
Composite cognitive scores						
Educational expectations (age 14)	$EduExp$	–	–	–	x	–
Detailed SES measure		–	–	–	–	x

Hence, the regression models look as follows:

$$EduExp_i = \underbrace{\beta_0 + \beta_1 SES_i + \beta_2 r_i + \beta_3 \delta_i + \gamma_1 D_i + \gamma_2 H_i}_{\text{M1, M2, M3}} \underbrace{+\gamma_3 I_i}_{\text{M2, M3}} \overbrace{+\gamma_4 C}^{\text{M3}} + \epsilon_i \tag{4.8}$$

For a less biased estimation of β_1, β_2, and β_3, the error term, ϵ, needs to have little correlation with the outcome variable, given all included explanatory variables. Therefore, model M3 can be expected to have the smallest bias since a wide range of external, household, and individual characteristics are covered. However, factors not included in my analysis such as an individual's general motivation, the ability to translate cognitive aptitude into school grades[6], or how much an individual enjoys learning new things, may lead to the error term to be correlated with the outcome variable. Therefore, it is important to note that despite the rich set of background data included, I do not make causal claims.

Furthermore, I look at what socio-economic status, risk attitudes, and time preferences *add* to the formation of educational expectations between the age of 14 and 17. I do this by controlling for educational expectations at age 14:

$$EduExp_i^{\text{age 17}} = \beta_0 + \beta_1 SES_i + \beta_2 r_i + \beta_3 \delta_i + \underbrace{\gamma X_i}_{\text{background variables in M3}} + \rho EduExp_i^{\text{age 14}} + \epsilon_i \tag{4.9}$$

By conditioning the educational expectations at age 17 on educational expectations observed at age 14, I can draw inferences on whether SES, risk attitudes, and time preferences play a role beyond the age of 14. I refer to this as model M4.

Finally, in model M5, I alter the model specifications of M3 (all control variables, no educational expectations at age 14) by replacing the SES measure constructed as described in Section 4.2 with its individual components. This is to better understand which element of socio-economic status might be most important in explaining differences in educational expectations. These elements are permanent income, income volatility, proportion of time the household lives in an owned home instead of renting, proportion of time the household is workless or a single-carer household, and highest parental education level. Model M5 also serves as a robustness check for the association between economic preferences and educational expectations. In case the composite SES variable omits the correlation between risk or time preferences and one of the SES contributors, this can be detected in model M5.

[6]See Appendix C.2 for regression results including GCSE grades for a subset of English students.

Robustness checks As shown in the histogram in Figure 4.1, educational expectations are concentrated at the margins at 0% and 100%. The linear models introduced above do not take into account the censored nature of the data and allow for predicted values to fall outside the 0–100% range. Therefore, I present the result from a Tobit model in Table C.2 (Appendix C.2) as a robustness check. Furthermore, for English pupils, I include GCSE exam results as a control variable in robustness checks in Table C.3. Lastly, I use simplified binary measures for risk attitudes and time preferences based solely on the MCS variables and not on the estimated shape of cohort members' utility functions. See Appendix C.2 for more details about robustness checks.

4.3.3. Interactions Between Explanatory Variables

With the methods described above I estimate how SES, risk attitudes, and time preferences *individually* are associated with educational expectations. To better understand the interactions between these explanatory variables, I next add interaction terms to my regression analysis.

For this, I run two regressions. First, in Model I1, I add the interaction between SES and risk attitudes as well as SES and time preferences. In Model I2, I further look at the interaction between risk attitudes and time preferences. This results in the following regression model:

$$\begin{aligned} EduExp_i = &\beta_0 + \beta_1 SES_i + \beta_2 r_i + \beta_3 \delta_i + \overbrace{\beta_4 SES_i \times r_i + \beta_5 SES_i \times \delta_i}^{\text{Model I1}} \\ &+ \underbrace{\beta_6 r_i \times \delta_i}_{\text{Model I2}} + \gamma Controls_i + \epsilon_i \end{aligned} \tag{4.10}$$

4.3.4. Reasons Not to go to University

All cohort members who report educational expectations below 100% are then asked what their main reason not to go to university is. As this variable is binary, I estimate which of the explanatory variables – SES, risk attitudes, and time preferences – are associated with naming the cost of a university education as the main reason not to go to university using three different logistic regressions:

$$logit(Reason_i) = \underbrace{\beta_0 + \beta_1 SES_i + \beta_2 r_i + \beta_3 \delta_i}_{\text{R1, R2, R3}} \overbrace{+\gamma_1 D_i + \gamma_2 H_i + \gamma_3 I_i + \gamma_4 C}^{\text{R2, R3}} \underbrace{+\xi EduExp_i}_{\text{R3}} + \epsilon_i \quad (4.11)$$

As the above equation shows, in the base model R1, I include all three explanatory variables of interest – SES, risk attitudes, and time preferences. Model R2 further contains all background variables as also controlled for in Model M3. Finally, in model R3, I also control for educational expectations at age 17. As mentioned in Section 4.2.6, educational expectations in those cohort members who mention monetary reasons as the main reason not to go to university tend to be higher than in cohort members who do not mention financial reasons.

4.4. Results

4.4.1. Unconditional Associations

First, I begin the analysis of the association between socio-economic status, risk attitudes, and time preferences with educational expectations by exploring correlations. This is to understand how each individual explanatory variable relates to the likelihood 17-year-olds think there is of them going to university (model C1 – C3). Building on this, I explore how these associations change once I account for other explanatory variables (model C4 – C7).

Table 4.4 shows models C1, C2, and C3 in which I regress each explanatory variable individually on educational expectations without controlling for any background characteristics. Model C1 shows a clear positive correlation between socio-economic status and educational expectations. An increase in SES of one standard deviation is associated with an increase in educational expectations of more than 9 percentage points. This relationship is significant at the 0.1% level. Furthermore, SES alone – not accounting for any other background characteristics – explains more than 8% of the variance in educational expectations among cohort members. Model C2 estimates there to be no statistically significant relationship between risk attitudes and educational expectations. However, the estimates from model C3 suggest that patience (larger δ) is positively associated with educational expectations ($p < 0.001$). In particular, if delta increases by 0.2 (around one standard deviation), this correlates with an increase in educational expectations of almost 5 percentage points.

Next, Table 4.5 shows models C4 – C7. In these, I regress different combinations of two explanatory variables on educational expectations (C4 – C6) and all three explanatory variables together (C7). Again, I do not control for any background characteristics. In these different models, both SES and time preferences remain strongly and significantly associated with educational expectations. Again, risk attitudes are not significantly associated with educational expectations with the exception of model C6 in which only risk and time preferences were regressed on educational expectations. The magnitude of these associations are similar but smaller than the ones shown in Table 4.4.

Overall, these results indicate a potential link between socio-economic status and economic preferences – in particular, time preferences – and educational expectations. The analysis using different subsets of the three explanatory variables has also shown that SES and time preferences are independently correlated with educational expectations with both regression coefficients decreasing only slightly when regressed in combination.

Table 4.4.: Unconditional associations of SES, risk attitudes, and time preferences with educational expectations

Variable	C1	C2	C3
SES	9.413***		
	(0.666)		
Risk attitudes r		-1.217	
		(1.957)	
Time preferences δ			24.58***
			(2.795)
R^2	0.084	0.000	0.019

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Number of observations: 6,382. Unconditional associations between SES (C1), risk attitudes (C2), and time preferences (C3) shown. No control variables included. The SES regression coefficient shows how much a change in one standard deviation of SES is associated with educational expectations in percentage points. The risk attitudes and time preference coefficients show how much a 1-unit change in r and δ, respectively, is associated with differences in educational expectations. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis.

Table 4.5.: Bivariate associations of SES, risk attitudes, and time preferences with educational expectations

Variable	C4	C5	C6	C7
SES	9.419***	9.040***		8.978***
	(0.667)	(0.675)		(0.678)
Risk attitudes r	0.419		-5.585**	-3.005
	(1.779)		(2.024)	(1.847)
Time preferences δ		19.28***	26.68***	20.45***
		(2.497)	(2.939)	(2.614)
R^2	0.084	0.095	0.021	0.096

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Number of observations: 6,382. Associations with educational expectations shown for combined SES & risk attitudes (C4), SES & time preferences (C5), risk attitudes & time preferences (C6), and all three explanatory variables (C7). The SES regression coefficient shows how much a change in one standard deviation of SES is associated with educational expectations in percentage points. The risk attitudes and time preference coefficients show how much a 1-unit change in r and δ, respectively, is associated with differences in educational expectations. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis.

4.4.2. Conditional Associations

In the following paragraphs, I present the results from my regression analyses when including control variables. As detailed in Section 4.3, I begin by stepwise adding more background information in models M1 to M3. Table 4.6 shows the estimates for the associations between SES, risk attitudes, and time preferences with educational expectations, adding demographics and parental health, educational investments, and cognitive and behavioural scores.

In all four models, socio-economic status and time preferences are statistically significantly associated with educational expectations at the 0.1% level, while no link can be measured for risk attitudes. In model M1, an increase in SES by one standard deviation is estimated to be linked to 9.5 percentage point higher educational expectations. When including parental health and educational investments (model M2), the point estimate goes down to around 8 percentage points. Similarly, increasing the time preference parameter, δ, by 0.1 (around half a standard deviation) increases educational expectations by 1.6 percentage points (M1 & M2). However, when including cognitive ability and behavioural issues in the analysis, the point estimate

Table 4.6.: Conditional associations of SES, risk attitudes, and time preferences with educational expectations at age 17

Variable	M1	M2	M3
SES	9.492***	8.194***	3.914***
	(0.719)	(0.700)	(0.617)
Risk attitudes r	-3.217	-2.838	-1.783
	(1.766)	(1.721)	(1.602)
Time preferences δ	16.04***	15.55***	12.58***
	(2.581)	(2.549)	(2.320)
Demographics & health	x	x	x
Educational investments	–	x	x
Behavioural and cognitive scores	–	–	x
R^2	0.195	0.205	0.288

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Number of observations: 6,382. The SES coefficient corresponds to a one-standard-deviation change, coefficients for r and δ represent 1-unit changes in the respective variables. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis.

for the association of socio-economic status is reduced by more than half to around 4 percentage points for a standard deviation increase in SES. The change in my estimate for time preferences is less pronounced: the association measured in M3 estimates that an increase in δ (more patient) by half a standard deviation increases educational expectations by 1.3 percentage points.

Previous research has shown that economic preferences are correlated with cognitive ability (Dohmen, Falk, Huffman & Sunde 2010). Therefore, observing the association between patience and educational expectations change when including cognitive measures is unsurprising. Dohmen, Falk, Huffman & Sunde (2010) find high-ability pupils to be more patient. Also, universities select students based on their ability such that high-ability students are more likely to meet the criteria to enter higher education. Hence, when including only economic preferences as a regressor and not cognitive ability as a control variable, this would lead to an overestimation of the association between economic preferences and educational expectations.

Next, in order to better understand the impact SES and economic preferences have on the formation of educational expectations, I control for educational expectations at age 14. In Table 4.7, I present the results from model M3 for those 5,884 cohort members for whom I observe educational expectations at age 14 and 17 as well as the results from model M4. My results indicate that SES and time preferences are associated with educational expectations at age 17 even when controlling for educational expectations at age 14. In particular, consider an example with two cohort members who have the same educational expectations at age 14 and otherwise have identical background characteristics. The only difference being that cohort member A has a socio-economic status of one standard deviation higher than cohort member B. My results suggest that at age 17, A estimates the likelihood of going to university to be around 2.7 percentage points higher than B's estimate. Similarly – all other things equal – a one-standard-deviation more-patient individual with the same educational expectations at age 14 estimates the likelihood of going to university at age 17 at 2.2 percentage points higher than a more impatient individual.

Last, I examine the individual contribution of each component of the composite SES indicator. Recall that the SES measure is a composite measure consisting of permanent income, income volatility, home ownership, worklessness, single parenthood, and parental education. Table 4.8 shows the association of economic variables (1), worklessness and single parenthood (2), parental education (3), and a combination of all of these (4) with educational expectations. Across these regressions, different

Table 4.7.: Conditional associations with educational expectations at age 17 controlling for educational expectations at age 14

Variable	M3	M4
SES	3.850***	2.653***
	(0.664)	(0.676)
Risk attitudes r	-1.164	-0.753
	(1.752)	(1.649)
Time preferences δ	12.04***	10.82***
	(2.501)	(2.338)
Educational expectations at age 14		0.475***
		(0.0206)
R^2	0.293	0.399

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Number of observations: 5,884. The SES coefficient corresponds to a one-standard-deviation change, coefficients for r and δ represent 1-unit changes in the respective variables. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis.

variables show to be statistically significant at times. The pattern visible in (1), (2), and (3) is that income, living in a two-parent household, and high education are positively associated with higher educational expectations. However, the estimates in (4) can be misleading due to the strong correlation between them (multi-collinearity). Therefore, I show the F-statistic for a test of joint significance at the bottom of the regression table. In all four models, I find that the SES measures included are highly significantly associated with educational expectations at age 17. Furthermore, regardless of which SES measures are included, my estimates for the economic preferences measures are robust.

