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Essays on social mobility: the influence of educational attainment, bursaries, and the COVID-19 pandemic

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Declaration

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

Signed:

Date:

Abstract

This thesis investigates three topics on intergenerational income persistence in a recent cohort in England and examines how factors such as educational attainment, bursaries, and the COVID-19 pandemic affect social mobility. All three chapters use longitudinal data on young people born in 1989-90 in England who are part of the cohort study Next Steps. The goal of this thesis is to provide evidence on the latest trends in social mobility in England and inform policymaking in equalising opportunities and reducing inequality.

Chapter 1 introduces and motivates the thesis. Chapter 2 explores the level of intergenerational income persistence among sons, which is measured as the association between family income in childhood and later adult earnings, as well as examines its contributing factors using the most recent data available. Building on previous work, we then contextualise this persistence by comparing the younger cohort to the 1970 birth cohort. We focus on cognitive skills, non-cognitive traits, and educational attainment as mediating factors. Our results highlight the consistent intergenerational income mobility at age 25/26 across the two cohorts and the important role of education in explaining the persistence for both cohorts.

In Chapter 3, I examine the impact of a financial programme targeted at low-income young people in England – the Education Maintenance Allowance (EMA) – on higher education (HE) participation and attainment. Combining regression modelling with entropy balancing, a statistical matching technique, I find that two-year EMA recipients are more likely to participate in higher education than non-recipients. However, the results show that EMA has no statistically significant impact on attendance at high-status institutions and degree classification. Moreover, the impact of receiving EMA for two-years has heterogeneous effects by gender. These findings indicate that even though EMA is a costly programme, it is beneficial for young people, especially young men, in the long run.

The fourth chapter of this thesis compares the impact of the COVID-19 pandemic on the labour market outcomes of first-in-family (FiF) graduates to the impact on their non-FiF peers, those young people whose parents have university degrees. We find a differential impact of the pandemic for FiF graduates by gender when we look at what happened to

those who did not keep working. Among women, FiF graduates became more likely to leave work or be on unpaid leave and less likely to go on furlough or paid leave than non-FiF graduates. However, we do not find a significant differential effect for FiF versus non-FiF male graduates. This highlights the exacerbated disadvantage arising from the intersectionality of socio-economic background and gender during the pandemic.

Impact Statement

Next Steps, previously known as the Longitudinal Study of Young People in England (LSYPE), has been surveying around 16,000 people born in 1989-90 since 2004 when the cohort members were in Year 9 and follows their lives into adulthood (University College London, UCL Institute of Education, Centre for Longitudinal Studies, 2021). This thesis analyses data collected from participants taking part in Next Steps and provides insights into what determines the educational and labour market outcomes in this recent cohort. In line with Sustainable Development Goals (Goal 4 and Goal 10 specifically) adopted by the United Nations, the aim of this thesis is to investigate ways we can use policy to increase social mobility and reduce inequality in England and the UK. The empirical evidence resulting from this thesis is therefore relevant for both academic discussions and policy debates.

Understanding the role of education in driving social mobility

In the UK, intergenerational income persistence is high by international standards and has increased over time when comparing the 1958 cohort and 1970 cohort. However, there is little evidence on cohorts born after the 1980s. The second chapter in this thesis expands the existing literature by providing evidence on intergenerational income mobility among sons in England born in 1989-90. We also analyse the contributing factors for intergenerational income persistence and find that education plays an increasingly important role in explaining income persistence. Beyond enriching the academic literature, this chapter suggests that widening education participation and improving achievement among children from disadvantaged backgrounds are effective ways for policymakers to increase social mobility and reduce inequality in the country.

Providing a retrospective analysis of a conditional cash transfer (CCT) programme

Previous studies have shown that Educational Maintenance Allowance (EMA), which is a conditional cash transfer (CCT) programme aiming to encourage 16-19-year-olds from low-income families to stay in education after the school-leaving age, has positive impacts on participation, retention, and attainment in secondary education. Chapter 3 contributes to the previous literature by providing a retrospective analysis of the EMA, focusing specifically on its impact on higher education participation and attainment. Regarding the benefits outside academia, this work can help policymakers in England to re-evaluate the costs and benefits of this cash transfer programme, considering the returns to higher education. Moreover, it can potentially affect policymakers' decisions on how to encourage participation and retention in post-compulsory education in other countries.

Supporting policymakers to reduce inequality in the labour market

The COVID-19 pandemic has dramatically affected many aspects of people's lives in the UK, especially for disadvantaged groups, and has exacerbated some of these pre-existing inequalities. Focusing on a non-privileged group, first-in-family (FiF) graduates, Chapter 4 enriches the literature by providing the first analysis comparing the labour market outcomes of FiF graduates with their non-FiF graduate peers during the COVID-19 pandemic in England. Beyond contributing to the academic literature, this chapter also provides a discussion of policy inventions to help disadvantaged groups. To reduce inequality in labour market, policymakers should ensure that parental leave is shared more equally between male and female workers, more affordable childcare is available, and future furloughing policies, such as those based on the Coronavirus Job Retention Scheme (CJRS), should target disadvantaged groups.

During the four years of my PhD, I have had opportunities to present my research at conferences and discuss the results of my research with scholars and policymakers. I will continue disseminating my outputs by seeking opportunities to publish my work in peer-reviewed journals and present my policy-relevant research studies both inside and outside academia.

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During the past three years, I have been fortunate to gain teaching experience as a Postgraduate Teaching Assistant at the UCL Social Research Institute. I would like to thank Neus Bover-Fonts, Lorraine Dearden, David Frost, Hedvig Horvath, and Antonia Simon for allowing me to teach and giving me advice on teaching related-work. The teaching experience has been invaluable in enabling me to develop and hone my educational and interpersonal skills.

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Last but not least, I want to express my appreciation to my family. Thank my grandparents

for giving me the opportunity to grow up on a university campus where I started my dream of being a "scientist" one day at a very young age. Thank my parents for the emotional and financial support all the time. They always believe in me, and I would not be as strong and confident as I am without their encouragement over the past 27 years.

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Chapter 1.

Introduction

1.1. Background and motivation

Social mobility, including intragenerational mobility and intergenerational mobility, is the shift in an individual's socio-economic status (e.g. income, education level, and occupation) from one status to another. Previous studies of intergenerational mobility usually examine the average persistence across generations by socio-economic status (SES) to understand the association between the SES of parents and the socio-economic outcomes of their children in adulthood. Traditionally, intergenerational persistence can be measured by the occupation, income, education and social class of parents and children. While most sociologists tend to investigate the intergenerational mobility of social class, most economic research focuses on intergenerational economic mobility, which is measured by income and earnings across the two generations.

Over the past few decades, social mobility has been of great interest among researchers and has become a topic of political concern in the UK. The UK has been traditionally considered a country with low intergenerational income mobility by international standards, so a strong association between parents' and children's incomes exists (Corak, 2006; Gregg et al., 2013; Bratberg et al., 2017). Moreover, previous studies on intergenerational income mobility have suggested that in the UK, mobility is in decline when comparing the 1958 cohort and 1970 cohort (Blanden et al., 2007, 2004; Gregg et al., 2017a). Despite the extensive research focusing on those born before the 1980s in England, there is little evidence of intergenerational mobility, especially income mobility, in younger cohorts. In this thesis, I mainly focus on intergenerational income mobility, which refers to changes between one's own income position and the income position of one's parents, among a young cohort born in 1989-1990.

Why is social mobility important? On the one hand, lack of upward mobility could mean that children from lower SES backgrounds struggle to climb up the social ladder no matter how hard they work, resulting in a waste of talent and human potential. On the other hand, lack of downward mobility indicates important resources, both monetary and non-monetary, as well as opportunities for access to good education and health services are persistently possessed by those in the higher SES groups. Researchers believe that mobility is an indicator of inequality and the level of equal opportunities in society. (Bishop et al., 2014; Corak, 2013; Durlauf and Seshadri, 2018). A strong association between the SES of parents and the socio-economic outcomes of their children as adults indicates low intergenerational mobility as children from less affluent families have a lower chance of being in a high SES than their wealthier peers when they grow up just because they have fewer family resources and opportunities. On the contrary, in a society with a higher degree of intergenerational mobility, the SES of the second generation is more likely to be determined by their ability and hard work rather than solely by inherited advantages, showing a promising sign of equal opportunities and low inequality in the society.