Robustness checks To test whether model specifications and variable construction drive my results, I perform a series of robustness checks. First, as educational expectations are a truncated variable with many observations at the boundaries at 0% or 100%, I estimate my models using a Tobit regression. The resulting estimates confirm that teenagers with high socio-economic status and more patience have higher educational expectations. Second, I include GCSE scores for pupils from England as a control variable. Because of limited data availability and a therefore reduced sample size, I do not control for GCSE scores in the main body of this study. While

Table 4.8.: Conditional associations of SES components and economic preferences with educational expectations

Variable	(1)	(2)	(3)	(4)
Permanent income (log)	14.97***			15.07***
	(2.043)			(2.471)
Income volatility	0.0168			-0.336
	(0.563)			(0.561)
Home ownership rate	-2.576			-0.840
	(1.569)			(1.624)
Worklessness rate		2.782		11.27***
		(2.197)		(2.770)
Single-carer rate		-7.609***		-3.034
		(2.212)		(2.291)
Highest parental education level (base: none)				
Overseas qual only			-0.983	-1.099
			(4.916)	(4.833)
NVQ level 1			-1.891	-1.656
			(4.223)	(4.121)
NVQ level 2			-4.122	-4.322
			(3.523)	(3.648)
NVQ level 3			0.126	-0.992
			(3.644)	(3.864)
NVQ level 4			5.425	2.450
			(3.229)	(3.434)
NVQ level 5			8.845**	4.405
			(3.328)	(3.602)
Risk attitudes r	-1.792	-1.802	-2.032	-1.713
	(1.604)	(1.592)	(1.606)	(1.607)
Time preferences δ	12.70***	13.03***	12.62***	12.29***
	(2.297)	(2.333)	(2.353)	(2.280)
R^2	0.293	0.283	0.292	0.302
F-statistic (joint test of SES variables)	24.51	5.92	12.45	12.35
$Prob > F$	0.0000	0.0029	0.0000	0.0000

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Number of observations: 6,382. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis.

results generally confirm the role of SES and time preferences, the point estimates – in particular for SES – are considerably smaller compared to those presented above. Last, I replace the continuous risk attitudes and time preference variables constructed as described in Section 4.2 with binary indicators dividing the sample in high and low risk aversion and patient and impatient. Again, results from this regression confirm that SES and patience are positively associated with educational expectations while risk attitudes do not influence young people's expectation of going to university.

4.4.3. Interactions

In the following, I present the results when including interaction terms between the explanatory variables of interest. This helps to better understand not only the direct associations of each explanatory variable, but also how they interact with each other in predicting educational expectations.

Table 4.9 shows the results from regression analyses when adding interaction terms.

Table 4.9.: Conditional associations with interaction terms

Variable	M3	I1	I2
SES	3.914***	4.088***	4.078***
	(0.617)	(0.610)	(0.610)
Risk attitudes z_r	-0.554	-0.574	-0.599
	(0.498)	(0.458)	(0.465)
Time preferences z_δ	2.561***	2.940***	3.043***
	(0.472)	(0.454)	(0.495)
SES $\times$ z_r		-0.0400	-0.0553
		(0.539)	(0.539)
SES $\times$ z_δ		1.232**	1.240**
		(0.442)	(0.441)
$z_r \times z_\delta$			0.282
			(0.499)
R^2	0.288	0.289	0.289

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Number of observations: 6,382. The SES, r, and δ coefficients corresponds to a one-standard-deviation change. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis.

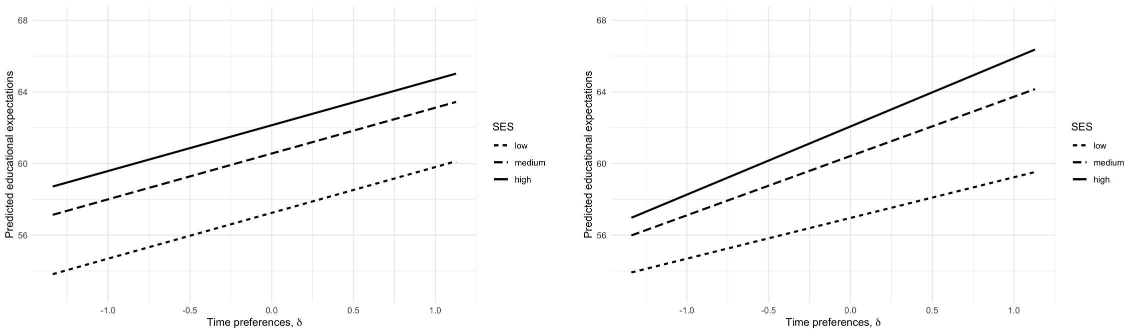
Note that for better interpretability of the interaction terms as well as the direct associations, I present estimates for standardised risk attitudes and time preferences.

The first observation is that both socioeconomic status as well as time preferences are associated with educational expectations at a similar or slightly higher magnitude when interaction terms are included. This can be interpreted as follows. For teenagers from average SES-background, with average risk attitudes, and average time preferences, (a) an increase of SES of one standard deviation is associated with an increase in educational expectations of 4 percentage points; and (b) an increase in patience level of one standard deviation is associated with an increase of education expectations of around 2.5 to 3 percentage points.

Second, the interaction term between SES and time preferences is positively associated with educational expectations. This means that high-SES teenagers, patience levels matter more than for low-SES teenagers. Similarly, for more patient teenagers differences in SES are associated with stronger differences in educational expectations compared to impatient teenagers.

Third, as in all other regressions and associations presented in this study, I do not find an association between risk attitudes and educational expectations – directly or as part of an interaction term. This confirms that risk attitudes appear to not matter for the formation of educational expectations: risk averse teenagers estimate their chance of going to university at comparable levels to their risk-taking peers.

Figure 4.5.: Predicted educational expectations by time preferences and SES



(a) No interaction terms (M3) (b) Interactions terms included (I1)

Notes: Predicted educational expectations computed for a white, female cohort member from an advantaged neighbourhood in the South-East of England, non-smoking household. All other variables held at average. Low, medium, and high SES corresponds to 25th percentile, median, and 75th percentile, respectively. Time preferences shown as z-scores with mean 0 and standard deviation 1.

Figure 4.5 shows the relationship between SES, time preferences, and predicted educational expectations as modelled in M3 (left panel) as well as I1 (right panel). Assuming a hypothetical average individual with the most common background characteristics – white, female, from an advantaged neighbourhood in the South-East of England – I show the predicted educational expectations (y-axis) for different time preferences (x-axis) and SES levels (lines). The solid line represents cohort members from a high-SES background (75th percentile), the dashed line shows predicted values for median SES, and the dotted line represents low SES (25th precentile). This figure highlights the strong difference in educational expectations depending on SES level and time preferences. All three lines show how educational expectations increase in levels of patience.

In particular, panel (a) shows that – in absence of interaction terms – more patient cohort members from a medium-SES background are predicted to fully compensate for their SES disadvantage if their time preference, δ, increases by 0.1 – equivalent to half a standard deviation. On the other hand, high-SES individuals with very low δ (i.e. very impatient) at around the 10th percentile are predicted to have almost the same educational expectations as very patient (90th percentile) cohort members from a low-SES background.

However, panel (b) highlights that – once including interaction terms between the explanatory variables – the difference between low and high SES teenagers is more pronounced for patient youths. Hence, even very patient low-SES teenagers have lower educational expectations than their medium-SES peers with average patience level. Thus, while patience matters regardless of SES, it has the strongest impact on educational expectations in high-SES teenagers.

4.4.4. Reasons Not to go to University

All cohort members reporting to be less than 100% sure of going to university are asked what their main reason for not attending university would be. Possible answers include not having good enough grades, rather wanting to get a job, or that they and their family cannot afford to pay for a university education. Around 13% of cohort members say the main reason for them not to go to university is money.

Table 4.10 shows the estimates of the association between SES, risk attitudes, and time preferences with the likelihood for cohort members to mention money as the main reason for them not to attend university. In model R1, not controlling for any background characteristics, I find that cohort members with a one-standard-deviation-higher SES are 2.7 percentage points less likely to report money as their main reason. Furthermore, I observe a statistically significant ($p < 0.05$) positive

Table 4.10.: Main reason not to attend university

Variable	R1	R2	R3
SES	-0.0276***	-0.0211**	-0.0251**
	(0.00597)	(0.00762)	(0.00767)
Risk attitudes r	-0.00100	-0.00229	-0.0000862
	(0.0199)	(0.0195)	(0.0197)
Time preferences δ	0.0666*	0.0489	0.0384
	(0.0298)	(0.0299)	(0.0298)
Educational expectations (age 17)			0.000998***
			(0.000189)
Demographics & health	–	x	x
Educational investments	–	x	x
Behavioural and cognitive scores	–	x	x

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Number of observations: 5,307. The SES coefficient corresponds to a one-standard-deviation change, coefficients for r and δ represent 1-unit changes in the respective variables. All reported coefficients are average marginal effects showing how a 1-unit change of the explanatory variable corresponds with a change in likelihood of monetary reasons being the main reason not go to university. For example, the coefficient for educational expectations at age 17 means that a 10 percentage points higher educational expectation at age 17 is associated with a 1 percentage point higher likelihood of monetary reasons being the main reason not to go to university. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis.

association between patience (higher δ) and money being the main reason not to attend university. In model R2, I control for all observed background characteristics. In this model, I estimate the association between SES and reasons not to attend university to be around -2.1. My estimate for time preferences is not statistically significant in this model. Lastly, model R3 controls for educational expectations at age 17. Again, an increase in SES of one standard deviation is associated with a decrease of 2.5 percentage points in the likelihood to report monetary reasons as the main cause not to attend university.

In summary, these results indicate that adolescents from a lower SES background are significantly more likely to expect not to go to university for financial reasons. This holds true even when controlling for cognitive and behavioural scores and other background characteristics. The point estimates suggest that lowering SES by one standard deviation makes it 2 to 3 percentage points more likely for money to play a role in university attendance. In the context of only around 13% of 17-year-olds naming financial reasons as their main reason, low SES is a very strong predictor of money being an important factor in educational decisions. While not entirely unexpected, as SES is strongly associated with household income and wealth, this result highlights that money is a key factor in keeping disadvantaged children from pursuing a university education.

However, I do not find risk attitudes and time preferences to be associated with money as the main reason not to attend university. The absence of an association between risk attitudes and 'money as reason' contrasts with the narrative that more-risk-averse individuals prefer to avoid student fees and therefore do not go to university. Together with previous results, risk aversion appears to neither be associated with educational expectations nor with the reasoning not to go to university. This indicates that the student financing system in the UK may be successful at buffering concerns of financial risks associated with student fees. However, as both risk and time preferences are measured using only one set of questions, measurement error and resulting attenuation bias could be driving this result.

The mechanism via which time preferences are expected to influence behaviour is through *impatience*: high valuation of present utility compared to future utility. Financial concerns about the cost of higher education, on the other hand, are not related to the timing (after graduation) of the reward (higher earnings). Hence, finding no association between impatience and financial concerns around attending university – conditional on individual and household background characteristics – is in line with my hypotheses.

4.5. Conclusion

Overall, my results paint a clear picture: the socio-economic status in which a young person grows up as well as the level of patience are strongly associated with educational expectations; risk attitudes, however, do not contribute to the formation of educational expectations. The magnitude of these associations suggest that both SES and patience are major contributors to the belief of going to university and may subsequently result in the decision of going to university. This holds true even when controlling for comprehensive cognitive measures from age 3 until 14. Hence, given all observable characteristics, including economic preferences, SES matters; and given all observable characteristics including SES, patience matters. Moreover, for high-SES individuals the association between time preferences and educational expectations is stronger.

Furthermore, I observe that lower SES cohort members are substantially more likely to report money as the main reason keeping them from going to university. My finding that risk aversion is not linked to lower educational expectations due to financial concerns indicates that the UK student financing system may successfully buffer financial concerns around student fees.

The main limitation of this study is that – despite the rich set of control variables – the causal link remains somewhat questionable. Partly, this is due to the nature of measures such as SES. Socio-economic status is likely to not change much during adolescence for many people. Therefore, I cannot meaningfully apply econometric methods exploiting differences in SES. Similarly, economic preferences may be formed through a long period in childhood and adolescence and be relatively fixed at the age of 17. Furthermore, despite the background information I can rely on for my analysis being very detailed and comprehensive, certain possible confounders are not part of my analysis. Another shortcoming of this research is that – despite the likely link between educational expectations and future decision-making – I cannot observe actual educational decisions, yet. Only in a few years' time will MCS data be able to verify if the link I observe between SES and impatience with educational expectations prevails into the decision of whether or not to go to university.

As my results are robust against several model specifications in my analyses, it is reasonable to assume that higher SES during childhood also improves educational expectations – all other factors held equal. Social or economic policies leading to levelled-up socio-economic status (for example, through increased low incomes) could therefore affect educational expectations in children growing up in these households. This, in turn, could lead to higher intergenerational mobility. Similarly, making an individual more patient alone contributes to higher educational expectations. As more-patient youths appear to be more likely to apply for university after finishing school, this has some potential implications for policymakers to reduce the gap in university attendance. Especially among low-SES pupils, using measures that improve patience might – among other positive ramifications – also improve educational expectations. However, my results indicate that increasing patience would be most effective in high-SES pupils. Hence, improving patience levels in teenagers across the board could lead to a widening of the SES-gap.

One possible reason for lower educational expectations in low-SES individuals is the lack of role models. If neither their parents nor their friends' parents went to university, this in itself might be a deterrent. Mentoring initiatives in which university students peer up with disadvantaged children can effectively help young people find their path in post-secondary education (Resnjanskij et al. 2021). One channel through which this mentoring programme improves low-SES pupils' educational outcomes is by making them more patient. Raising awareness of both teachers and parents to address the benefits of considering future improvements in quality of life might further contribute to improving educational attainment of otherwise equally capable but more impatient young people. Another possible way to improve university attendance of impatient individuals would be by not changing their patience level but by making university education resonate more with their economic preferences. Clearly communicating the benefits of obtaining a university degree might change the decision for some impatient adolescents.

Additionally, as low-SES cohort members themselves more regularly report money as an important contributing factor in their educational decisions, improving the (perceived) affordability of a university education may help further decrease the gap in educational expectations between low- and high-SES individuals. While the UK's income-contingent student loan system might not result in more-risk-averse individuals disproportionately being deterred from a university education, my results indicate that low-SES pupils are more concerned about the cost of higher education. For example, universities adjusting the communication of their student fees by putting the income-contingent nature of the student fee system at the centre might further encourage young people from disadvantaged backgrounds.