The negative relationship between inequality and intergenerational mobility is widely known as “The Great Gatsby Curve”, which suggests that countries with low levels of intergenerational mobility, such as the US and UK, tend to have greater levels of income inequality (Jerrim and Macmillan, 2015). The Great Gatsby Curve can be explained using a macro-micro-macro scheme, which is also referred to as Coleman’s boat (Graaf and Wiertz, 2019). A higher degree of economic inequality in society encourages parents to invest in children’s education and career, leading to an unequal investment in children’s education and career by parents’ socio-economic status. Thus, children from disadvantaged families tend to attend lower-quality schools (Gorard and Siddiqui, 2018; Mayer, 2002) and have lower educational achievements in schools (Blanden and Gregg, 2004; Broer et al., 2019; Sirin, 2005) than their peers from more affluent backgrounds, resulting in a lower chance to participate in higher education (Crosnoe and Muller, 2014; Galindo-Rueda et al., 2004; James, 2001) and then get access to a better-paid job (Blundell et al., 2000; O’Leary and Sloane, 2005). These disparities bring about more unequal labour markets and then a low degree of intergenerational mobility in society. Thus, a low degree of intergenerational mobility is both the cause and result of inequality.

There are mainly two ways to increase intergenerational mobility and reduce inequality.

The first one is predistribution, which tries to prevent inequalities from happening in the first place. The predistribution approaches include but are not limited to investments in education, childcare provision, regional job creation, anti-discriminatory policies, and minimum wages. These approaches affect labour market outcomes by changing the value of people's endowments. The other way is redistribution, such as taxes and cash transfers, which converts the distribution of market incomes into a distribution of final incomes. This thesis focuses on the predistribution approach, especially the influence of education.

A growing body of literature has shown education plays a key role in driving intergenerational mobility (Congbin and Weifang, 2008; Gregg et al., 2017a; Jerrim and Macmillan, 2015; Torche, 2015) as mobility is strongly associated with socio-economic gaps in education (Blanden et al., 2007). High mobility suggests that children from different backgrounds with the same ability have equal opportunities to receive education, and thus children from lower SES are not in a disadvantaged place when entering the labour market. Moreover, existing literature has highlighted the returns to education, particular returns to a degree. Walker and Zhu (2011) use data from UK Labour Force Surveys to estimate the impact of higher education qualifications on the earnings of graduates in the country. They find high average returns for female graduates for all subjects (15-20%) as well as very large returns for Law, Economics and Management (LEM) male graduates (25-30%). Apart from qualifications themselves, performance at university also matters for labour market outcomes. Using a regression discontinuity design, Feng and Graetz (2017) estimate the causal effect of degree class on graduates' labour market outcomes and find that graduates with higher degree classes are more likely to work in a high-wage industry, leading to higher wages and annual salaries. These effects are larger for male graduates and those with math-intensive degree programmes.

To explore the influence of education on intergenerational mobility, previous studies have employed the mediation analysis method, which follows a commonly used two-step decomposition approach. This approach not only identifies the associations between parental income, educational attainment, and children's earnings but also demonstrates the mechanism by which parental income affects children's earnings through education. Blanden et al. (2005) decompose income persistence across generations using two UK cohorts born in 1958 and 1970 and find that education accounts for approximately 35 to 40 per cent of intergenerational persistence. Thus, providing equal opportunities for access to education and improving the quality of education for all are effective ways to help remove obstacles to social mobility and equal society.

Nevertheless, equality of education is not the only part of the story, as intergenerational mobility is determined by both education equality and returns to education. Previous studies in developed countries, such as the US, France, and Sweden, have found that intergenerational associations are weaker among those with a higher level of schooling (Breen, 2004; Breen and Jonsson, 2007; Torche, 2011). However, these findings have been challenged by higher education expansions and an increase in higher degrees, which could lead to a dilution of returns to higher education qualifications. Work focusing on more recent cohorts has shown that there are inequalities in earnings even among those elite groups of people who have a degree. Manzoni and Streib (2019) investigate the wage gap between first- and continuing-generation graduates 10 years after completing university in the US and find a raw gap of 11% and 9% for male and female graduates, respectively. However, the wage gap fades after controlling for individual characteristics for females and labour market characteristics for males. Focusing on a recent cohort in the UK, Adamecz-Völgyi et al. (2022) find an 8.3% wage penalty for first-generation female graduates when comparing their wages to the wages of their non-first generation peers, but no evidence of this kind of penalty for first-generation males. Therefore, it is also important to promote equal opportunities in the labour market and offer support to young people from disadvantaged backgrounds when they enter the labour market.

1.2. Thesis structure

This thesis consists of three essays that aim to measure social mobility in a recent cohort in England and examine how mobility is influenced by educational attainment, bursaries, and the COVID-19 pandemic. Our analysis is based on Next Steps, a longitudinal cohort study following the lives of a nationally representative group of nearly 16,000 young people born in 1989-90 (University College London, UCL Institute of Education, Centre for Longitudinal Studies, 2021). Using econometric models and quantitative methods, we estimate the intergenerational income persistence in the chosen cohort and investigate the role of non-cognitive skills, ability, and education in driving social mobility. Focusing on the disadvantaged group, this thesis also provides evidence on how educational bursaries narrow the socio-economic gap in education and how the COVID-19 pandemic exacerbates pre-existing inequalities in the labour market.

In the first essay, in the second chapter, we examine the intergenerational income persistence for males born in 1989-90 in England. In the UK, intergenerational income persistence is high by international standards and increased over time when comparing the 1958 cohort and 1970 cohort. Even though well-established literature has examined intergenerational income mobility for those born before the 1980s in the UK, relatively little work has been done using more recent birth cohorts. Our work contributes to the existing literature by using recent income data for a relatively young generation, those born in 1989-90.

We establish the level of intergenerational persistence among sons, which is measured as the association between average parental income when the children were aged 14, 15, 16 and 17 and later adult earnings at child age 25. To minimise the influence of classic measurement errors and lifecycle biases arising from the fact that earnings measured at suboptimal ages do not equal lifetime earnings, we report the estimates of intergenerational income elasticity (IGE) as well as the rank-rank coefficient. The latter focuses on the association between parents' and child's positions in the income distribution and thus reduces the biases in the measurement of absolute values of income and earnings. Building on previous work, we then contextualise the persistence by comparing the younger cohort to the 1970 birth cohort. Our best estimate of intergenerational income persistence among sons born in 1989-90 is 0.224, which is comparable to that for the 1970 cohort (0.223). As the lifecycle bias and measurement errors exist, we acknowledge that it is likely the true intergenerational income persistence of two generations is underestimated.

We also analyse the contributing factors for intergenerational income persistence by a commonly used two-stage decomposition approach. We focus on cognitive skills, non-cognitive traits, and educational attainment as mediating factors. We first estimate the relationship between parental income and the mediating factors and then estimate a series of regressions, regressing the sons' earnings at age 25 on the mediators, conditional on average parental income. Our results suggest that education continues to play an important role in explaining income persistence in England.

To provide a lifecycle view of intergenerational income persistence in this recent cohort, we also predict the income persistence from age 30 to 42 using the returns to education and direct parental income impact across the lifecycle in the 1970 cohort combined with the associations between parental income and educational attainment in Next Steps. Our projections show that IGE at age 42 for the 1990 cohort is approximately 2-8 percentage points below that for the 1970 cohort assuming the returns to education are the same as in the two cohorts over the lifecycle.

As it has been shown that education is a strong driver of social mobility and there has been a long-existing socio-economic gap in education, the next chapter of this thesis then focuses on the Education Maintenance Allowance (EMA), a means-tested conditional cash transfer scheme which aimed to encourage participation, retention, and achievement in post-compulsory education among young people, especially those from low-income families. The EMA programme began in 15 pilot areas in 1999 and has been rolled out nationally since September 2004 in the UK. By providing cash incentives to children from less affluent backgrounds, this programme can relieve the difficulties of paying tuition fees and living expenses faced by poor children and their families and thus offer an equal opportunity of access to post-compulsory education. Although previous studies have shown that the EMA had a positive impact on participation, retention, and achievement in secondary school, there is little evidence of its impact over the longer term. As the EMA was abolished at the end of the academic year 2010/11 in England, this essay provides a retrospective empirical analysis by using longitudinal data from England to examine the medium-term impact of the means-tested conditional cash transfer programme on higher education participation and attainment and discuss the possible impact of the abolition of the conditional cash transfer scheme.