5. Summary and Conclusions

5.1. Key Findings

The results of Chapters 2 and 3, in which I study the relationship between household worklessness and educational investments, are mixed. First, when looking at monetary investments, there is a clear difference in early childcare at age 1 and 3: children in workless households are a lot less likely to have had paid-for childcare compared to those in working households. This holds true when controlling for a rich set of background variables as well as when applying causal identification strategies. As childcare has been found to contribute to a child's educational success later in life (Sylva 2014) and educational investments of all sorts are considered to be more effective at a young age (Cunha & Heckman 2007; Cunha, Heckman et al. 2006; Hernández-Alava & Popli 2017), this finding suggests that children growing up in workless households may face disadvantage through this channel. However, note that Blanden, Del Bono, Hansen et al. (2021) highlights the importance of childcare quality and finds overall low positive impact of attending childcare. When looking at the difference in extra lessons, both my analysis of PISA and MCS data shows no difference between workless and working households when accounting for background characteristics. This may indicate that children in workless households are on a comparable level to those from other low-SES households and commercial tutoring may be in demand only from the well-educated middle class. Lastly, in the PISA study parents were asked to assess how much money they spend on their child's education. Workless parents reported spending significantly less than those in working households.

Next, when moving to time investments, an interesting pattern emerges. While household worklessness appears to cause sufficient time supply (parents reporting they have enough time with their child), this translates into almost no additional time investments. While household worklessness is associated with reading to young children, I do not observe a robust causal link. Moving to helping with education through teaching the child how to read, write, or do simple maths, and homework help, my results indicate that children in workless households receive just as much of these time investments as their peers in working households. This may in part be because many other possible time investments – taking ones child to the library, visiting museums, observing bedtimes, etc. – were outside the scope of this thesis. However, research such as Parsons et al. (2014) find that workless households was associated with taking a child to the library less regularly and being worse at observing bedtimes. This would even indicate that workless households may have lower time investments in other categories. However, it is important to note that these findings were generated without attempting reduce bias using causal methods.

In summary, my findings suggest that when children are young, workless parents are less likely to spend money on childcare. At the same time, I do not find strong and robust evidence for compensation through time investments. However, at an older age, household worklessness does not impact monetary investments through commercial tutoring; at the same time, workless parents do not spend more time helping their child with homework. This further refines findings by Parsons et al. (2014). While in their study they find that workless households *invest less* time in form of reading to their child, in including a rich set of background variables and using methods to reduce bias, I cannot confirm this finding but find a null or positive association between household workless and reading to child. Furthermore, I add to the literature using methods aimed at causal inference around household worklessness. Macmillan (2010) use an instrumental variable constructed around industries hard-hit during recession and Mäder, Riphahn et al. (2015) create an instrument based on industry-specific and regional unemployment risk. I add to these potential instruments by exploiting changes in worklessness rate in specific job categories.

In Chapter 4, I moved away from household worklessness as a source of disadvantage towards the link between wider socio-economic status with educational expectations. Moreover, I looked at the contribution economic preferences make to the formation of young people's expectations of going to university.

The results from this analysis are very clear: higher SES and more patience correspond with higher educational expectations. This is an important addition to the analyses of disadvantage in Chapters 2 and 3. While previously I discussed disadvantage through investments made by parents, individuals' (expected future) decisions in adolescence define which trajectory adult life may and may not take. Observing that young adults growing up in lower SES households do not expect to go to university at the same rates as their higher SES peers – controlling for aptitude – means disadvantage in upbringing influences decision-making. Moreover, as I analyse the influence economic preferences play *simultaneously*, this accounts for patience or risk attitudes being the underlying cause.

This result is in line with Anders (2017) and Anders & Micklewright (2015) and indicates that also 10 years later pupils from disadvantaged families estimate their likelihood of going to university to be lower than those from higher SES families. This leaves room for policymakers to target programmes at lower SES pupils to encourage them to go to university. As my research finds that lower SES pupils are also more likely to name money concerns as the main reason not to go to university, this may be a possible starting point for new policies.

Aside from socio-economic status, time preferences themselves play a crucial role in explaining who thinks of going to university and who does not. The more patient individuals are more likely to think they will pursue a degree – controlling for SES and cognitive aptitude. However, I do not find a relationship between risk attitudes and educational expectations. While the former result fits into the narrative of future orientation being a good predictor for prudent choices, the latter indicates that high student fees are likely not viewed as a risk that more-risk-averse individuals try to avoid. Future policy could aim at impatient young people by encouraging them to focus more on future rewards for education.

While I do not look at outcome later in life in this thesis, my research can help inform how differences in educational investments between social groups might impact wages later in life. First, the impact of my finding that children in workless households are less likely to receive paid-for childcare may have some ramifications for outcomes at adult age. However, as Blanden, Del Bono, Hansen et al. (2021) highlights, the small positive effects of high-quality childcare are not persistent over time. Thus, while childcare may be a factor in a child's development, difference in childcare attendance between children from working and workless households is unlikely to contribute substantially to wages and social mobility later in life. This argument extends to further findings around educational investments into children from workless households. For most researched categories, associations are comparably weak or null, suggesting that differences in educational investments are likely not driving inequalities of opportunity. Poorer households spending less on children's education (Kornrich & Furstenberg 2013; Mauldin et al. 2001) and lower parental education levels being associated with educational spending (Black, Devereux & Salvanes 2005) are likely dominant contributors to the disadvantage children from workless households face. Once controlling for these substantial factors, worklessness in and by itself appears to add only marginally to the existing disadvantage. While parental education and income are associated with time investments (Guryan et al. 2008), my findings suggest no further added disadvantage through worklessness. Hence, outcome later in life are likely to be impacted more strongly through parental education and parental income – which are strongly associated with household worklessness – than through household worklessness.

My results relating to the association between SES and economic preferences with educational expectations likely have more direct ramifications for young people's lives. My findings suggest that lower SES pupils have lower educational expectations. As Anders (2017) notes that educational expectations predict future university attendance well, this means that lower educational expectations in low-SES and impatient teenagers are likely to lead to lower rate of university degrees in these groups. Furthermore, as having a university education is strongly linked with higher earnings in life (Belfield et al. 2018), my results indicate that impatient and low-SES young people on average have lower lifetime earnings later on – controlling for a rich set of background characteristics including cognitive scores and school grades.

5.2. Limitations

While this thesis contributes to the scientific literature in answering questions around household worklessness and socio-economic status in new ways, all my results come with limitations.

5.2.1. Data

PISA data The data used – international data from the PISA study and UK specific data from the MCS – has limitations common to survey data. First, as PISA data is focussed on comparing education systems and student performance across the world, information relating to both household worklessness and educational investments is not detailed. Household worklessness is reported by children alone and the strong disparity between UK worklessness rates calculated from PISA data (7%)

and MCS data (17–20%) indicates potentially large measurement error. Similarly, as the PISA questionnaire touches on many different areas, information indicating time and money investments is limited to commercial tutoring and parental homework help.

Second, cross-sectional by design, in the PISA dataset I only observe each individual at one point in time at the age of 15. This means I do not observe educational investments at a younger age. Furthermore, I cannot use methods to see the impact of moving in and out of worklessness on educational investments.

Third, while these issues may be less pronounced in the MCS data, the longitudinal nature of such a cohort study leads to *sample attrition*: people do not respond to later sweeps and therefore drop out of the data I can analyse. While I account for attrition by using appropriate weights, these weights can only take into account observed characteristics leading to attrition. Attrition can cause bias if non-responders are different from those participating in unobserved characteristics correlated with the variables I analyse.

Fourth, MCS data contains information about economic preferences, but not in great detail. Studies focussing on risk attitudes and time preferences attempt to measure these character traits with multiple questions to obtain reliable and detailed estimates of these constructs. MCS data, on the other hand, only contains one data point for both risk attitudes and time preferences for each cohort member. This likely results in noisy estimates, potentially biasing my estimates towards 0.

5.2.2. Household Worklessness

Household worklessness is a construct closely related with both parents' relationship status and income. A single-earner household in which parents divorce might result in a workless household. Attributing differences in investments to the shift from working to workless or from two-parent to single-parent is challenging. Similarly, workless households typically have lower income as compared to working households. The disadvantage from a change in occupation status likely, in part, comes from the change in income. However, my research is focussed on worklessness and how the disadvantage from household worklessness is different from disadvantage from loss in income.

Another difficulty of household worklessness is the range of what worklessness can mean. Some households are involuntarily and temporarily out of work. Parents might have health issues or are temporarily unemployed. For these households at the margin of worklessness, causal estimation of the ramifications of transitioning in and out of worklessness is meaningful. However, some households are long-term workless. This, again, can be due to various reasons such as health or general economic inactivity. As these households do not transition in and out of worklessness, it becomes difficult to attribute educational investments made by parents *causally* to their employment status.

Furthermore, I discuss worklessness in a binary setting: a household is either workless or not. While being true to the letter of what household worklessness means and how household worklessness is discussed in the literature, this means (involuntarily) underemployed households are in the same category as households with two full-time employed carers. Households in which parents may work only a few hours per week are considered working households throughout my thesis.

5.2.3. Causal Inference

In this thesis, I show a mixture of associations and causal estimates. While associations controlled for by rich background information are highly informative, the question of how parents change their behaviour *due to* worklessness is of interest. However, this comes with some difficulties. First, as discussed above, only a subset of workless households are at the margin of worklessness. For this group, causal inference is feasible. Children in long-term workless households contribute to associations measured but not to causal inference through fixed effects estimation or using instrumental variables. Second, as I introduce different ways of estimating the causal impact of worklessness, constructing suitable instrumental variables or exploiting the longitudinal nature of the data, at times, results in inconclusive evidence for the causal impact of household worklessness.

5.3. Future Research Areas

Overall, my thesis has narrowed some gaps in the literature around educational investments, but questions for future research remain.

First, while household worklessness appears to be a possible source of disadvantage, disentangling this from other factors such as parental education, household income, or single parenthood remains a challenge. As my research confirms, many differences between workless-background and working-background children may be explained by other household background characteristics. Therefore, a solid definition of what constitutes a workless household and why researching worklessness instead of unemployment or poor health is valuable might be needed.

Second, certain subgroups of workless households (for example households which are short-term workless for labour market reasons) could be researched further using causal methods. A large proportion of research around household worklessness focusses on associations rather than causal estimates. This might be in part due to the difficulties in finding suitable methods to measure causality in the context of household worklessness or because the researched subgroup using causal methods is not equal to all workless households. However, finding and establishing suitable methods for causal worklessness research likely helps advance the research area. Causal estimates might help advise policymakers on how to meaningfully address disadvantage through worklessness. Similarly, causal estimates might also result in null results emphasising the need to treat each underlying cause of worklessness differently.

Third, my analyses of the ramifications of household worklessness compare workless households to households with any degree of employment. Further research could look at worklessness in a more continuous sense. For example, researching the impact of underemployment in different forms – such as one parent staying at home or households with no full-time employment – could paint a more detailed picture of how parental employment matters for child development.

Fourth, while I present up-to-date evidence for the link between household SES and educational expectations, future research could aim to confirm that this translates into an attainment gap in young adults. If the 'disadvantage' were to only manifest in expectations not actions, there would be no action required from policymakers. While it can be expected that indeed 17-year-olds who have lower educational expectations will attend university at lower numbers later in life, confirming the role of SES and educational attainment for this birth cohort would strengthen my findings.

Fifth, my research is one of the first to analyse the role economic preferences play in UK adolescents and their decision-making. Further research could build on this and study associations between economic preferences and educational outcomes, wages, and other outcomes. As the MCS offers rich and representative data, research around the long-term impact of economic preferences at a young age would be of great interest.

Sixth, future research could aim at better understanding how these preferences are formed and which role socio-economic differences play in that. This would add to the existing evidence around the formation of economic preferences. Given the rich data from the MCS and possibly from future cohort studies, this could add insights into the key determinants of economic preferences.

Last, the rich and unique UK birth cohort studies allow for the study of economic preferences over the course of life. Analysing how life events might alter economic preferences and, through this, shape actions would be of great interest. This would add to the information about initial preference formation and would allow a better understanding of how events such as getting married, having children, divorce, promotion, or unemployment affect economic preferences.

5.4. Policy Implications

First, my research clearly shows that household worklessness causes parents not to use professional childcare services. While this result cannot be strictly generalised to the current policy of 15 hours of free childcare for every child in the UK and an additional 15 hours for working parents, my results indicate that worklessness might cause parents to not take up professional childcare offers. This result was found controlling for families' socio-economic situations, including household income. Thus, this may be a starting point of early disadvantage of children from a workless background. While their peers learn from each other and from professional staff at childcare facilities, children from a workless background might be less likely to have this experience. Hence, actively advertising early childcare opportunities to workless households and encouraging parents to take up this offer may help reduce potential disadvantage for workless-background children. Moreover, extending free childcare to 30 hours per week for all children regardless of their parents' employment status might help provide all children with an as-equal-as-possible starting point once they enter school (Sutton Trust 2021). However, it is important to note that the potentially positive impact of childcare is debated in the literature. For example, Blanden, Del Bono, Hansen et al. (2021) find no positive impact of low-quality childcare, especially when provided by private childcare facilities. As childcare may have a different impact on children from low-SES and workless households, better understanding the impact of childcare on workless background children would be helpful to inform future policies.

Second, as my research finds that more-patient adolescents have higher educational expectations, this opens up the possibility to improve university attendance among young people with low patience. In particular, two approaches could be taken. One, it could become an integral part of the education system to use techniques to improve (economic) patience. For example, encouraging pupils to think beyond their time in school and plan for the future could improve patience. By introducing the idea that further education can be viewed as an investment in future earnings, this could help improve patience levels in those students that do not have regular conversations about their career prospects at home. Such policies could result in higher patience rates among all young people which, in turn, affects life decisions. Two, it would be possible to target subgroups of the population with lower patience levels. For example, as Resnjanskij et al. (2021) show, targeted mentoring programmes aimed at low-SES teenagers approaching school-leaving age might help improve their patience levels and with that future life outcomes. However, as this study only looks at teenagers close to graduating secondary education, similar measures could be taken from a younger age.

These measures could help close the gap between higher and lower SES groups. For example, from the MCS data I find that low-SES pupils have lower patience levels compared to their high-SES peers. Thus, improving patience in low-SES individuals and closing the ‘patience gap’ could possibly help close the gap in university attendance between different socioeconomic groups. However, my findings suggest that higher patience levels are particularly effective in improving educational expectations in high-SES individuals, limiting the potential of patience improving policies on university attendance.

Third, this finding could be used to check future education-related policies on the impact they may have on impatient individuals. In the context of university education, patient individuals value the future rewards more strongly relative to the cost of education compared to their more-impatient peers. Emphasising the (monetary) rewards of university education and lowering the perceived cost in the way universities communicate student fees may help encourage more-impatient adolescents to enter tertiary education. In particular, while research such as Belfield et al. (2018) clearly shows that university degrees have a positive impact on earnings later in life, this message might not reach pupils in all demographics. While it may be well established in high-SES communities that university education positively impacts earnings, the same might not be true for lower-SES individuals in which none of the parents have attended university. This would support my result that patience levels are less effective in low-SES pupils: perceived future rewards of education may be lower leading to lower effectiveness of patience in low-SES pupils.

Appendices

A. Supplementary Results From Chapter 2

A.1. Additional Tables

Table A.1.: Overview of all countries and jurisdictions participating in the PISA 2012 cycle.

Country	N_0	P^{workless}	N_{SQ}	N_{SQ}^{workless}	N_{SQ}^{matched}	N_{PQ}	N_{PQ}^{workless}	N_{PQ}^{matched}
Albania	4,743	0.12	2,394	386	768			
Argentina	5,908	0.09	3,040	344	604			
Australia	14,481	0.06	8,558	597	1,180			
Austria	4,755	0.03	2,871	97	188			
Belgium	8,597	0.06	5,119	318	628	7,777	518	1,022
Brazil	19,204	0.13	9,117	1,657	3,314			
Bulgaria	5,282	0.05	2,844	173	338			
Canada	21,544	0.04	12,860	548	1,084			
Chile	6,856	0.08	3,964	369	720	5,934	560	1,096
Colombia	9,073	0.10	4,115	611	1,220			
Costa Rica	4,602	0.12	2,403	366	580			
Croatia	5,008	0.15	3,171	527	984	4,746	750	1,488
Czechia	5,327	0.03	3,335	105	206			
Denmark	7,481	0.09	4,488	474	938			
Estonia	4,779	0.04	2,844	119	228			
Finland	8,829	0.05	5,262	315	600			
France	4,613	0.05	2,729	148	294			
Germany	5,001	0.03	2,500	92	174	3,857	149	282
Greece	5,125	0.11	3,147	373	726			
Hong Kong SAR China	4,670	0.07	2,923	220	430	4,362	333	646
Hungary	4,810	0.07	2,930	242	462	4,406	357	714
Iceland	3,508	0.03	2,117	76	134			
Indonesia	5,622	0.11	2,373	409	742			
Ireland	5,016	0.10	3,036	323	634			
Israel	5,055	excluded						
Italy	31,073	0.05	19,402	958	1,894	29,185	1,460	2,912
Japan	6,351	0.02	3,969	66	132			
Jordan	7,038	0.18	3,361	860	1,503			
Kazakhstan	5,808	0.12	3,441	459	854			
Latvia	4,306	0.04	2,385	121	222			
Liechtenstein	293	excluded						
Lithuania	4,618	0.08	2,736	251	494			
Luxembourg	5,258	0.04	3,170	152	294			

Country	N_0	P^{workless}	N_{SQ}	N_{SQ}^{workless}	N_{SQ}^{matched}	N_{PQ}	N_{PQ}^{workless}	N_{PQ}^{matched}
Macau SAR China	5,335	0.05	3,287	151	276	4,928	242	470
Malaysia	5,197	0.12	2,913	427	679			
Mexico	33,806	0.11	17,626	2,514	4,386	26,430	3,743	6,898
Montenegro	4,744	0.16	2,769	480	926			
Netherlands	4,460	0.05	2,674	121	220			
New Zealand	4,291	0.07	2,640	194	362			
Norway	4,686	0.03	2,845	87	160			
Perm Russia	1,761	0.04	1,014	44	88			
Peru	6,035	0.13	3,258	562	1,114			
Poland	4,607	0.08	2,837	219	432			
Portugal	5,722	0.06	3,342	223	410	5,022	341	672
Qatar	10,966	0.09	5,193	622	1,070			
Romania	5,074	0.15	2,849	529	1,040			
Russia	5,231	0.06	2,950	201	374			
Serbia	4,684	0.12	2,750	381	758			
Shanghai China	5,177	0.08	3,180	275	544			
Singapore	5,546	0.04	3,381	146	272			
Slovakia	4,678	0.06	2,760	205	394			
Slovenia	5,911	0.05	3,588	168	332			
South Korea	5,033	0.05	3,012	172	324	4,528	270	520
Spain	25,313	0.07	15,490	1,084	2,138			
Sweden	4,736	0.03	2,801	97	188			
Switzerland	11,229	0.03	6,888	250	496			
Taipei China	6,046	0.06	3,755	221	438			
Thailand	6,606	0.10	3,098	428	856			
Tunisia	4,407	0.12	2,155	330	566			
Turkey	4,848	0.21	2,598	690	1,291			
United Arab Emirates	11,500	0.15	6,095	1,135	1,900			
United Kingdom	12,659	0.07	7,408	561	1,054			
United States	4,978	0.05	2,862	195	370			
Uruguay	5,315	0.06	2,746	211	402			
Vietnam	4,959	0.37	2,807	1,227	2,352			

Notes: N_0: total number of participating students in PISA 2012. $NA^{workless}$: proportion of workless observations. N_{SQ}: number of observations suitable for analysis of dependent variables from the student questionnaire. $N_{SQ}^{workless}$: number of workless *observations for analysis of student questionnaire. $N_{SQ}^{matched}$: number of observations after propensity score matching. N_{PQ}: number of suitable observations from parent questionnaire in PISA 2012. $N_{PQ}^{workless}$: number of suitable workless observations from parent questionnaire. $N_{SQ}^{matched}$: number of observations after propensity score matching of parent questionnaire data.*

Table A.2.: Monetary and time investments for all countries with a parent questionnaire.

	Monetary investments		*Time investments*	
Data	Estimate	Standard error	Estimate	Standard error
Belgium	0.008	0.035	0.043	0.039
Chile	-0.065**	0.028	-0.045	0.035
Croatia	-0.026	0.025	-0.011	0.028
Germany	-0.134*	0.078	0.108*	0.061
Hong Kong SAR China	-0.071*	0.040	0.013	0.041
Hungary	-0.078**	0.040	0.026	0.032
Italy	-0.027	0.017	0.017	0.022
Macau SAR China	0.013	0.048	-0.003	0.050
Mexico	-0.028**	0.013	-0.011	0.012
Portugal	-0.125***	0.045	0.082*	0.042
South Korea	-0.074*	0.044	-0.017	0.044

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Results from an ordered logistic regression pooling single-parent and two-parent households.

A.2. Details About Methods

A.2.1. Education Expense Variable From Parent Questionnaire

This section describes how the categorical data from the monetary expense variable obtained from the parent questionnaire is transformed to ensure better comparability across countries. In Table A.3 the original education expense categories as reported in the PISA 2012 data are shown. The actual monetary values defining the categories are created for each country separately. Even though the PISA technical report specifies how those categories should be constructed, it remains rather non-transparent in practice. In the course of this paper, relative expenses within each country are used. For this, each category should include a comparable amount of observations across countries. As Table A.3 highlights, the amount of observations in each category varies tremendously across countries. For instance, the lowest expense category contains around 1.6% of observations in Belgium and about 20.6% in Germany. In countries such as Hungary and Mexico the highest three categories contain only very few observations, whereas in Italy the highest category is the second largest.

For better comparability, those six categories are regrouped to become three new categories aiming at balancing category sizes across countries. Table A.4 shows the sizes of those new categories. Even though balancing is not perfect, the categories

Table A.3.: Education expenses for all countries with parent questionnaire.

	0	0–W	W–X	X–Y	Y–Z	>Z
Belgium	0.016	0.057	0.234	0.321	0.167	0.205
Chile	0.113	0.283	0.433	0.084	0.024	0.063
Croatia	0.201	0.151	0.255	0.148	0.086	0.159
Germany	0.206	0.122	0.295	0.152	0.133	0.092
Hong Kong SAR China	0.101	0.281	0.152	0.361	0.077	0.027
Hungary	0.212	0.325	0.293	0.094	0.035	0.042
Italy	0.041	0.174	0.270	0.155	0.101	0.259
Macau SAR China	0.063	0.471	0.221	0.125	0.054	0.065
Mexico	0.148	0.423	0.380	0.024	0.010	0.015
Portugal	0.142	0.228	0.571	0.047	0.010	0.003
South Korea	0.067	0.321	0.267	0.170	0.102	0.073

Notes: Data from the parent questionnaire of PISA 2012. Displayed are the six spending categories as in the PISA dataset without recoding. The absolute values for W, X, Y, and Z differ in each country and are not reported in the PISA technical report.

help ensure better comparability across countries. Note that categories are merged for each country separately as each country has specific characteristics that need to be taken into account.

A.3. Robustness Checks

A.3.1. Heterogeneity Analysis

I obtained the results shown earlier in this section by pooling a large set of countries which are different in many aspects such as education and welfare system, overall economic power as well as the prevalence of commercial tutoring and parental homework help. In this section I show my estimates when pooling over different subsets of countries.

First, parents might adjust their behaviour according to the education system they raise their children in: the need for parental money and time to be invested in children's education could be lower in countries with a highly prioritised education system. I use data on public spending on education as a proportion of GDP (UNESCO Institute for Statistics (UIS) n.d.) and split the PISA countries at their median spending into low- and high-spending countries.

Second, there might be a difference between wealthy and less wealthy countries. Therefore, I split up the dataset into high and low GDP per capita (purchasing

Table A.4.: Education expenses for all countries with parent questionnaire. Three new categories created from the original six categories with increased balance are shown.

	Low	Medium	High
Belgium	0.307	0.321	0.372
Chile	0.396	0.433	0.171
Croatia	0.352	0.403	0.245
Germany	0.328	0.448	0.225
Hong Kong SAR China	0.383	0.514	0.104
Hungary	0.212	0.618	0.170
Italy	0.216	0.425	0.360
Macau SAR China	0.535	0.221	0.244
Mexico	0.571		0.429
Portugal	0.370	0.571	0.060
South Korea	0.387	0.267	0.345

Notes: Recoded educational expense categories based on data from the PISA 2012 parent questionnaire. No medium *category built for Mexico.*

power equivalents) countries according to World Bank (2019a).

Third, the prevalence of commercial tutoring and parental homework help differs substantially between countries. This might be reflected in the magnitude of my estimates. To account for this potential difference, I analyse countries separately depending on the proportion of commercial and parental tutoring, respectively, again splitting up the dataset into below and above median.

Table A.5 shows the estimates for the association between parental worklessness and commercial tutoring. I find no significant results for any of the subsets. The point estimates differ depending on which subset is analysed. Point estimates are higher in countries with more common commercial tutoring. Children growing up in single-parent households may have a stronger disadvantage in countries with low public spending on education and countries with a low overall GDP. However, these differences should be taken with a pinch of salt as standard errors for all point estimates are large, leaving wide confidence intervals for all estimates.

When focussing on the association between worklessness and parental homework help, the heterogeneity analysis is inconclusive with estimates changing in the opposite directions for two-parent and single-parent households. As before, all differences in estimates are possibly random effects and are well within the respective confidence intervals.

Next, I present country-specific ordered logistic regression estimates for the eleven

Table A.5.: M1 – Heterogeneity analysis for the association between parental worklessness and commercial tutoring.

	Two-parent household		*Single-parent household*	
Data	Estimate	Standard error	Estimate	Standard error
Public spending on education as % of GDP				
High	-0.013	0.012	-0.003	0.010
Low	-0.012	0.011	-0.017	0.012
GDP per capita (PPP)				
High	-0.008	0.015	-0.003	0.011
Low	-0.010	0.009	-0.010	0.011
Prevalence of commercial tutoring				
High	-0.014	0.012	-0.018	0.013
Low	-0.002	0.008	0.003	0.009

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Linear probability model on matched sample run separately for two-parent and single-parent households. Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, and immigration status. Standard errors clustered at country level. Country fixed effects.

Table A.6.: M2 – Heterogeneity analysis for the association between worklessness and parental homework help.

	Two-parent household		*Single-parent household*	
Data	Estimate	Standard error	Estimate	Standard error
Public spending on education as % of GDP				
High	0.015*	0.009	0.023*	0.013
Low	0.009	0.011	0.028*	0.015
GDP per capita (PPP)				
High	0.021*	0.011	0.022	0.014
Low	0.008	0.008	0.031**	0.014
Prevalence of parental homework help				
High	0.009	0.008	0.029**	0.014
Low	0.018	0.012	0.025*	0.013

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Linear probability model on matched sample run separately for two-parent and single-parent households. Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, and immigration status. Standard errors clustered at country level. Country fixed effects.

countries with a parent questionnaire. Recall that overall I find a statistically significant association between workless parents and educational expenses and no association for parental mathematics homework help. I compute the country-specific estimates not differentiating between two-parent and single-parent households to maximise sample sizes for each regression. In nine out of 11 countries, I find a negative association between worklessness and monetary investments. In Germany, Hong Kong, and South Korea these estimates are statistically significant on the 10% level; in Chile, Hungary, and Mexico estimates are statistically significant on the 5% level; and in Portugal I find an association statistically significant on the 1% level. For mathematics homework help, I find a positive association in six out of 11 countries, with only Germany and Portugal having estimates statistically significant at the 10% level.