Focusing on students from low-income backgrounds only, I estimate a multivariate regression model to compare the educational outcomes of EMA recipients to non-recipients, the latter being those who either had incomes too high to be eligible for EMA or who were eligible for EMA but did not receive it. To reduce the impact of unobserved factors and the systematic differences between those who received EMA and those who did not (for example, pupils with higher prior attainment were more likely to receive EMA), I combine regression modelling with an entropy balancing approach, a statistical matching technique, to balance characteristics of the treatment and control groups. I find that two-year EMA recipients are more likely to participate in higher education, obtain a first degree and achieve at least NVQ Level 4 than non-recipients. However, the results show that EMA has no statistically significant impact on attendance at high-status institutions and degree classification. Moreover, the impact of EMA by gender is also explored in this chapter. The result suggests that the impact of the allowance is smaller on higher education participation but more substantial on degree completion for male students than their female peers, indicating that males benefit more from the allowance in a longer term. As part of the programme of the budget cut, the government under the Conservative/Liberal Democrat Coalition stopped the scheme at the end of the academic year 2010/11 and replaced the EMA scheme with the 16 to 19 Bursary Fund. Unlike EMA, the new scheme targets a much narrower group of students and provides funds to schools and institutions instead of giving cash directly to the students. However, our findings suggest that even though EMA is a costly scheme, it does benefit young people, especially young males, over a longer time frame.

As shown in the first two essays and existing studies, socio-economic gaps in educational and labour market outcomes in the UK have been a problem for policymakers for decades. Since the start of 2020, the outbreak of the COVID-19 pandemic has had a significant impact on social and economic life. Thus, we are naturally interested in whether the pandemic has exacerbated pre-existing inequalities in England. To answer this question, the final essay in this thesis examines the impact of the COVID-19 recession on labour market outcomes for a non-privileged group, first-in-family (FiF) graduates, those who are first-generation university graduates and obtained a university degree even though their parents did not. Adamecz-Völgyi et al. (2020) provide a robust analysis of a range of widening participation indicators, which shows the share of students from different SES backgrounds attending higher education, and suggests that FiF is a good indicator for widening university participation as about 82% of potential FiF graduates also face at least one other disadvantage[1]. This chapter contributes to the previous literature by providing the first analysis of the labour market outcomes for FiF graduates during the COVID-19 pandemic in England using a relatively recent cohort.

[1] Other disadvantage indicators include special educational needs (SEN), Free School Meals (FSM), low social class, income deprivation, young carer, non-White, living with disability, single-parent, care leaver, and multiple deprivations.

We compare the labour market outcomes of FiF graduates with their non-FiF graduate peers using linear probability models with multiple waves of data collected during the pandemic, which has been linked to eight existing waves of Next Steps data. We find substantial differences in the outcomes of graduates who did not continue working, and these differences are heterogenous by gender. Female FiF graduates were more likely to stop working altogether or to be put on unpaid leave and less likely to be put on furlough or paid leave than non-FiF female graduates. However, we find no such differences between FiF and non-FiF male graduates. Our results highlight how the COVID-19 recession has exacerbated the disadvantage arising from the intersectionality of socio-economic background and gender and the prolonged impact of parental human capital for women.

To spread education opportunities more equally across England and create a 'fairer' society, the UK government has released a number of programmes, such as "Opportunity for All" and "Levelling Up the United Kingdom" (Department for Education, 2022; Department for Levelling Up, 2022). Despite these efforts from the government, there is still substantial intergenerational income persistence in the country, and this persistence could have been strengthened by the COVID-19 pandemic. The thesis focuses on a relatively recent cohort born in 1989-90 and reviews the social mobility situation in England. Our findings suggest that education still plays an important role in driving social mobility in the country, and inventions increasing participation and achievements in education among disadvantaged children, such as EMA, can equalise opportunities for education and thus promote upward mobility in society.

Chapter 2.

Accounting for intergenerational income persistence in a new cohort: noncognitive skills, ability and education

2.1. Introduction

The relationship between family wealth and resources and future earnings for children has been widely discussed for decades. The strength of this relationship determines how socially mobile society is; intergenerational income mobility is the extent to which income levels can change across generations. There is plenty of evidence showing that children from wealthier families have access to more family resources and opportunities (Breen and Jonsson, 2005), which contributes to their higher probability of getting a professional job and earning more throughout their life course than their peers from more deprived families (Beller and Hout, 2006; Björklund and Jäntti, 2011; Blanden et al., 2007). Studies of how this varies across countries and by the degree of income inequality in a country, i.e. the Great Gatsby curve, illustrate the strong correlation between the level of intergenerational mobility and the extent of equality of economic and social opportunity in society (Corak, 2013; Durlauf and Seshadri, 2018; Jerrim and Macmillan, 2015). There is also interest in understanding how this has changed over time within a society, especially given the expansion of higher education and other policies aimed at promoting social mobility.

The UK, along with the US, has a comparatively low level of income mobility across generations by international standards (Blanden et al., 2005; Gregg et al., 2017a; Solon, 2002). As for the mobility trend within the country across time, intergenerational income persistence increased in the UK, comparing the 1958 cohort and 1970 cohort (Blanden et al., 2007, 2004; Gregg et al., 2017b). Specifically, Blanden et al. (2004) use income and earnings data on children at age 33 in the National Child Development Study (NCDS) born in 1958 and age 30 in the British Cohort Study (BCS) born in 1970, finding that the intergenerational income elasticity increased from 0.205 to 0.297 across these two generations. As the 1970 cohort grew older, Gregg et al. (2017a) present more comparable estimates at age 34 in the BCS, suggesting that the intergenerational income elasticity is even more significant in the younger cohort (0.324). Recent studies, however, have found that the impact of family income on a child's education level has declined for those born after the 1980s (Blanden and Macmillan, 2014; Gregg and Macmillan, 2010), suggesting an improvement in educational equality. Yet, whether intergenerational income mobility has improved for those younger generations remains unclear, as it depends on both educational equality, which is measured by the associations between parental income and children's educational outcome, and returns to education. The returns to education are unlikely to stay the same if the supply of workers with qualifications increases in the job market. Thus, even though educational equality has declined recently, the trend in the returns to education is hard to predict. This chapter estimates intergenerational mobility for the cohort of young people born in1989-90 and investigates how factors, including noncognitive skills, ability and education, affect mobility.

A growing literature has shown that education has been playing an important part in explaining intergenerational income persistence. Firstly, children of high-income parents tend to have more years of schooling and better educational outcomes (see, for example, Blanden and Machin, 2004; Chevalier et al., 2013; Gregg and Macmillan, 2010). Secondly, better educational outcomes lead to higher economic outcomes in the labour market (see Harmon and Walker (1995) for return to schooling and Walker and Zhu (2011) for return to a degree). Thus, it is likely that parental income during childhood affects children's later adult earnings partly through education. Blanden et al. (2007) examine the contributing factors of the intergeneration income mobility for sons born in 1970 and find that educational attainment at and after age 16 accounts for 0.10 points of the 0.32 intergenerational coefficient (31.1%).

Apart from later educational attainment, previous studies suggest that the association between childhood parental income and sons' adult earnings can also be partially explained by cognitive skills and noncognitive traits. Children from more affluent families have higher cognition and better behaviours in their early years (Benenson et al., 2007; Bradley and Corwyn, 2002; Falk et al., 2021). Cognitive skills and non-cognitive traits can affect their education choices and attainment and influence their labour market outcomes both directly and indirectly through education (Bolt et al., 2021; Carneiro et al., 2007; Heckman et al., 2006; Roberts et al., 2007). Bolt et al. (2021) find that cognition, along with years of schooling, is the main driver of intergenerational mobility, while noncognitive traits only account for a small and insignificant proportion of income persistence. This is consistent with Blanden et al. (2007) that cognitive skills explain a larger fraction (7.3%) of the IGE than the noncognitive traits (5.8%).

Despite the fact that well-established literature has examined intergenerational income mobility and the role of education in driving mobility for those born before the 1980s in the UK, relatively little work has been done using more recent birth cohorts. This paper contributes to the existing literature by using recent income data for a relatively young generation, those born in 1989-90 and surveyed in Next Steps (formerly the Longitudinal Study of Young People in England, LSYPE) (University College London, 2022). First, we estimate the relationship between parental income and sons' income by regressing log children's earnings on log parental income and comparing it to previous cohorts. In order to be comparable to the results in previous studies, this paper focuses on sons' income only. We also estimate the rank-rank coefficients and compare them to the estimates of intergenerational elasticity (IGE) of income to reduce lifecycle biases.

Based on our preferred measure, we find that the IGE and rank-rank coefficient are 0.125 and 0.224 at age 25 for sons in Next Steps (born in 1990), which are similar to the estimates from those born in 1970 from the BCS. We suggest that it is likely that we underestimate the true intergenerational income persistence of parents and sons in the Next Steps as the lifecycle bias and measurement errors exist. In addition to this, we implement a mediation analysis approach to examine how mediating factors, including educational attainment, cognitive skills and noncognitive traits, explain the intergenerational persistence in income. Our findings suggest that education is playing an increasingly important role in driving mobility when we compare the 1990 cohort with the 1970 cohort.