Table A.7.: M3 & M4 – Country-specific estimates.

	Educational expenses		*Mathematics homework help*	
Country	Estimate	Standard error	Estimate	Standard error
Belgium	0.008	0.035	0.043	0.039
Chile	-0.065**	0.028	-0.045	0.035
Croatia	-0.026	0.025	-0.011	0.028
Germany	-0.134*	0.078	0.108*	0.061
Hong Kong SAR China	-0.071*	0.040	0.013	0.041
Hungary	-0.078**	0.040	0.026	0.032
Italy	-0.027	0.017	0.017	0.022
Macau SAR China	0.013	0.048	-0.003	0.050
Mexico	-0.028**	0.013	-0.011	0.012
Portugal	-0.125***	0.045	0.082*	0.042
South Korea	-0.074*	0.044	-0.017	0.044

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Estimates computed by using an ordered logistic regression with two-parent and single-parent households pooled together for larger sample sizes. Average marginal effects presented.

A.3.2. Continuous Dependent Variable

The dependent variables from the student questionnaire – commercial tutoring and parental homework help – are both continuous variables with values between 0 and 30. For the purpose of the main analyses, I recode them to become a binary variable indicating whether or not a student receives any commercial tutoring or parental homework help on a weekly basis. Tables A.8 and A.9 show the results when applying a linear model to the original continuous variable. Overall, I find similar results: no association between worklessness and commercial tutoring and a positive association between worklessness and parental homework help. However, standard errors are larger and some of the initially significant estimates for OECD and partner countries, respectively – especially for single-parent households – are now statistically not significant. This could partly be explained by a larger influence of unrealistic outliers (30 hours per week of parental homework help).

Table A.8.: Association between worklessness and commercial tutoring from a linear model.

	Two-parent household		*Single-parent household*	
Data	Estimate	Standard error	Estimate	Standard error
All countries	-0.054	0.038	0.008	0.042
OECD	-0.028	0.046	0.022	0.037
Partner countries	-0.071	0.056	-0.003	0.081
PQ	0.001	0.051	-0.031	0.056

$*\ p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$

Notes: Regression on matched sample run separately for two-parent and single-parent households. Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, and immigration status. Standard errors clustered at country level. Country fixed effects.

Table A.9.: Association between worklessness and parental homework help from a linear model.

	Two-parent household		*Single-parent household*	
Data	Estimate	Standard error	Estimate	Standard error
All countries	0.062*	0.037	0.089**	0.045
OECD	0.101**	0.048	0.065	0.058
Partner countries	0.033	0.055	0.120	0.073
PQ	0.070	0.069	0.101	0.087

$*\ p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$

Notes: Regression on matched sample run separately for two-parent and single-parent households. Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, and immigration status. Standard errors clustered at country level. Country fixed effects.

A.3.3. No Matching

All results presented in the main body of this paper preprocess the PISA data using matching techniques to improve balance in many background characteristics between workless and non-workless households. In the following, I present estimates resulting from regression analyses without prior matching. As before, I find no association between worklessness and commercial tutoring and a significant association between worklessness and educational expenses. I find a notable difference to the results presented in the main body of this paper in the association between worklessness and homework help in two-parent households: before, I found no association in countries with a parent questionnaire, whereas in the unmatched sample I find an association in data from the student questionnaire, and – to a lesser extent – in data from the parent questionnaire.

A.3.3.1. Monetary investments

Table A.10.: Association between worklessness and commercial tutoring from a linear probability model applied to different subsets of the matched PISA data – no matching.

	Two-parent household		*Single-parent household*	
Data	Estimate	Standard error	Estimate	Standard error
All countries	0.008	0.010	0.003	0.006
OECD	-0.001	0.012	0.006	0.007
Partner countries	0.011	0.012	-0.002	0.011
PQ	0.016**	0.007	0.002	0.008

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Regression on unmatched sample run separately for two-parent and single-parent households. Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, and immigration status. Standard errors clustered at country level. Country fixed effects.

Table A.11.: Association between parental worklessness and monetary investments using data from the parent questionnaire – no matching.

	Two-parent household		*Single-parent household*	
Regression	Estimate	Standard error	Estimate	Standard error
low | medium, high	-0.050***	0.015	-0.043***	0.014
low, medium | high	-0.030*	0.018	-0.025**	0.010
Ordered logistic regression	-0.047***	0.017	-0.038***	0.010

$*\ p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$

Notes: First two rows – linear probability models with different cut-points for the categorical dependent variable: between low income and merged medium and high income (first row) and between merged low and medium income and high income (second row). Standard errors clustered at country level. Country fixed effects.
Third row – ordered logistic regression. For comparability I report the average marginal effect *and the corresponding standard error, which allows the magnitude of the regression coefficients to be compared. Standard errors clustered at country level. Country dummies included (no country fixed effects).*
Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, immigration status, and mothers' and fathers' age.

A.3.3.2. Time investments

Table A.12.: Association between worklessness and parental homework help from a linear probability model applied to different subsets of the matched PISA data – no matching.

	Two-parent household		*Single-parent household*	
Data	Estimate	Standard error	Estimate	Standard error
All countries	0.035***	0.006	0.031***	0.008
OECD	0.038***	0.008	0.022***	0.009
Partner countries	0.023***	0.007	0.040***	0.014
PQ	0.019***	0.007	0.017	0.015

$*\ p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$

Notes: Regression on unmatched sample run separately for two-parent and single-parent households. Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, and immigration status. Standard errors clustered at country level. Country fixed effects.

Table A.13.: Association between parental worklessness and parental mathematics homework help using data from the parent questionnaire – no matching.

	Two-parent household		*Single-parent household*	
Regression	Estimate	Standard error	Estimate	Standard error
A | BCDE	0.017*	0.008	0.001	0.020
AB | CDE	0.018	0.013	-0.003	0.015
ABC | DE	0.024*	0.010	0.015	0.012
ABCD | E	0.010	0.007	0.002	0.008
Ordered logistic regression	0.022*	0.011	0.005	0.017

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: First four rows – linear probability models with different cut-points for the categorical dependent variable, indicated by ' | '. Abbreviations: A: 'Never or hardly ever'; B: 'Once or twice a year'; C: 'Once or twice a month'; D: 'Once or twice a week'; E: 'Every day or almost every day'. Standard errors clustered at country level. Country fixed effects.

Last row – ordered logistic regression. For comparability I report the average marginal effect *and the corresponding standard error, which allows the magnitude of the regression coefficients to be compared. Standard errors clustered at country level. Country dummies included (no country fixed effects).*

Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, immigration status, and mothers' and fathers' age.

A.3.4. Coarsened Exact Matching

CEM requires exact matches on all variables included in the algorithm. While exact matching is impractical for continuous variables, CEM allows setting up categories, within which exact matches are required. I use this as a robustness check. As exact matches are increasingly difficult to find the more variables are included in the algorithm, I perform matching using only parental occupation and education levels (four variables). For countries with high proportions of missing data of mothers' occupation, I additionally require exact matching on a missing data dummy for mothers' occupation. I divide parents' occupation variables into 10 equally sized categories to make exact matching possible. As with propensity score matching, I run the algorithm separately for single- and two-parent households.

Since CEM is a very restrictive matching approach as all categories must be matched exactly, more observations remain unmatched: more than 3,000 out of 9,859 children living in single-parent households remain unmatched. This results in a sample less representative of workless-background children than for propensity score matching in which the amount of unmatched observations remains comparably low. On the other hand, more working-background children are included in the matched dataset when matching with CEM, making estimates more robust.

Tables A.14 and A.15 show balance improvements in all variables of interest when applying CEM to student and parent questionnaire data, respectively. As guaranteed by CEM, parental education levels are now exactly matched. Occupation levels improve really well as they are required to fall into a very narrow range. However, as no matching is performed on gender and immigration status, balance in these variables does not improve. For the parent questionnaire data, balance is strongly reduced for most variables indicating parental age. Furthermore, the amount of workless background children in the final matched dataset is lower than under propensity score matching. However, as more working-background children are included as a control (making the application of weights necessary for all analyses), estimates can be expected to be more precise.

Overall, CEM comes with the advantage of having close-to-perfect matches in variables chosen for matching. This comes with a simple trade-off: the more variables are included for CEM, the fewer workless-background children can be matched to similar enough working-background peers. Hence, I choose to match only on the most important parental background variables, i.e. mothers' and fathers' education

Table A.14.: Absolute standardised bias in means before and after matching – student questionnaire.

Variable	*Two-parent household* Before	After	Improvement (in %)	*Single-parent household* Before	After	Improvement (in %)
Gender	0.06	0.03	54.51	0.03	0.06	-68.38
Immigration status	0.01	0.03	-175.29	0.12	0.09	21.34
Occupation level father	0.59	0.01	98.18	0.16	0.00	98.12
Occupation level mother	0.56	0.00	99.87	0.35	0.00	99.49
Education level father - low	0.51	0.00	100.00	0.23	0.00	100.00
Education level father - medium	0.10	0.00	100.00	0.06	0.00	100.00
Education level father - high	0.53	0.00	100.00	0.18	0.00	100.00
Education level mother - low	0.60	0.00	100.00	0.38	0.00	100.00
Education level mother - medium	0.13	0.00	100.00	0.01	0.00	100.00
Education level mother - high	0.63	0.00	100.00	0.41	0.00	100.00

Notes: Matched dataset generated as described in this section; i.e. CEM. All numbers are averaged over all 30 imputations.
Two-parent household*: Workless-background children discarded for lack of common support: 0. Unmatched workless-background children: 743-866. Total number of observations in matched dataset: 121,525-123,870.*
Single-parent household*: Workless-background children discarded for lack of common support: 0-38. Workless-background children unmatched: 3056-3195. Total number of observations in matched dataset: 19,119-19,649. Variation in figures due to random differences between the 30 imputed datasets.*

Table A.15.: Absolute standardised bias in means before and after matching – parent questionnaire.

	Two-parent household			*Single-parent household*		
Variable	Before	After	Improvement (in %)	Before	After	Improvement (in %)
Gender	0.08	0.06	25.21	0.05	0.07	-34.33
Immigration status	0.02	0.06	-269.32	0.01	0.04	-152.81
Occupation level father	0.68	0.02	97.69	0.26	0.00	98.45
Occupation level mother	0.69	0.00	99.48	0.48	0.01	98.81
Education level father - low	0.52	0.00	100.00	0.28	0.00	100.00
Education level father - medium	0.27	0.00	100.00	0.10	0.00	100.00
Education level father - high	0.40	0.00	100.00	0.23	0.00	100.00
Education level mother - low	0.60	0.00	100.00	0.44	0.00	100.00
Education level mother - medium	0.34	0.00	100.00	0.20	0.00	100.00
Education level mother - high	0.46	0.00	100.00	0.34	0.00	100.00
Father Age <36	0.02	0.10	-445.66	0.05	0.05	-18.46
Father Age 36-40	0.04	0.14	-308.55	0.01	0.08	-2072.11
Father Age 41-45	0.13	0.15	-19.79	0.12	0.09	22.71
Father Age 46-50	0.26	0.11	58.28	0.11	0.04	68.62
Father Age >51	0.30	0.37	-21.86	0.18	0.21	-12.00
Mother Age <36	0.10	0.08	20.82	0.04	0.10	-161.36
Mother Age 36-40	0.03	0.13	-328.42	0.01	0.06	-1933.03
Mother Age 41-45	0.20	0.11	48.41	0.15	0.05	62.91
Mother Age 46-50	0.11	0.05	51.66	0.06	0.01	74.02
Mother Age >51	0.23	0.27	-14.25	0.19	0.20	-1.78

Notes: Matched dataset generated as described in this section; i.e. coarsened exact matching. All numbers are averaged over all 30 imputations.
Two-parent household*: Workless-background children discarded for lack of common support: 0. Unmatched workless-background children: 57-80. Total number of observations in matched dataset: 61,943-63,303.*
Single-parent household*: Workless-background children discarded for lack of common support: 0-7. Workless-background children unmatched: 414-485. Total number of observations in matched dataset: 9,302-9,598. Variation in figures due to random differences between the 30 imputed datasets.*

and occupation levels.

A.3.4.1. Monetary investments

The results from a CEM-matched sample show – as for the results from the main body of this paper – that no significant association between worklessness and commercial tutoring can be found.

Table A.16.: Association between worklessness and commercial tutoring from a linear probability model applied to different subsets of the matched PISA data – coarsened exact matching.

	Two-parent household		*Single-parent household*	
Data	Estimate	Standard error	Estimate	Standard error
All countries	-0.001	0.008	-0.005	0.008
OECD	-0.003	0.010	0.002	0.010
Partner countries	-0.005	0.010	-0.014	0.014
PQ	0.008	0.007	-0.011	0.013

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Regression on CEM-matched sample run separately for two-parent and single-parent households. Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, and immigration status. Standard errors clustered at country level. Country fixed effects.

Table A.17.: Association between parental worklessness and monetary investments using data from the parent questionnaire – CEM.