The remainder of this chapter is organised as follows. In section 2.2, we introduce the data used in our analysis and some descriptive statistics. Our estimates of intergenerational income persistence are presented in section 2.3, and the role of education in driving social mobility is examined in the following section. Section 2.5 predicts the persistence across the lifecycle. The last section provides our conclusions and recommendations.

2.2. Data and descriptive statistics

We first use the information from the Next Steps for our main analysis and then use data from the British Cohort Study (BCS) for comparison and prediction. Next Steps, previously known as the First Longitudinal Study of Young People in England (LSYPE), follows around 16,000 young people born in England between 1st September 1989 and 31st August 1990 from 2004 when they were in Year 9. Until 2010, the cohort members were interviewed annually by the Department for Education (DfE) about their family and home life, friends, health and happiness, education, employment, behaviours and attitudes, and aspirations for the future. The last wave, the Age 25 Survey, took place in 2015/16, collects information on the lives of young adults today (University College London, UCL Institute of Education, Centre for Longitudinal Studies, 2022).

2.2.1. Variables

Instead of measuring the associations between the income of two generations, we focus here on the influence of childhood circumstances on the adult earnings of a child. Parental income, to some extent, represents the family resources in childhood. Moreover, we include sons only in our sample to avoid the problems of female labour force participation. In addition, we want our estimates to be comparable to previous UK estimates, most of which used parental income and sons' earnings (Blanden et al., 2007; Gregg et al., 2019, 2017b). This chapter, therefore, estimates intergenerational income mobility using parental income and sons' earnings.

Parental income and age

In Next Steps, neither net income nor tax information is available for parents of the cohort members. Thus, this study uses gross parental income data, which are banded and available at child ages 14 to 17 (waves 1-4). We use parental income data in four waves to minimise the impact of measurement errors. There are 91 income bands in wave 1, eight bands in wave 2, and 12 bands in waves 3 and 4. First, to estimate intergenerational income elasticity, we convert continuous income variables in each wave using interval regression[2], which assigns expected values to censored data such as income. For wave 1, higher income bands (bands 82-90), continuous income cannot be predicted from interval regression. Thus, we imputed midpoint estimates for these bands. All income data are deflated to 2004 prices. We then average the continuous parental income in waves 1-4 to create the average parental income variable and derive the average monthly income from the annual income data. If income is missing in one or more wave (s), the average income is then imputed using the average income in the other waves[3]. Finally, we take the log of the income. Our explanatory variable used in section 3.3 is the log of the imputed average parental income. Because the income information is self-reported, the top and bottom 1% of average parental income are trimmed to reduce the influence of misreporting and extreme outliers. Furthermore, we carry out a number of robustness checks on the parental income measures, comparing the results of our sample to the results of the untrimmed sample, midpoint estimates of parental income, sample of those with at least two observed parental income at age 15-17 and a sample of those with observed parental income at age 16 and 17.

We estimate the intergenerational income elasticity controlling for average parental age and age-squared obtained in waves 1-4 of the Next Steps. The average age of the main parent and the age of the second parent is taken in each wave, and then we construct the average parental age from the four waves. Missing values in parental age in our sample are replaced with the sample mean. Missing flags are used for any missing values in parental income and ages.

Sons' earnings

The sons' earnings are available at age 25 in Next Steps. The respondents were asked about the amount of their gross pay and the length of their pay period; gross pay per week was

[2] Here we use an empty interval regression which only includes the upper and lower bonds of each income band.
[3] As discussed below in section 2.2.2, we only include those who have at least two waves of parental income data available in our sample.

derived from their current gross pay and pay period. We then obtain the monthly earnings by multiple the gross weekly pay by 4.3. Earnings are deflated to 2004 prices, and the log of earnings is taken. We, therefore, use the log of the sons' monthly earnings at age 25 as our outcome variable in section 2.3 and exclude the highest 1% and the lowest 1% of the sons' earnings in the sample as we do for parental income.

Measures of education

In order to explore the role of education in explaining intergenerational income mobility, we take advantage of linked administrative education data from Next Steps. The secure access version of this dataset includes national exam results from throughout an individual's schooling career (the National Pupil Database). We use their Key Stage 2 mathematics and English points, which are standardised to mean zero, and standard deviation one, as a measure of early cognitive skills. This is comparable to measures available in the BCS. We also use total standardised Key Stage 4 (GCSE) points and number of GCSEs, standardised A level total points, and number of A levels. We include a missing flag for any missing values and impute the mean value for continuous variables with a missing value.

Other factors

Following Blanden et al. (2007), we also consider the role of non-cognitive traits as mediators. We include a measure of academic self-concept from age 13/14, which is based on the following questions: *I get good marks for my work; How good YP thinks YP is at school work; How good teachers think YP is at school work; and how good or bad at this subject: English, maths, science and information and communication technology (ICT)*. We conduct a principal component analysis to form an academic self-concept scale (the eigenvalue of this factor is greater than one). We also use the General Health Questionnaire (GHQ-12) (Goldberg and Williams, 1988) for ages 14/15. This is a measure of mental health on a twelve-point scale where a higher score indicates a higher probability of mental ill health. Again, we impute the mean value for any missing values and include a missing flag.

2.2.2. Sample restrictions

As in previous studies, the sample is restricted to all sons who were in full-time employment (not including those self-employed) when the survey was carried out at age 25. Moreover, our sample excludes those who have one or no parental income observation from age 14-17. Those sons with the highest 1% and lowest 1% of parental income and their earnings are also excluded from our sample. These sample restrictions result in 1,713 individuals in the available sample for section 2.3.

2.2.3. Descriptive statistics

To see if our sample is representative of the whole population, we present the summary statistics of parental income and sons' earnings in Next Steps and compare them with income measures in external data sources. Our parental income measures are compared with total household income in the Family Resource Survey (FRS) in 2004-2007. In order to be comparable to our sample, we generate gross monthly income from gross weekly income and focus only on households living in England with teenagers aged 11-19 in the FRS. Since the FRS reports individual income instead of parental income, we use the income of the head of the household and the partner as parental income. As income data are continuous in FRS, we convert the continuous income into 12 income bands based on the proportion of cohort members in each band in Next Steps in 2006. Then we convert the new continuous income variables using interval regression. For sons' earnings, we derive the sons' monthly earnings from their gross weekly pay in the Quarterly Labour Force Survey (QLFS) from October to December 2015. Then, we compare our measure in the Next Steps with the gross monthly pay in the QLFS. The sample in the QLFS is restricted to all male workers in England aged 24-29 working full-time in their main job. As sons' earnings are continuous, those with the highest 1% and lowest 1% in the QLFS are excluded as we do for Next Steps.

Table 2.1. shows the comparison of parental income and sons' earnings in Next Steps, FRS and QLFS. We present summary statistics of weighted data, using final weights[4] for each

[4] In Next Steps, wave 1 final weights combine design weights with non-response weights and weights to match the population, while wave 2-4 and 8 final weights are composed of design weights and attrition weights.

wave in the Next Steps, sample weights for each wave in the FRS and person income weights in the QLFS. For the years 2005 - 2007, the means, medians and SDs of parental income in the Next Steps are comparable to those in the FRS, though incomes in the Next Steps are more diverse in 2005. For 2004, however, both the mean and median of parental income in the Next Steps are slightly smaller than in the FRS, and the SD is much higher. One possible reason for this could be that participants in Next Steps misunderstood the questions and reported their weekly or monthly income rather than their annual income. Thus, in the next section, we check the robustness of our results using three-year (2005-2007) and two-year (2006-2007) average parental income. As for sons' earnings, the distribution of sons' monthly earnings in Next Steps resembles the distribution in the QLFS. Yet, it is noteworthy that the sample size in the QLFS is quite small, just over 400. Figure 2.1 also shows that the distribution of sons' earnings in Next Steps has a similar pattern as the distribution in the QLFS though sons' earnings in Next Steps have a slightly higher mean and larger variance. Generally, we can conclude that, except for parental income in 2004, our measures of parental income and sons' earnings in Next Steps are comparable to measures in external data sources.

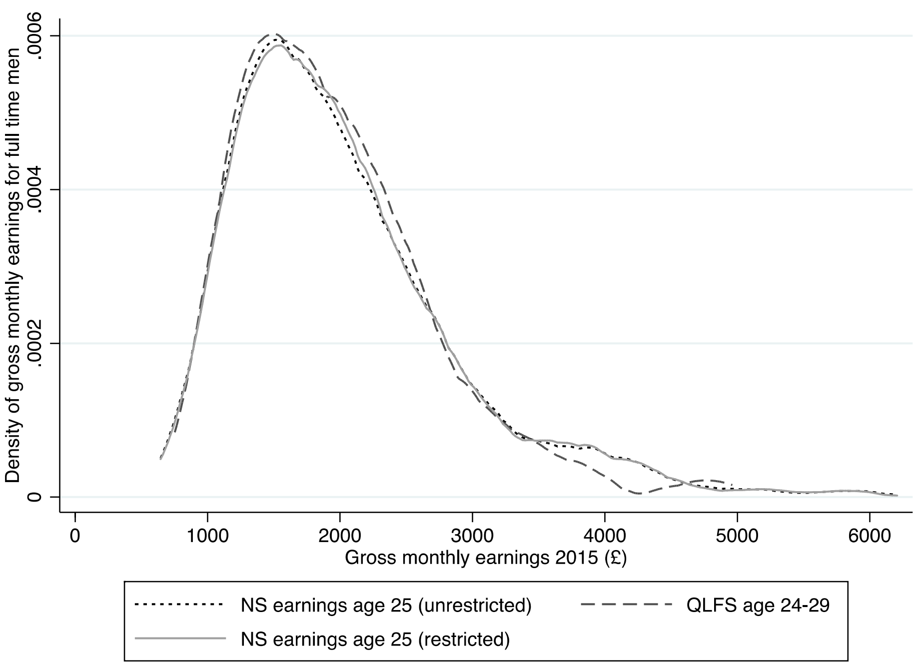
Table 2.1 Comparison of the log of parental income and sons' earnings for the restricted sample (regression sample)

		Next Steps	FRS	QLFS
Parental monthly income (2004)	Mean	7.553	7.665	
	Median	7.630	7.717	
	SD	0.929	0.623	
	Obs.	1,424	3,569	
Parental monthly income (2005)	Mean	7.749	7.653	
	Median	7.707	7.719	
	SD	0.754	0.683	
	Obs.	1,244	3,549	
Parental monthly income (2006)	Mean	7.755	7.677	
	Median	7.883	7.717	
	SD	0.631	0.644	
	Obs.	1,577	3,189	
Parental monthly income (2007)	Mean	7.710	7.687	
	Median	7.841	7.724	
	SD	0.659	0.623	
	Obs.	1,521	2,970	
Average parental monthly income (2004-2007)	Mean	7.632		
	Median	7.685		
	SD	0.611		

	Obs.	1,713	
Sons' monthly earnings (2015/16)	Mean	7.214	7.189
	Median	7.191	7.181
	SD	0.386	0.355
	Obs.	1,713	410

Notes: Weighted using final weights for each wave in the Next Steps, sample weights for each wave in the FRS and person income weights in the QLFS. All income data are deflated to 2004 prices.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a), Department for Work and Pensions, National Centre for Social Research, Office for National Statistics, Social and Vital Statistics Division (2014a, 2014b, 2014c), National Centre for Social Research, Office for National Statistics, Social and Vital Statistics Division, Department for Work and Pensions (2014), and Office for National Statistics, Social Survey Division, Northern Ireland Statistics and Research Agency, Central Survey Unit (2019e).

Figure 2.1 Distributions of sons' monthly earnings in NS and QLFS



Notes: Weighted using wave 8 weights in the Next Steps and person income weights in the QLFS.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a) and Office for National Statistics, Social Survey Division, Northern Ireland Statistics and Research Agency, Central Survey Unit (2019e).

Table 2.2 Income matrix of parental income and sons' earnings (weighted count reported)

	Sons' Earnings Quintiles					
Parental Income Quintiles	1	2	3	4	5	Total
1	140.5	111.3	83.94	58.37	55.49	449.6
	(.3126)	(.2475)	(.1867)	(.1298)	(.1234)	(1)
2	131.7	87.14	74.5	59.9	75.74	429
	(.307)	(.2031)	(.1737)	(.1396)	(.1766)	(1)
3	85.22	76.91	88.51	80.36	47.6	378.6
	(.2251)	(.2031)	(.2338)	(.2123)	(.1257)	(1)
4	65.36	75.35	71.06	73.17	78.38	363.3

	(.1799)	(.2074)	(.1956)	(.2014)	(.2157)	(1)
5	29	63.2	72.06	87.53	95.18	347
	(.0836)	(.1821)	(.2077)	(.2523)	(.2743)	(1)
Total	451.8	413.8	390.1	359.3	352.4	1967
	(.2296)	(.2104)	(.1983)	(.1826)	(.1791)	(1)

Notes: Weighted using wave 8 weights. Cell proportions in parentheses. Number of observations =1,713.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a).

The relationship between parental income and sons' earnings is first explored by an income matrix. Table 2.2 demonstrates the income matrix of average parental income at age 14-17 and sons' earnings at age 25. We divide income measures in each generation into five equal-sized quintiles to see how much intergenerational income persistence exists. Overall, sons from the bottom two parental income quintiles are more likely to end up in the bottom quintile than any other quintile, while those from the top two parental income quintiles are more likely to stay in the top. Specifically, for those sons who were born with parents in the bottom income quintile, 31% of them remain in the bottom income quintile while only 12% migrate to the top. As for sons who have the least deprived parents, they have a 27% chance to remain there, but only 8% move down to the bottom. Our results are similar to the results in Blanden et al. (2013) using a cohort born in 1958, where they find 30% and 27% of children in the top and bottom income quintiles remained where they were, while 13% moved from the bottom to the top and 12% move from the top to the bottom. They also compare the results of the 1970 cohort to those of the 1958 cohort, suggesting that income persistence increased significantly over time. Thus, the results from the income matrix of parental income and sons' earnings indicate that the intergenerational income persistence in Next Steps falls when compared to the 1970 cohort but remains substantial.

2.3. Intergenerational income mobility

This section explores the intergenerational income mobility among sons in Next Steps. We start with an empirical framework and then discuss the potential problems of point-in-time estimates. To minimise the influence of measurement errors and lifecycle bias, which results from using earnings at suboptimal ages as a proxy of lifetime earnings, we report the estimates of both intergenerational income elasticity and rank coefficient using average parental income. The last part of the section presents a number of robustness checks using the untrimmed sample, midpoint estimates of parental income, a sample of those with at least two observed parental income observations at age 15-17 and a sample of those with observed parental income at age 16 and 17.

2.3.1. Methodology

Empirically, intergenerational income mobility is generally measured by intergenerational income elasticity (IGE) which is the association between parents' lifetime income and child's lifetime income. In this paper, we use an ordinary least square (OLS) regression to estimate the IGE as shown in the following equation (2.1):

$$Y_i^{son} = \alpha_1 + \beta_1 Y_i^{parent} + \varepsilon_i \tag{2.1}$$

where Y_i^{son} is the log of sons' earnings at age 25, Y_i^{parent} is the log of average parental income at child age 14-17, i identifies the cohort member, ε_i is the error term, and α and β are the parameters we estimate. The estimated coefficient, $\widehat{\beta_1}$, captures the IGE and $(1 - \widehat{\beta_1})$ can be recognised as a measure of mobility.

Ideally, we want to examine the relationship between parents' permanent income and sons' permanent income, which are not available in our longitudinal dataset as cohort members were just 25 in the last wave. We instead report the post-in-time estimates of intergenerational income mobility as in previous studies. To better proxy permanent income, we use the average parental income of four periods, at child age 14, 15, 16 and 17, and estimate the influence of average parental income on sons' earnings at age 25, controlling for parental age and age-squared.

One of the problems that has been addressed frequently by intergenerational income mobility studies is the lifecycle bias. Grawe (2006) and Nybom and Stuhler (2016) point out that intergenerational income persistence rises as the permanent income variance increases over the lifecycle. Early observations of earnings are likely to underestimate true lifetime earnings. This has a larger effect on those from more affluent families as they tend to have higher levels of education compared to those from more deprived families, and their returns to education are not fully realised until around age 40. This lifecycle bias underestimates the difference between the permanent income of those from more affluent and more deprived backgrounds and thus understates the true IGE. Although lifecycle bias influences both generations, it is more problematic for sons' earnings in our paper as we only have one point-in-time observation for each individual at a comparably early age, 25. Using the 1970 BCS cohort, Gregg et al. (2017a) estimate the IGE across the lifecycle of sons and find that the IGE rises from 0.203 at age 26 to 0.397 at age 42

Another issue in estimating intergenerational income mobility is the attenuation bias. Both parental income and sons' earnings in Next Steps are self-reported, so they may not accurately reflect income and earnings. Rather than adjusting the income by the pay period as with sons' earnings, parents in Next Steps were asked to give their total income in one year. It is likely that some parents gave their daily, weekly or monthly income instead of annual income. In our case, parental income is likely to be more affected by measurement error than sons' earnings, and thus we focus on exploring the error in the measure of parental income. Blanden et al. (2013) suggest that the measurement error in permanent parental income will result in an underestimation of the true IGE using OLS and thus overstate income mobility. Moreover, Bound et al. (2001) argue that a common issue in self-reported income parental income is the mean aversion: high-income individuals tend to under-report their income while low-income ones tend to over-report. This reporting bias leads to correlated errors within individuals and thus understates income mobility. Overall, the underestimation of income mobility generated by the reporting bias offsets the impact of attenuation bias. Following the approach taken by the previous studies (see, e.g. Gregg et al., 2017a; Mazumder, 2005), we use the average of four observations of parental income to minimise the bias.