	Two-parent household		*Single-parent household*	
Regression	Estimate	Standard error	Estimate	Standard error
low | medium, high	-0.049***	0.013	-0.046***	0.015
low, medium | high	-0.031**	0.014	-0.024**	0.010
Ordered logistic regression	-0.030***	0.008	-0.036**	0.015

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Linear probability models with different cut-points for the categorical dependent variable: between low income and merged medium and high income (first row) and between merged low and medium income and high income (second row). For comparability I report the average marginal effect *and the corresponding standard error for the ordered logistic regression, which allows the magnitude of the regression coefficients to be compared. Standard errors clustered at country level. Country fixed effects (linear probability model) and country dummies included (ordered logistic regression). Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, immigration status, and mothers' and fathers' age.*

A.3.4.2. Time investments

As in the main body of this paper, I find a significant association between worklessness and parental homework help.

Table A.18.: Association between worklessness and parental homework help from a linear probability model applied to different subsets of the matched PISA data – coarsened exact matching.

	Two-parent household		*Single-parent household*	
Data	Estimate	Standard error	Estimate	Standard error
All countries	0.016**	0.006	0.024**	0.012
OECD	0.029***	0.009	0.012	0.013
Partner countries	0.004	0.008	0.040**	0.018
PQ	0.009	0.007	0.008	0.022

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Regression on CEM-matched sample run separately for two-parent and single-parent households. Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, and immigration status. Standard errors clustered at country level. Country fixed effects.

Table A.19.: Association between parental worklessness and parental mathematics homework help using data from the parent questionnaire – CEM.

	Two-parent household		*Single-parent household*	
Regression	Estimate	Standard error	Estimate	Standard error
A | BCDE	0.009	0.009	-0.006	0.024
AB | CDE	0.009	0.014	-0.012	0.020
ABC | DE	0.016	0.010	0.006	0.016
ABCD | E	0.006	0.006	0.003	0.008
Ordered logistic regression	0.012	0.011	-0.004	0.021

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Linear probability models with different cut-points for the categorical dependent variable, indicated by ' | '. Abbreviations: A: 'Never or hardly ever'; B: 'Once or twice a year'; C: 'Once or twice a month'; D: 'Once or twice a week'; E: 'Every day or almost every day'. For comparability I report the average marginal effect *and the corresponding standard error for the ordered logistic regression, which allows the magnitude of the regression coefficients to be compared. Standard errors clustered at country level. Country fixed effects (linear probability model) and country dummies (ordered logistic regression). Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, immigration status, and mothers' and fathers' age.*

A.3.5. Senate Weights

The number of observations from each country included in my analysis depends on two factors. First, how many students participated in the PISA study in each country. While countries such as Canada (21,544), Italy (21,073) and Mexico (33,806) have very high numbers of observations, in most other countries only around 5,000 pupils are part of the PISA sample. Second, the reported worklessness rate. The higher the worklessness rate the more pupils from this country become part of my final sample. While Italy and Mexico have a comparable PISA sample size, Mexico's higher rate of pupils in workless households (11% compared to 5% in Italy) results in a final matched sample size of 1,894 in Italy compared with 4,386 in Mexico.

As a robustness check to see if my results are driven by countries with large matched samples, I analyse the data using senate weights: each country contributes to my final results equally.

A.3.5.1. Monetary investments

Table A.20.: Association between worklessness and commercial tutoring from a linear probability model applied to different subsets of the matched PISA data – senate weights.

	Two-parent household		*Single-parent household*	
Data	Estimate	Standard error	Estimate	Standard error
All countries	-0.009	0.010	-0.008	0.010
OECD	-0.004	0.014	0.002	0.012
Partner countries	-0.016	0.015	-0.021	0.017
PQ	-0.002	0.021	-0.015	0.020

$*\ p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$

Notes: Regression on matched sample run separately for two-parent and single-parent households. Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, and immigration status. Standard errors clustered at country level. Country fixed effects. Senate weights applied.

Table A.21.: Association between parental worklessness and monetary investments using data from the parent questionnaire – senate weights.

	Two-parent household		*Single-parent household*	
Regression	Estimate	Standard error	Estimate	Standard error
low | medium, high	-0.029*	0.017	-0.032	0.021
low, medium | high	-0.043*	0.025	-0.062***	0.020

$*\ p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$

Notes: Linear probability models with different cut-points for the categorical dependent variable: between low income and merged medium and high income (first row) and between merged low and medium income and high income (second row). Standard errors clustered at country level. Country fixed effects. Senate weights applied. Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, immigration status, and mothers' and fathers' age.

A.3.5.2. Time investments

Table A.22.: Association between worklessness and parental homework help from a linear probability model applied to different subsets of the matched PISA data – senate weights.

	Two-parent household		*Single-parent household*	
Data	Estimate	Standard error	Estimate	Standard error
All countries	0.022*	0.011	0.033***	0.012
OECD	0.034**	0.017	0.028	0.017
Partner countries	0.008	0.015	0.038**	0.019
PQ	0.000	0.022	0.003	0.026

$*\ p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$

Notes: Regression on matched sample run separately for two-parent and single-parent households. Adjusted for gender, mothers' and fathers' occupation level, mothers' and fathers' education level, and immigration status. Standard errors clustered at country level. Country fixed effects. Senate weights applied.

Table A.23.: Association between parental worklessness and parental mathematics homework help using data from the parent questionnaire – senate weights.

	Two-parent household		*Single-parent household*	
Regression	Estimate	Standard error	Estimate	Standard error
A | BCDE	0.014	0.021	0.020	0.026
AB | CDE	0.026	0.024	0.009	0.023
ABC | DE	0.032	0.025	0.020	0.017
ABCD | E	0.011	0.012	0.001	0.011

$* \; p < 0.1$, $** \; p < 0.05$, $*** \; p < 0.01$

Notes: Linear probability models with different cut-points for the categorical dependent variable, indicated by ‘ | ’. Abbreviations: A: ‘Never or hardly ever’; B: ‘Once or twice a year’; C: ‘Once or twice a month’; D: ‘Once or twice a week’; E: ‘Every day or almost every day’. Standard errors clustered at country level. Country fixed effects. Senate weights applied.

Adjusted for gender, mothers’ and fathers’ occupation level, mothers’ and fathers’ education level, immigration status, and mothers’ and fathers’ age.

B. Supplementary Results From Chapter 3

B.1. Details About Data Preparation

B.1.1. Instrumental Variable Approach

For the IV approach in this paper I need to know the occupation held by non-working household members prior to the period of worklessness. In all MCS sweeps the SOC category of the currently and last-held job is reported. In Sweep 2, only the partner respondent reports directly on current or last-held job, while the main respondent (usually the mother) is asked about their current employment only and subsequent questions focus on previous employment. However, the main respondent reports on their last job before the first child (if the cohort member (CM) was not the first child) and the first job after finishing full-time education.

For main respondents, the easiest and most straightforward way to build a last-held job variable for non-working respondents is to use data collected at a previous sweep: if a household member is workless in MCS Sweep 3 and 4 but was in employment at MCS Sweep 2, I use the SOC code from Sweep 2 as the job category prior to worklessness. If this information is not observed (e.g. because the household member has not worked in any previous sweep), I use information about the first job after full-time education (Fathers) and information about the last job prior to being pregnant with the first child which is not the CM and – in case this information is not available (e.g. because the CM is the first child) – I use the first job after full-time education (Mothers). For non-working partner respondents, I use the information provided in the current/last job question.

Change from SOC2000 to SOC2010 The SOC codes I use in creating the instrumental variable are adapted over time which results in changes in the coding. When SOC codes are observed at all times, this is not an issue as SOC codes in the Millennium Cohort Study change at about the same time as in the Labour Force Survey, making the datasets compatible. However, as described above, in case of missing values, I use previously observed SOC codes and roll them forward.

Due to the change in SOC coding, this could mean that the codes I roll forward are no longer existent. For around 5% of the observed SOC codes for mothers and 2% of SOC codes for fathers, I change the no longer existent SOC2000 codes into the closest match in SOC2010 coding. See Table B.1 for the categories I recode.

Table B.1.: Manual adjustment from SOC2000 to SOC2010 classification

SOC 2000		SOC 2010	
Code	Name	Code	Name
114	Quality and Customer Care Managers	246	Quality and Regulatory Professionals
123	Managers in Other Service Industries	125	Managers and Proprietors in Other Services
232	Research Professionals	211	Natural and Social Science Professionals
322	Therapists	222	Therapy Professionals
343	Media Associate Professionals	247	Media Professionals
414	Administrative: Communications	722	Customer Service Managers and Supervisors
549	Skilled Trades n.e.c	544	Other Skilled Trades
611	Healthcare & Related Personal Services	614	Caring Personal Services
914	Elementary Goods Storage Occupations	926	Elementary Storage Occupations
922	Elementary Personal Service Occupations	927	Other Elementary Services Occupations

Notes: Occupation names from the Labour Force Survey data.

Creating the instrument The instrument is the difference between the household's current worklessness risk and the average worklessness risk of the occupations held by the household members:

$$IV_t = \underbrace{r_{t,M}^{SOC} \cdot r_{t,F}^{SOC}}_{\text{Household risk at time } t} - \overbrace{\bar{r}_{M}^{SOC} \cdot \bar{r}_{F}^{SOC}}^{\text{Average sector specific household risk}}. \tag{B.1}$$

B.2. Methods

B.2.1. Linear Probability Model Versus Logit/Probit

The choice between the computationally more efficient and easier to interpret Linear Probability Models (LPM) and binary choice models such as logit and probit models has to be made several times throughout this thesis. In the following paragraphs, I explain the reasons for my preferred models for my analyses.

In general, studies such as Hellevik (2009) suggest LPMs might be preferable over logit/probit models as they often yield very similar results, the violations of the OLS assumptions do not matter too much in practice, and results are generally easier to interpret. However, Scott-Long (1997) suggests that logit/probit models are preferable to linear probability models when the probability of the outcome variable is very low or high; the rule of thumb being that a linear probability model results in reliable estimates when the binary outcome variable takes the value 1 in 20% to 80% of cases.

Instrumental variable approach To make causal inferences, I use an instrumental variable approach for which I use data from the UK Labour Force Survey (ONS 2020) to measure UK-wide worklessness by occupation over time. Both my variables of interest (e.g. whether parents pay for childcare) and the endogenous variable (household worklessness) are binary. The models I can choose from in this setting are the following:

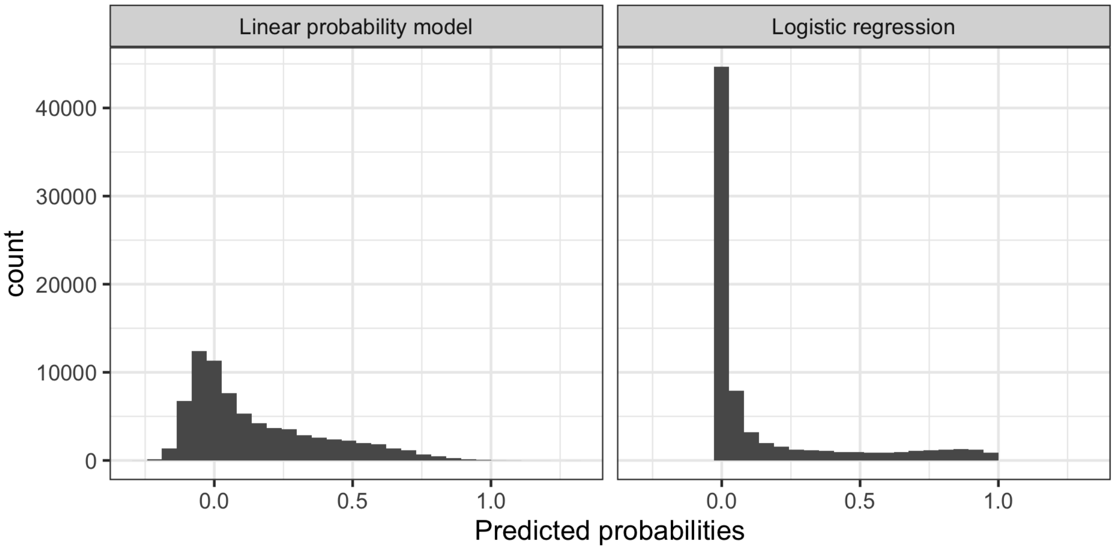
1. Linear probability model
2. Linear probability model using a pre-computed additional instrument
    - Regress background variables and the instrument (household worklessness risk) on the binary household worklessness variable (i.e. the endogenous variable)
    - Compute the fitted values of this pre-first stage
    - Use these predicted values as an additional instrument in a two-stage least-squares estimation where both stages are linear probability models
3. Bivariate probit

As mentioned before, LPMs work well for an overall probability of the outcome occurring between 20% and 80%. In the context of my study, the second stage generally does not require a probit or logit approach as most of my outcome variables fall into that range. However, the first stage is problematic: the proportion of workless households falls below the 20% threshold. As Figure B.1 shows, using a linear probability model for the first stage of an instrumental variable approach results in more than one in three values falling outside of the $[0, 1]$ probability range.

Therefore, I rule out using only a linear probability model as first stage. Including a pre-computed instrument obtained from a probit/logit model helps overcome this problem of the pure LPM instrumental variable approach. However, in my analyses presented in the main body of this paper, I use the bivariate probit model, as it appears to perform better than the linear probability model (Chiburis et al. 2011).

Fixed effects For all outcome variables, I estimate a fixed effects model. For binary outcome variables, one can either apply a linear probability model for which the fixed effects estimates are obtained by including household dummies, or a conditional logistic regression. As most outcome variables take the value 1 for between 20% and 80% of observations, the linear probability model can be expected to be reliable. It even has some very desirable properties: its regression coefficients are easy to interpret and it is not computationally demanding to run it for a large dataset. Therefore, I rely on a fixed effects linear probability model for estimation purposes and use the conditional logit model as a robustness check.

Figure B.1.: First stage linear probability model and logistic regression



Notes: Histograms for the probability of worklessness, higher values indicating higher probability for households to be workless.

B.3. Robustness Checks

B.3.1. Full Sample Size

Table B.2.: Enough time with child – all available observations included

	(1) Pooled probit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Workless	0.142***	0.0836***	0.0986***	0.119***
	(0.00737)	(0.0212)	(0.00697)	(0.00834)
Single-carer	-0.143***	-0.137***	-0.0990***	-0.138***
	(0.00715)	(0.00974)	(0.00805)	(0.00835)
Observations	87,299	75,884	87,306	77,587

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Categorical outcome variable recoded as in main body of this paper. Regression 3 shows results from a fixed effects linear probability model. All other results are average marginal effects. Cluster robust standard errors and sample weights applied.

Table B.3.: Reading to child

	(1) Pooled probit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Workless	0.0257***	0.0835***	0.00526	0.0220**
	(0.00696)	(0.0173)	(0.0113)	(0.00777)
Single-carer	-0.137***	-0.186***	-0.0772***	-0.123***
	(0.00994)	(0.0134)	(0.0153)	(0.0112)
Observations	44,281	38,716	44,281	40,866

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Categorical outcome variable recoded as in main body of the paper. Regression 3 shows results from a fixed effects linear probability model. All other results are average marginal effects. Cluster robust standard errors and sample weights applied.

Table B.4.: Helping child with reading, writing, and maths

(a) Dependent variable: help with reading

	(1) Pooled probit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Workless	-0.00826	-0.00314	0.0314	-0.00758
	(0.0112)	(0.0215)	(0.0200)	(0.0129)
Single-carer	-0.0172	-0.0265*	0.00230	-0.00664
	(0.0111)	(0.0130)	(0.0262)	(0.0129)
Observations	28,647	25,263	28,647	26,241

(b) Dependent variable: help with writing

	(1) Pooled probit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Workless	0.000666	-0.0122	0.0445*	0.000219
	(0.0130)	(0.0308)	(0.0202)	(0.0148)
Single-carer	-0.0132	-0.0125	-0.0361	-0.0139
	(0.0130)	(0.0163)	(0.0275)	(0.0151)
Observations	28,645	25,261	28,645	26,239

(c) Dependent variable: help with maths

	(1) Pooled probit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Workless	0.0187	-0.00149	0.0239	0.0151
	(0.0119)	(0.0300)	(0.0193)	(0.0134)
Single-carer	-0.0147	-0.0128	0.0222	-0.0133
	(0.0119)	(0.0154)	(0.0265)	(0.0140)
Observations	28,651	25,265	28,651	26,245

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Categorical outcome variable recoded as binary categories. Helping child with the respective subject at most 'once or twice a week' to the child is coded as '0' and helping child at least 'several times a week' is coded as '1'. Regression 3 shows results from a fixed effects linear probability model; all corresponding conditional logit models are not significant. All other results are average marginal effects. Cluster robust standard errors and sample weights applied.

Table B.5.: Homework help

	(1) Pooled probit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Workless	0.0178	0.00378	0.00983	0.0322
	(0.0156)	(0.0298)	(0.0264)	(0.0202)
Single-carer	-0.0587***	-0.0600***	-0.0301	-0.0466*
	(0.0145)	(0.0156)	(0.0281)	(0.0200)
Observations	24,344	22,016	24,353	20,149

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Categorical outcome variable recoded as binary categories. Homework help 'Never' or 'Sometimes' is coded as '0' and homework help 'Usually' or 'Always' is coded as '1'. Regression 3 shows results from a fixed effects linear probability model, conditional logit fixed effects estimates supporting the results. All other results are average marginal effects. Cluster robust standard errors.

Table B.6.: Paying for childcare

	(1) Pooled probit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Workless	-0.203***	-0.119***	-0.0600***	-0.171***
	(0.0147)	(0.0278)	(0.0102)	(0.0166)
Single-carer	0.183***	0.160***	0.0580***	0.173***
	(0.0148)	(0.0189)	(0.0162)	(0.0168)
Observations	33,913	28,227	33,913	30,939

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Binary outcome variable. Sweeps 1 and 2. Regression 3 shows results from a fixed effects linear probability model with a conditional logit fixed effects model confirming the estimated significance level (not in table). All results are average marginal effects. Cluster robust standard errors and sample weights applied.

Table B.7.: Extra lessons

	(1) Pooled probit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Workless	-0.00842	-0.0292	-0.0252*	-0.00989
	(0.0109)	(0.0221)	(0.0117)	(0.0138)
Single-carer	0.0161	0.0170	-0.0176	0.0129
	(0.00939)	(0.0101)	(0.0145)	(0.0120)
Observations	24,526	22,189	24,533	20,221

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Binary outcome variable. Sweeps 5 and 6. Regression 3 shows results from a fixed effects linear probability model, a conditional logit fixed effects model results in a non-significant estimate. All results are average marginal effects. Cluster robust standard errors and sample weights applied.

B.3.2. Change in Cut-Points and Ordered Logistic Regression

Table B.8.: Enough time with child – ordered logistic regression and change in cut-points

	(1) Pooled probit/ologit	(2) BiProbit	(3) Fixed Effects	(4) Future WL
Cut-point (lower)	0.126***	0.151***	0.0865***	0.110***
	(0.00888)	(0.0195)	(0.00713)	(0.00949)
Ordered logit	0.707***			
	(0.0377)			
Lower household value	0.162***	0.197***	0.243***	0.152***
	(0.00592)	(0.0149)	(0.00936)	(0.00639)
Ordered logit	1.294***			
	(0.0383)			

Notes: Cut-point (lower) below the cut-point reported in the main section: '0' assigned to 'Not quite enough time' or lower and '1' assigned to categories higher or equal to 'Just enough time'. This results in 20% of observations being coded as '0'. The associated ordered logistic regression focusses on the highest reported value in the household. 'Lower household value' takes the value '1' if both parents report to have 'Plenty of time', 'More than enough time' or 'Too much time'. This results in 79% of observations being coded as '0'. The associated ordered logit focusses on the lowest reported value in the household. All results except for ordered logistic regression are marginal effects. Cluster robust standard errors. Sample weights and inverse probability weights applied.

Table B.9.: Reading to child – ordered logistic regression and change in cut-points

	(1) Pooled probit/ologit	(2) BiProbit	(3) Fixed Effects	(4) Future WL
Changed cut-point	0.0378**	0.126***	0.0120	0.0394**
	(0.0128)	(0.0264)	(0.0163)	(0.0137)
Parent reading least	0.0407**	0.0645*	0.0140	0.0457**
	(0.0134)	(0.0283)	(0.0154)	(0.0143)
Parent reading most	0.0318***	0.101***	-0.00182	0.0311**
	(0.00942)	(0.0215)	(0.0137)	(0.0100)
Ordered logit (comb)	0.263***			
	(0.0516)			
Ordered logit (least)	0.154**			
	(0.0571)			
Ordered logit (most)	0.172**			
	(0.0580)			

Notes: Changed cut-point below the cut-point reported in the main section: '1' assigned when two parents read to their child at least 'Once or twice a week' or at least one parent 'Several times a week'; '0' assigned when parents read to their child less frequently. This results in 40% of observations being coded as '0'. 'Parent reading least' limits the analysis to the parent reading to the child less often if values are observed for two parents. Around 51% of observations are coded '0' as the lower household value is lower or equal to 'Once or twice a week'. 'Parent reading most' limits the analysis to the parent reading to the child most often if values are observed for two parents. Around 19% of observations are coded '0' as the lower household value is lower or equal to 'Once or twice a week'. 'Ordered logit comb' analyses combined categories of both parents accounts. The remaining two ordered logits focus on the lower and higher household value, respectively. All results except for ordered logistic regression are marginal effects. Cluster robust standard errors and sample weights applied.

Table B.10.: Help child with reading, writing, and maths – ordered logistic regression and change in cut-points

(a) Dependent variable: Help child with reading

	(1) Pooled probit/ologit	(2) BiProbit	(3) Fixed Effects	(4) Future WL
Cut-point 1	-0.00868	-0.00173	0.0312	-0.0114
	(0.0113)	(0.0190)	(0.0202)	(0.0124)
Cut-point 2	0.0172	0.0234	0.0126	0.0173
	(0.0147)	(0.0297)	(0.0243)	(0.0161)
Ordered logit	0.0429			
	(0.0621)			

(b) Dependent variable: Help child with writing

	(1) Pooled probit/ologit	(2) BiProbit	(3) Fixed Effects	(4) Future WL
Cut-point 1	-0.0106	-0.00601	0.0157	-0.0151
	(0.0131)	(0.0259)	(0.0221)	(0.0143)
Cut-point 2	0.00994	-0.0355	0.0488*	0.0000885
	(0.0119)	(0.0268)	(0.0214)	(0.0129)
Ordered logit	0.00471			
	(0.0619)			

(c) Dependent variable: Help child with maths

	(1) Pooled probit/ologit	(2) BiProbit	(3) Fixed Effects	(4) Future WL
Cut-point 1	-0.00449	0.0218	-0.00722	-0.00356
	(0.0127)	(0.0260)	(0.0225)	(0.0137)
Cut-point 2	0.0178	-0.0182	0.0251	0.00851
	(0.0114)	(0.0263)	(0.0215)	(0.0125)
Ordered logit	0.0382			
	(0.0616)			

Notes: Number of households: 12,898. Number of household-sweep observations: 23,210. Cut-point 1 below the cut-point reported in the main section: '0' assigned to 'Once or twice a month' or less; '1' assigned to categories higher or equal to 'Once or twice a week'. This results in the proportion of of observations being coded as '0' to be 18% (help with reading), 26% (help with writing), and 30% (help with maths). Cut-point 2 above the cut-point reported in the main section: '0' assigned to 'Several times a week' or less; '1' assigned to 'Every day or almost every day'. This results in the proportion of of observations being coded as '0' to be 58% (help with reading), 81% (help with writing) and 80% (help with maths). All results except for ordered logistic regression are marginal effects. Cluster robust standard errors. Sample weights and inverse probability weights applied.

Table B.11.: Homework help – ordered logistic regression and change in cut-points

	(1) Pooled probit/ologit	(2) IV BiProbit	(3) Fixed Effects	(4) Future WL
Cut-point 1	-0.00533	-0.0222	-0.0135	0.0200
	(0.0123)	(0.0199)	(0.0218)	(0.0151)
Cut-point 2	0.0268	-0.000303	0.00557	0.0186
	(0.0180)	(0.0328)	(0.0310)	(0.0202)
Ordered logit	0.133			
	(0.0841)			

Notes: Number of households: 10,387. Number of household-sweep observations: 18,261 Cut-point 1 below the cut-point reported in the main section: '0' assigned to 'Never of almost never'; '1' assigned to categories higher or equal to 'Sometimes'. This results in 10% of observations being coded as '0'. Cut-point 2 above the cut-point reported in the main section: '0' assigned to 'Usually' or less; '1' assigned to 'Always'. This results in 73% of observations coded as '0'. All results except for ordered logistic regression are marginal effects. Cluster robust standard errors and sample weights applied.

B.3.3. Cross-Sectional Causal Estimates

Table B.12.: Effect of worklessness on 'Enough Time' variable – cross-sectional analysis

	(1) Probit	(2) BiProbit	(3) Future Worklessness
9M	0.208***	0.137***	0.186***
	(0.0215)	(0.0409)	(0.0220)
3Y	0.271***	0.263***	0.240***
	(0.0217)	(0.0437)	(0.0231)
5Y	0.114***	0.0518	0.102***
	(0.0177)	(0.0429)	(0.0193)
7Y	0.116***	0.110*	0.102***
	(0.0196)	(0.0435)	(0.0215)
11Y	0.0875***	0.0385	0.0537*
	(0.0234)	(0.0375)	(0.0262)
14Y	0.140***	0.140*	0.129***
	(0.0249)	(0.0576)	(0.0294)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Number of households: between 13,609 (age 9M) and 8,411 (age 14). Cluster robust standard errors. Sample weights and inverse probability weights applied.

Table B.13.: Causal relationship between worklessness and reading to child – cross-sectional analysis

	(1) Probit	(2) BiProbit	(3) Future Worklessness
3Y	-0.000783	0.0377	-0.00590
	(0.0121)	(0.0318)	(0.0131)
5Y	0.0346**	0.0875***	0.0334**
	(0.0109)	(0.0261)	(0.0119)
7Y	0.0466**	0.150***	0.0496**
	(0.0164)	(0.0351)	(0.0178)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Number of households between 12,470 (age 3) and 11,027 (age 7). Cluster robust standard errors. Sample weights and inverse probability weights applied.

Table B.14.: Causal relationship between worklessness and helping child with reading, writing, and maths – cross-sectional analysis

(a) Dependent variable: help with reading

	(1) Probit	(2) BiProbit	(3) Future Worklessness
5Y	-0.00505	0.0598*	-0.00253
	(0.0122)	(0.0264)	(0.0135)
7Y	0.0208	-0.00189	0.0184
	(0.0228)	(0.0510)	(0.0250)

(b) Dependent variable: help with writing

	(1) Probit	(2) BiProbit	(3) Future Worklessness
5Y	0.0178	0.00931	0.0148
	(0.0204)	(0.0435)	(0.0223)
7Y	-0.00926	-0.0224	-0.0134
	(0.0211)	(0.0499)	(0.0233)

(c) Dependent variable: help with maths

	(1) Probit	(2) BiProbit	(3) Future Worklessness
5Y	0.0238	-0.00238	0.0154
	(0.0198)	(0.0448)	(0.0217)
7Y	0.00640	-0.0291	0.00178
	(0.0186)	(0.0416)	(0.0203)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Number of households: 12,183 (age 5) and 11,027 (age 7). Cluster robust standard errors. Sample weights and inverse probability weights applied.