The validity of our results is also challenged by data missingness and sample selection. First, the data missingness in our sample is not random, as cohort members with higher parental income and better educational attainments are more likely to respond. Calderwood (2018) suggests that data missingness could cause biases in estimates if the likelihood of non-response or dropping out of the survey is correlated with some sociodemographic characteristics of the cohort members. Although we use the sample weights to deal with the sample attrition, the issue of item non-response is still problematic. Moreover, our sample is restricted to all sons who were in full-time employment (not including those self-employed) at age 25, with at least two parental income observations between ages 14-17. Thus, our estimates cannot be representative of the whole population as it does not include those self-employed, unemployed or in part-time employment. To deal with the unemployment problem, a number of existing studies impute values for the zero earners and suggest that excluding those with zero earnings would understate the true IGE (Drewianka and Mercan, 2009; Mitnik et al., 2015; Mitnik and Grusky, 2020).

In order to minimise the biases discussed above, some researchers turn to a different approach, a rank-rank measure, which explores the association between parents' and child's positions in the income distribution (Chetty et al., 2014; Dahl and Deleire, 2008; Gregg et al., 2017b). Chetty et al. (2014) suggest that the IGE can be divided into two parts, the correlation between parents' and children's ranks and the income inequality across generations. As a scale-invariant measure, the rank-rank measure is more robust across specifications than the IGE (Chetty et al., 2014). Gregg et al. (2017a) also point out that rank-based estimation is less sensitive to lifecycle bias, classic measurement errors, and bias from zero earners because it eliminates the problem of scale mis-measurement and is only influenced by positional inaccuracy. Thus, we rank the parents and sons according to their income and earnings relative to other parents and sons in our sample and estimate the relationship between parents ranks and son ranks using equation (2.2) below:

$$Rank_{Y_i}^{son} = \alpha_2 + \beta_2 Rank_{Y_i}^{parent} + \varepsilon_i \tag{2.2}$$

where $Rank_{Y_i}^{son}$ is the rank of sons' earnings and $Rank_{Y_i}^{parent}$ is the rank of average parental income. In this paper, we report both rank-rank coefficients, β_2, and the conventional OLS estimates of the IGE to give a comprehensive view of intergenerational mobility and to reduce biases. For the regression analysis, we use the standardised points for educational attainments. To ensure variables used for regression analysis are of similar scales and to provide a more straightforward explanation for the regression results, we multiply the ranks of parental income and sons' earnings by five and divide them by the number of observations, N. After rescaling, the range of the ranks of parental income and sons' earnings is between 0 and 100. Thus, the rank-rank results can be explained as one percentile increase in the rank of average parental income at age 14-17 is associated with $\widehat{\beta_2}$ percentile increase in the rank of sons' earnings at age 25.

2.3.2. Results

Table 2.3 reports the estimates of IGE and rank-rank coefficients from the regression of sons' earnings at age 25 on average parental income at age 14-17 in Next Steps controlling for average parental age and age-squared. The IGE is 0.125, whereas the rank-rank coefficient, which removes the scale mis-measurement issue, is comparably higher at 0.224. Both coefficients are significant at the 1% level. However, our results are very likely to underestimate the true intergenerational income persistence of two generations because of the lifecycle bias and the existence of measurement errors as discussed above.

Compared to results in Gregg et al. (2017a), we find that our age 25 estimates sit between their age 23 estimates for the 1958 cohort in the NCDS and age 26 estimates for the 1970 cohort in the BCS, and our results are more comparable to their results for the later cohort. Even though the IGE and the rank-rank coefficient in the BCS are 0.227 and 0.235, slightly higher than in Next Steps, it is too early to conclude the intergenerational income mobility has increased in the UK as sons' earnings in the BCS are measured one year later than in the Next Steps. Another concern is that Next Steps is carried out solely in England while the NCDS and the BCS cover the whole UK. Thus, the smaller coefficients in Next Steps may simply suggest the level of intergenerational income mobility is higher in England than in the rest of the UK. Moreover, the higher education participation rate in the UK more than doubled over the past three decades (The World Bank, 2022), and children from more affluent families are more likely to participate in higher education than those from less affluent families (Chowdry et al., 2013; Crawford and Greaves, 2015). Thus, the lifecycle bias is more severe for our sample as more participants in Next Steps enrol in higher education and enter the job market later than those in the BSC. In addition, Gregg et al. (2017a) have imputed the average benefit level available for those out of work and the imputation can reduce the downward biases for estimating the IGE.

Table 2.3 Intergenerational income elasticity (IGE) and rank-rank coefficient among sons in Next Steps

Regression of earnings at age 25 on average parental income at age 14-17		
IGE	Rank-rank coefficient	Sample Size

0.125	0.224	1,713
(0.021)	(0.030)	

Notes: Weighted using wave 8 weights. Standard errors in the parentheses.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a).

In order to obtain more comparable results, we obtain BCS data for the 1970 cohort and regress sons' earnings at age 26 on average parental income at age 10-16 using a similar approach as we do for the Next Steps cohorts. The results in Table 2.4 show that even though the IGE in the Next Steps is slightly lower than that in the BCS[5], the rank-rank coefficient remains quite stable, suggesting that there is no change in the association between the position of parental income and the position of sons' earnings in the two cohorts. Taking the sons' age into account, the small difference in IGE is negligible.

Table 2.4 Intergenerational income elasticity (IGE) and rank-rank coefficient among sons in the BCS

Regression of earnings at age 26 on average parental income at age 10-16		
IGE	Rank-rank coefficient	Sample Size
0.165	0.223	2,128
(0.018)	(0.022)	

Notes: Both sons' earnings and average parental income are trimmed at 1% and 99%. Sample is restricted to England only. Standard errors in the parentheses.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021b).

To check the robustness of our results, we also report the estimates from other specifications in Table 2.5 below. Panel A of Table 2.5 reports the IGE and rank-rank coefficient using an untrimmed sample. Compared to the results in Table 2.3, the estimated IGE and rank-rank coefficient for the untrimmed sample are 0.135 and 0.230, respectively, 0.010 and 0.006 higher than the coefficients for the trimmed sample. The existence of the outliers widens the distributions of average parental income and sons' earnings, and it has a larger impact on the IGE than on the rank-rank coefficient as the rank-based measure is scale-insensitive.

In the second panel of Table 2.5, we use the midpoints of income bands instead of interval regression to convert banded parental income into continuous income for each year. The

[5] The difference in the IGE results from the difference in the variance of parental income in the two cohorts. The variance of parental income in Next Steps is slightly higher than in BCS (e.g. 0.398 vs. 0.348 at age 16). A detailed comparison of parental income variance in NS and BCS as well as external datasets can be found in Appendix A1.

results show that both measures give very similar estimates though both the IGE and rank-rank coefficient in Panel B of Table 2.5 is slightly higher than in Table 2.3. The minor differences indicate that our estimates are not susceptible to the estimation methods of parental income. However, we prefer the results from interval regression as it weights the position of an individual within a band and is able to assign values to those in the open-top category.

Furthermore, we find that the parental income at ages 14 and 15, especially age 14, in the Next Steps is distributed differently compared to income data in the external dataset. Thus, the last two panels of Table 2.5 show the results using three and two years of average parental income at sons' ages 15-17 and 16-17. For results in Panel C, we impute average income over the other two waves if parental income is missing in one specific wave. The use of the three-year and two-year average parental income reduces our sample sizes to 1,581 and 1,440, respectively but are still comparable to the original sample. We find that the exclusion of parental income at age 14 raises the IGE from 0.125 to 0.141. As for the rank-rank coefficient, it increases from 0.224 to 0.248. The results in the last panel show that the exclusion of parental income at age 15 further increases the IGE to 0.145 but decreases the rank-rank coefficient to 0.241. Overall, the robustness checks show that different measures of parental income all give results similar to our main estimators.

The last panel of Table 2.5 uses all sons including those in part-time work and those not in the labour force. We here show the estimate of rank-rank association only as including part-time workers and non-participants would substantially increase the variance for son's earnings and thus lead to a surge in the IGE estimate.

Table 2.5 Robustness checks

IGE	Rank-rank coefficient	Sample Size
Panel A: Untrimmed sample		
0.135	0.230	1,779
(0.023)	(0.031)	
Panel B: Using midpoint estimates of average parental income		
0.127	0.227	1,717
(0.021)	(0.030)	

Panel C: Using average parental income at age 15-17		
0.141	0.248	1,581
(0.022)	(0.032)	
Panel D: Using average parental income at age 16-17		
0.145	0.241	1,440
(0.023)	(0.034)	
Panel E: Using all sons including part-time workers and those not in the labour force		
-	0.209	2,670
-	(0.026)	

Notes: Weighted using wave 8 weights. Standard errors in the parentheses.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a).

2.4. The role of education in driving social mobility

2.4.1. The decomposition approach

Following previous studies, we explore intergenerational income persistence by a commonly used two-stage decomposition approach. The mediating factors we consider follow Blanden et al. (2007), including cognitive skills, non-cognitive traits, and educational attainment. It needs to be noted that, in this section, we measure associations rather than causal relationships because of the influence of unobserved factors. First, we analyse the relationship between parental income and cognitive skills, noncognitive traits, and educational attainment using equations (2.3) and (2.4) below:

$$Ed_i^{son} = \alpha_3 + \gamma_1 Y_i^{parent} + \varepsilon_i \quad (2.3)$$

$$Noncog_i^{son} = \alpha_4 + \gamma_2 Y_i^{parent} + \varepsilon_i \quad (2.4)$$

where Ed_i^{son} and $Noncog_i^{son}$ are sons' measured education and noncognitive traits, Y_i^{parent} is the log of parental income, ε_i is the error term, and α and γ are the parameters we estimate. γ_1 and γ_2 capture the estimated effects of parental income on sons' measured education and noncognitive traits, respectively.

Then, in order to account for the labour market value of education, we estimate a series of regressions, regressing cognitive skills, noncognitive traits, and educational attainment on sons' earnings, conditional on parental income. The second stage of the decomposition can be written as the equation (2.5) below:

$$Y_i^{son} = \alpha + \lambda_1 Ed_i^{son} + \lambda_2 Noncog_i^{son} + \delta Y_i^{parent} + \varepsilon_i \tag{2.5}$$

where Y_i^{son}, Y_i^{parent}, Ed_i^{son} and $Noncog_i^{son}$ represent the log of sons' earnings, the log of parental income, sons' measured education and noncognitive traits, ε_i is the error term, and α, λ and δ are the parameters we estimate. λ_1 and λ_2 are the returns to education and noncognitive traits, while δ captures the direct impact of parental income on sons' earnings, controlling for sons' measured education and non-cognitive traits.

Combining equations (2.3) and (2.4) with equation (2.5), we can write the IGE β_1 as follows:

$$\beta_1 = \gamma_1\lambda_1 + \gamma_2\lambda_2 + \delta \tag{2.6}$$

where $\gamma_1\lambda_1$ measures the conditional contribution of education and $\gamma_2\lambda_2$ measures the conditional contribution of noncognitive traits. The IGE, β_1, is composed of two parts. The first part is the direct effect of parent income, represented by δ, and the second part is through education and noncognitive traits, captured by $\gamma_1\lambda_1$ and $\gamma_2\lambda_2$ respectively. This decomposition is also applicable to the rank-rank measure.

2.4.2. Results

The estimated results shown in the first columns of Tables 2.6 and 2.7 suggest that the associations between parental income and all chosen variables, except the GHQ-12 score, are statistically significant. Specifically, sons from more affluent families are more likely to have higher educational attainment from KS2 to A level, a greater chance to obtain a university degree, and better academic self-concept than those from less affluent backgrounds.

The second to the sixth column of Tables 2.6 and 2.7 present the estimates of the IGE accounting for cognitive skills, non-cognitive traits, and educational attainment. We enter the mediators additively. Column 1 reproduces the estimates from Table 2.3 without any mediators. In Column 2, we introduce measures of cognitive ability in Year 6 (Key Stage 2 mathematics and English points). In Column 3, we include the non-cognitive trait measures, academic self-concept and the GHQ-12 score. In Column 4, we add in GCSE total points and the number of GCSEs. In the final column, we include A level total points, the number of A levels, and whether the individual achieved a university degree.

The results in Columns 1 to 5 of Table 2.6 show that cognitive skills and educational attainment are the most important mediators of the IGE. The estimate in Model 1 of 0.125 is reduced to 0.085 by including cognitive skills measured at age 12. This estimate is not greatly affected by the introduction of non-cognitive traits in Model 3. Controlling for educational attainment further reduces the IGE to 0.064 in Model 4 and finally 0.059 in Model 5. This final estimate is statistically significant at the one per cent significance level. In the final model, the coefficients for GCSE total points and A total level are statistically significant at the five per cent significance level. Specifically, the results show that a standard deviation increase in GCSE and A level total points is associated with a 6.3% and 6.6% increase in sons' earnings, respectively, conditional on other education and non-cognitive factors. The results suggest that educational attainment plays a significant role in reducing the strength of the relationship between parental and sons' income.

We follow the same structure of models in Table 2.7 for the rank-rank estimates as in Table 2.6. The results in Table 2.7 tell a similar story. The rank-rank coefficient estimated without any mediators in Model 1 is reduced from 0.224 to 0.164 in Model 2 through the inclusion of early cognitive skills, such as KS2 mathematics and English points. The coefficient is not much affected by the inclusion of non-cognitive traits in Model 3 but significantly reduced in Models 4 and 5 via the inclusion of educational attainment. Including GCSE, A level, and degree attainment reduces the rank-rank coefficient from 0.166 in Model 3 to 0.122 in Model 5. All these estimated rank-rank coefficients are statistically significant at the one per cent significance level. In the final model, the estimated coefficients for GCSE total points and A level total points are statistically significant, with 4.4 and 4.8 percentile increases in the position of sons' earnings associated with a one standard deviation increase, respectively. These results again imply that educational attainment is an important mediator in reducing the strength of the intergenerational transfer of income.

Table 2.6 Intergenerational income elasticity (IGE) and the mediating factors of cognitive skills, non-cognitive traits, and educational attainment among sons in Next Steps

	Parental income	(1)	(2)	(3)	(4)	(5)
Log parental income		0.125	0.085	0.087	0.064	0.059
		(0.021)***	(0.020)***	(0.020)***	(0.020)***	(0.019)***
KS2 math points	0.298		0.057	0.051	0.015	0.014
	(0.060)***		(0.016)***	(0.016)***	(0.016)	(0.016)
KS2 English points	0.391		0.045	0.039	0.003	0.003
	(0.052)***		(0.018)**	(0.018)**	(0.018)	(0.018)
Academic self-concept	0.107			0.027	0.009	0.005
	(0.056)*			(0.012)**	(0.012)	(0.012)
GHQ-12 score	-0.007			-0.001	0.000	-0.001
	(0.123)			(0.005)	(0.005)	(0.005)
GCSE total points	0.517				0.071	0.063
	(0.056)***				(0.027)**	(0.028)**
Number of GCSEs	1.956				0.008	0.007
	(0.217)***				(0.006)	(0.006)
A level total points	0.060					0.066
	(0.033)*					(0.016)***
Number of A levels	0.091					-0.016
	(0.043)**					(0.009)*
University degree	0.136					-0.008
	(0.020)***					(0.024)
Constant		5.747	6.502	6.461	6.794	6.930
		(0.847)***	(0.827)***	(0.819)***	(0.795)***	(0.788)***
Observations	1,713	1,713	1,713	1,713	1,713	1,713
R-squared		0.059	0.115	0.119	0.146	0.156

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weighted using wave 8 final weights.
Source: University of London, Institute of Education, Centre for Longitudinal Studies (2021a, 2022).