Table B.15.: Causal relationship between worklessness and homework help – cross-sectional analysis

	(1) Probit	(2) BiProbit	(3) Future Worklessness
11Y	0.0127	0.0330	0.00235
	(0.0257)	(0.0413)	(0.0287)
14Y	0.0581*	-0.0241	0.103**
	(0.0291)	(0.0620)	(0.0349)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Number of households: 9,850 (age 11) and 8,411 (age 7). Cluster robust standard errors. Sample weights and inverse probability weights applied.

Table B.16.: Causal relationship between worklessness and paid-for childcare – cross-sectional analysis

	(1) Probit	(2) BiProbit	(3) Future Worklessness
9M	-0.207***	-0.133***	-0.179***
	(0.0266)	(0.0335)	(0.0276)
3Y	-0.220***	-0.109**	-0.196***
	(0.0220)	(0.0418)	(0.0241)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Number of households: 13,609 (age 9 months) and 12,470 (age 3). Cluster robust standard errors. Sample weights and inverse probability weights applied.

Table B.17.: Causal relationship between worklessness and paid-for extra lessons – cross-sectional analysis

	(1) Probit	(2) BiProbit	(3) Future Worklessness
11Y	-0.0321	-0.0501	-0.0332
	(0.0205)	(0.0308)	(0.0219)
14Y	0.0102	0.00261	0.0111
	(0.0167)	(0.0400)	(0.0187)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Number of households: 9,850 (age 11) and 8,411 (age 14). Cluster robust standard errors. Sample weights and inverse probability weights applied.

B.3.4. Parental Ability

Table B.18.: Robustness checks of all outcome variables – parental ability

	Pooled probit		IV BiProbit		Future WL	
Outcome	(1)	(2)	(1)	(2)	(1)	(2)
Time investments						
Enough Time	0.141***	0.141***	0.0999***	0.101***	0.120***	0.120***
	(0.0107)	(0.0106)	(0.0258)	(0.0259)	(0.0116)	(0.0116)
Read to Child	0.0389***	0.0386***	0.0999***	0.0943***	0.0390**	0.0369**
	(0.0113)	(0.0113)	(0.0234)	(0.0231)	(0.0120)	(0.0120)
Help child with:						
Reading	0.0183	0.0194	0.0141	0.0183	0.0263	0.0289
	(0.0168)	(0.0168)	(0.0294)	(0.0294)	(0.0180)	(0.0180)
Writing	0.00538	0.00848	0.00169	0.0128	0.00241	0.00843
	(0.0186)	(0.0186)	(0.0390)	(0.0390)	(0.0200)	(0.0200)
Maths	0.0124	0.0141	-0.0360	-0.0281	0.00718	0.0107
	(0.0170)	(0.0170)	(0.0377)	(0.0377)	(0.0184)	(0.0184)
Homework	0.0444*	0.0444*	0.0309	0.0336	0.0524*	0.0533*
	(0.0204)	(0.0204)	(0.0354)	(0.0354)	(0.0231)	(0.0231)
Monetary investments						
Childcare	-0.218***	-0.220***	-0.129***	-0.132***	-0.194***	-0.197***
	(0.0220)	(0.0217)	(0.0341)	(0.0342)	(0.0229)	(0.0226)
Extra Lessons	-0.0155	-0.0155	-0.0373	-0.0373	-0.0188	-0.0188
	(0.0143)	(0.0143)	(0.0254)	(0.0254)	(0.0154)	(0.0154)

Notes: Estimated effect of household worklessness on different outcome variables. Standard errors in parentheses. Number of households: 10,614. Only households included for which parental word recognition score from MCS Sweep 6 is observed. Regressions (1) show results from regressions as discussed in the main body. Regressions (2) show results when adding parental ability scores observed in MCS Sweep 6 as additional control variable. No fixed effects regressions shown as parental word recognition score is time-invariant (only observed once) and therefore does not change fixed effects results. All results are average marginal effects. Cluster robust standard errors and sample weights applied.

C. Supplementary Results From Chapter 4

C.1. Weights

As described in Section 4.2, the MCS data suffers from attrition and non-response, which I address by updating the original MCS sample weights. I do this by first computing the probability that an individual cohort member is responsive until age 17, given observations on sex, ethnicity, parental education, income, health, and other factors. These predicted probabilities from a logistic regression are then inverted to become inverse probability weights (IPWs), which can then be combined with the original sampling weights provided with the MCS data. In an alternative approach, I use the age-14 weights provided with the MCS data and update these weights using the inverse probability weights derived from probability to continue participation between age 14 and age 17.

The key difference between these two approaches is that the former relies on the sample weights only which account for larger sample sizes in different strata. These strata are a combination of country (England, Scotland, Wales, Northern Ireland) and whether or not an area is considered advantaged, disadvantaged or with a large share of the population being ethnic minorities (England only). The second approach uses MCS weights up until age 14 which are designed to account for attrition. These weights are then updated to account for those cohort members present at age 14 that are not part of my final sample at age 17.

In order to choose which weight performs better, I evaluate the weights as follows. As a metric of my comparison, I focus on variables observed at the first MCS sweep (age 1) only. These variables are cohort members' sex and ethnicity, their parents' age, education, income, housing situation, health, single parenthood, and household worklessness. The original sample weights are then applied to all observations available at the Age 1 Sweep, the weights designed to be applied to my final sample are applied only to those cohort members that are part of the final sample at age 17.

Table C.1 shows descriptive statistics of the aforementioned variables. The first column shows the mean and proportions when applying the sample weights to the full sample. In the second and third columns, I focus on the subsample that I use for my analyses in the main body and apply the weights calculated as detailed above. In particular, the second column shows results for the weights based on a combination of the MCS sample weights and inverse probability weights based on non-response patterns between the Age 1 and Age 17 Sweeps. The third column shows descriptive statistics when applying weights based on the MCS weights at age 14 – already including non-response adjustments – combined with inverse probability weights based on non-response patterns between age 14 and age 17. Overall, applying the weights I use for my analyses ('final weights'), results in nearly identical descriptive statistics as if the full sample at age 1 was used. When the alternative weights based on the non-response adjusted sample weights at age 14 are used, the descriptive statistics diverge substantially. In particular, the alternative weights over-represent Pakistani and Bangladeshi as well as Black and Black British ethnic groups. Furthermore, low-income, renting, low-education households are given too much weight. The use of the alternative weights leads to an overestimation of single-parenthood, household worklessness as well as parents with bad health.

In order to ensure representative results for children born in the UK around 2001, I use the final weights as they best recover the distribution of key background variables at age 1, compared to the use of the weights based on the MCS non-response adjusted weights at age 14.

Table C.1.: Descriptive statistics at age 1 using non-response weights

Variable	Category	Sample weights	Final weights	Alternative weights
Sex	Male	51.3%	51%	52.2%
	Female	48.7%	49%	47.8%
Ethnicity	White	87.7%	87.6%	84%
	Pakistani & Bangladeshi	3.8%	4%	5.3%
	Indian	1.8%	1.9%	2%
	Black	2.5%	2.5%	4.2%
	Mixed	3.1%	3%	3.1%
	Other	1.1%	1%	1.4%
Income	–	325.1	323.6	286.2
Housing	Own	63.5%	63%	53.4%
	Rent	30.5%	30.6%	39.1%
	Living with parents	3.8%	3.9%	4.8%
	Shared equity	0.4%	0.4%	0.4%
	Other	1.8%	2%	2.3%
Education (mother)	None of these	12.1%	11.8%	18.1%
	Overseas qual only	2.4%	2.2%	2.9%
	NVQ level 1	8.2%	8.2%	9.6%
	NVQ level 2	29.6%	28.9%	30.4%
	NVQ level 3	14.2%	13.5%	12.4%
	NVQ level 4	29.8%	31.4%	23.8%
	NVQ level 5	3.8%	3.9%	2.8%
Education (father)	None of these	10.2%	10.3%	13.8%
	Overseas qual only	2.8%	2.8%	3.3%
	NVQ level 1	6.7%	6.3%	7.3%
	NVQ level 2	27%	26.9%	28.1%
	NVQ level 3	15.5%	15.8%	15.7%
	NVQ level 4	31.5%	31.6%	26.7%
	NVQ level 5	6.3%	6.3%	5.1%
Single parenthood	Two-carer	86.1%	85.7%	81.8%
	Single-carer	13.9%	14.3%	18.2%
Workless household	Not workless	83.4%	82.6%	77.5%
	Workless	16.6%	17.4%	22.5%
Age (mother)	–	29.7	30.1	28.9
Age (father)	–	33.1	33.3	32.6
Health (mother)	Poor	2.6%	2.5%	3.7%
	Fair	13.7%	13%	14.7%
	Good	52%	51.7%	52.6%
	Excellent	31.7%	32.8%	29%
Health (father)	Poor	2.1%	2.4%	3%
	Fair	12.8%	12.2%	13.8%
	Good	51.6%	51.7%	51.5%
	Excellent	33.4%	33.7%	31.7%

C.2. Robustness Checks

To account for the left- and right-censored nature of the outcome variable (educational expectations fall between 0% and 100%), I use a Tobit model as robustness check of Model M3. In this model, I include the explanatory variables of interest – SES, risk attitudes, and time preferences – as well as demographic, health, educational investment and cognitive control variables. The Tobit model's regression coefficients can not be directly compared with regression coefficients from a linear regression. In Table C.2 I therefore show both the Tobit estimates as well as the corresponding marginal effects. Furthermore, I present the results from model M3 as reference. The estimates for both the regression coefficients of SES and time preferences are statistically significant in the Tobit specification, while risk attitudes are not statistically associated with educational expectations. This is consistent with the estimates from Model M3. The magnitude of the associations according to the marginal effects is slightly lower in the Tobit specification compared to the linear model. However, this difference is not statistically significant and falls within approximately one standard error of the estimated values.

Next, I include GCSE maths and English grades in the analysis to observe the impact feedback about chances of going to university through school grades has on my estimates. As GCSE grades are obtained and comparable within England but not in the devolved nations, I limit my analysis to English pupils only. Furthermore, as GCSE grades were changed from letter grades to numerical grades around the time that cohort members took GCSEs, I recode letter grades to their numeric equivalents. While previous analyses maintained a sample size of around 6,000 pupils, my analysis being limited to English students and those pupils who disclose their grades further reduces the sample size to 3,380. I use adjusted weights accounting for this further reduction in sample size.

The estimates shown in Table C.3 indicate that accounting for GCSE grades reduces the link between SES and educational expectations by half. Similarly, the point estimate for time preferences is reduced by one-third. Both associations remain statistically significant at the 5% and 1% level, respectively. Both maths and English grades have a strong positive relationship with educational investments, while the estimate for the cognitive score becomes insignificant once GCSE grades are included. This result indicates that academic feedback via grades is very important to pupils in assessing their future educational options. However, even when including GCSE grades, both low SES and impatience as predictors for lower educational expectations

Table C.2.: Robustness check for Model M3 using a Tobit regression

Variable	Tobit estimates	Tobit marginal effects	Reference M3
SES	5.303***	3.662***	3.914***
	(0.929)	(0.631)	(0.617)
Risk attitudes r	-1.459	-1.008	-1.783
	(2.224)	(1.536)	(1.602)
Time preferences δ	14.64***	10.11***	12.58***
	(3.266)	(2.247)	(2.320)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Number of observations: 6,382. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis. All estimates are obtained controlling for demographics, parental health, educational investments, and behavioural and cognitive scores.

prevail.

Finally, I test if my results are robust against the specification of risk attitudes and time preferences. In the main body of this study, I used economic theory on the shape of the utility function to derive estimates for risk attitudes, r, and time preferences, δ. As a robustness check, I create categorised variables for risk aversion and patience, both with categories 'low', 'medium', and 'high'. Around 21% of observations are classified as 'low risk aversion', 46% as 'medium', and 33% 'high'. Similarly, 18% fall into the category 'very impatient', 48% are 'moderately patient', and 34% 'very patient'. As shown in Table C.4, the estimate for the association between SES and educational expectations does not change significantly when categorised economic preferences are used instead of the economic preferences constructed in the main body of this study. Furthermore, just as with the continuous variable measuring risk preferences, r, the categorised variable shows no association between risk preferences and educational expectations. Last, time preferences continue to be statistically significantly associated with educational expectations. In particular, cohort members falling into the most patient category report educational expectations around 5.5 percentage points higher compared to those in the most impatient category.

Table C.3.: Robustness check for Model M3 including GCSE grades in English and mathematics

Variable	Reference M3	M3 with GCSEs
SES	3.979^{***}	1.958^{*}
	(0.802)	(0.815)
Risk attitudes r	0.298	-0.106
	(2.282)	(2.129)
Time preferences δ	12.55^{***}	8.591^{**}
	(3.254)	(3.193)
Cognitive ability	9.439^{***}	0.931
	(0.831)	(1.077)
GCSE Maths		4.189^{***}
		(0.475)
GCSE English		6.203^{***}
		(0.488)
R^2	0.255	0.360

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Number of observations: 3,380. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis. All estimates are obtained controlling for demographics, parental health, educational investments, and behavioural and cognitive scores.

Table C.4.: Robustness check for Model M3 using categorised risk attitudes and time preferences

Variable	Reference M3	M3 categorised
SES	3.914***	3.948***
	(0.617)	(0.617)
Risk attitudes r	-1.783	
	(1.602)	
Risk aversion (base level: low)		
medium		1.586
		(1.230)
high		1.434
		(1.275)
Time preferences δ	12.58***	
	(2.320)	
Patience (base level: low)		
medium		2.612
		(1.484)
high		5.548***
		(1.605)
R^2	0.288	0.286

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Number of observations: 6,382. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis. All estimates are obtained controlling for demographics, parental health, educational investments, and behavioural and cognitive scores.

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