Table 2.7 Rank-rank coefficient and the mediating factors of cognitive skills, non-cognitive traits, and educational attainment among sons in Next Steps

	Parental Income	(1)	(2)	(3)	(4)	(5)
Rank parental income		0.224	0.164	0.166	0.130	0.122
		(0.030)***	(0.030)***	(0.030)***	(0.030)***	(0.029)***
KS2 mathematics points	0.006		4.283	3.834	1.198	1.184
	(0.001)***		(1.195)***	(1.229)***	(1.208)	(1.214)
KS2 English points	0.008		3.043	2.639	-0.0367	-0.0300
	(0.001)***		(1.270)**	(1.296)**	(1.330)	(1.321)
Academic self-concept	0.003			1.831	0.580	0.300
	(0.001)**			(0.882)**	(0.881)	(0.890)
GHQ-12 score	-0.001			-0.135	-0.0474	-0.107
	(0.003)			(0.383)	(0.369)	(0.369)
GCSE total points	0.011				4.964	4.412
	(0.001)***				(1.979)**	(2.005)**
Number of GCSEs	0.043				0.628	0.570
	(0.005)***				(0.399)	(0.399)
A level total points	0.001					4.808
	(0.001)**					(1.166)***
Number of A levels	0.002					-1.012
	(0.001)**					(0.700)
University degree	0.003					-0.893
	(0.000)***					(1.812)
Constant		-2.792	31.00	29.55	41.70	47.97
		(58.28)	(56.97)	(56.62)	(54.96)	(54.40)
Observations	1,713	1,713	1,713	1,713	1,713	1,713
R-squared		0.068	0.121	0.124	0.150	0.160

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weighted using wave 8 final weights.
Source: University of London, Institute of Education, Centre for Longitudinal Studies (2021a, 2022).

Table 2.8 Decomposition of intergenerational income elasticity (IGE) and rank-rank association for Next Steps

	Decomposition IGE			Decomposition rank-rank association		
	1	2	3	1	2	3
Direct Av. parent income	**0.087**	**0.064**	**0.059**	**0.166**	**0.130**	**0.122**
Total through education	**0.033**	**0.059**	**0.055**	**0.051**	**0.091**	**0.084**
Total through missings	**0.005**	**0.002**	**0.011**	**0.007**	**0.003**	**0.018**
Total intergen elasticity	**0.125**	**0.125**	**0.125**	**0.224**	**0.224**	**0.224**
Maths at 10 / KS2	0.015	0.004	0.004	0.024	0.008	0.007
Reading at 10 / KS2	0.015	0.001	0.001	0.022	0.000	0.000
Application at 10/ Academic self-concept	0.003	0.001	0.001	0.005	0.002	0.001
Anxious at 10 / GHQ-12 score	0.000	0.000	0.000	0.000	0.000	0.000
Total through early skills	**0.033**	**0.006**	**0.006**	**0.051**	**0.010**	**0.008**
GCSE total points		0.037	0.033		0.055	0.049
Number of GCSEs		0.016	0.014		0.026	0.025
Total through compulsory		**0.053**	**0.047**		**0.081**	**0.074**
A level total points			0.004			0.007
Number of A-levels			-0.001			-0.002
Degree			-0.001			-0.003
Total through post-16			**0.002**			**0.002**
N	1,713	1,713	1,713	1,713	1,713	1,713

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: University of London, Institute of Education, Centre for Longitudinal Studies (2021a, 2022).

Table 2.8 shows the decomposition of the IGE and rank-rank association for the Next Steps. The income persistence is decomposed into the contribution of each factor by multiplying the coefficient of each mediating variable by its relationship with parental income. The results suggest that educational factors contribute a large part of the intergenerational income persistence in the Next Steps cohort. As we add more educational attainment variables into our models, the coefficients for average parental income and early skills decrease in magnitude. This suggests that parental income and early skills affect sons' earnings by influencing later educational attainments. In the final specification, the direct effect of parental income accounts for 47% of the IGE and 54% of the rank-rank coefficient in the Next Steps cohort, while early skills and education are responsible for 44% and 38% for the IGE and rank-rank coefficient, respectively. The rest of the intergenerational income persistence is accounted for by variable missingness. To compare our results to the results from the BCS cohort, we run the models again without GCSE and A level total points. The comparison of the decomposition of the overall income persistence in the BCS cohort and Next Steps cohorts can be founded in Appendix A.2. We find that the level of intergenerational income persistent in the Next Steps cohort is similar to that in the BCS cohort when considering the rank-rank coefficient, and sons' early skills and later educational attainment account for approximately one-third of the total persistence in both cohorts.

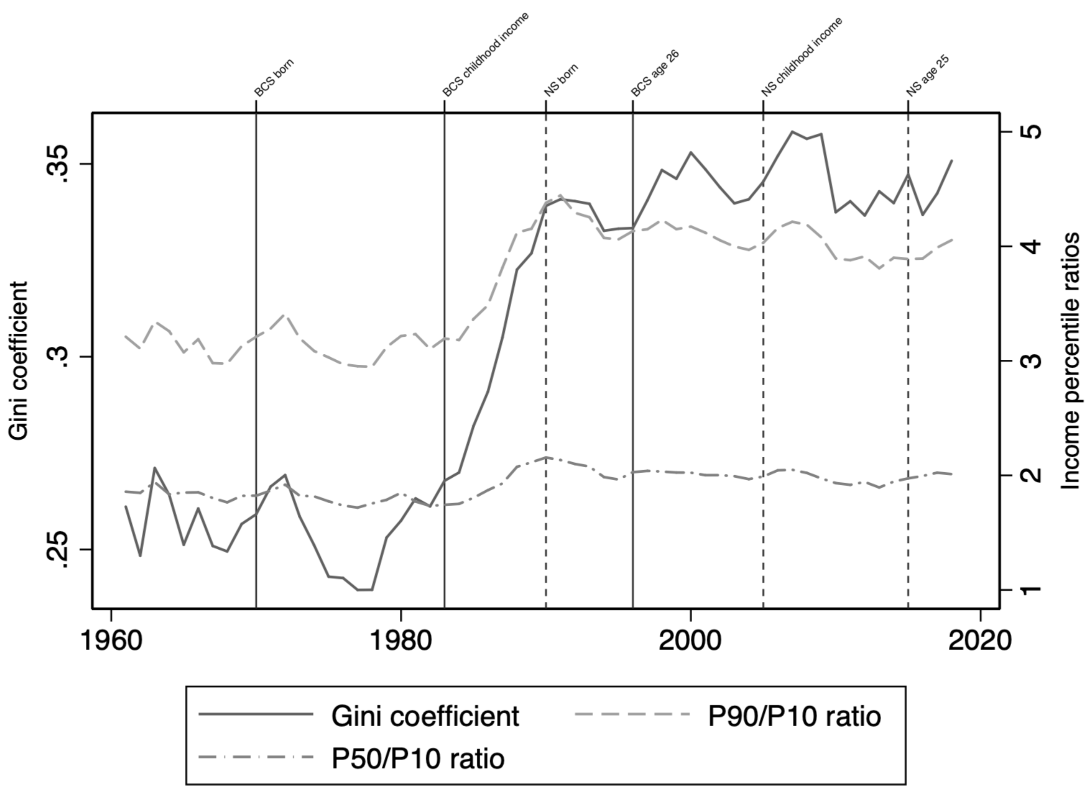
2.4.3. Discussion

As we have discussed in the previous sections, children from poor backgrounds are less likely to improve their SES as adults in countries with higher income inequality during the time when they were growing up. Low upward and downward motilities then lead to resources and opportunities concentrated on a small group of wealthy people. Thus, intergenerational income persistence is both the cause and result of income inequality. In this section, we will explore how our results are validated by the trend in income inequality and public expenditure on education in the UK.

Figure 2.2 illustrates three measures of income inequality from 1970 to 2020, including the Gini coefficient, the 90/10 percentile ratio (P90/P10 ratio), and the 90/50 percentile ratio

(P90/P50 ratio). Gini coefficient measures the extent to which the distribution of income within an economy is different from a perfectly equal distribution, while the P90/P10 (P90/P50) ratio is the ratio of the income at the 90th percentile to the income at the 10th (50th) percentile. A higher Gini coefficient and P90/P10 (P90/P50) ratio suggest a higher inequality within the economy. In Figure 2.2, the Gini coefficient in the UK experienced a small drop during the 1970s, followed by a surge from about 0.25 to 0.33 from 1980 to 1990, and then it fluctuated between 0.33 to 0.35 until 2020. The P90/P10 and P90/P50 ratios also followed a similar trend, increasing during the 1980s and then being stable after 1990. The trend of these three measures indicates that the BCS cohort was growing up with deteriorating income inequality, while the Next Steps cohort was facing a high but stable rate of inequality in their childhood when their parent income was measured. These results verify the trend of intergenerational income persistence estimated in the previous sections and existing studies: the intergenerational income persistence in the UK increased when comparing the 1970 cohort with the 1958 cohort and then became static in the 1990 cohort.

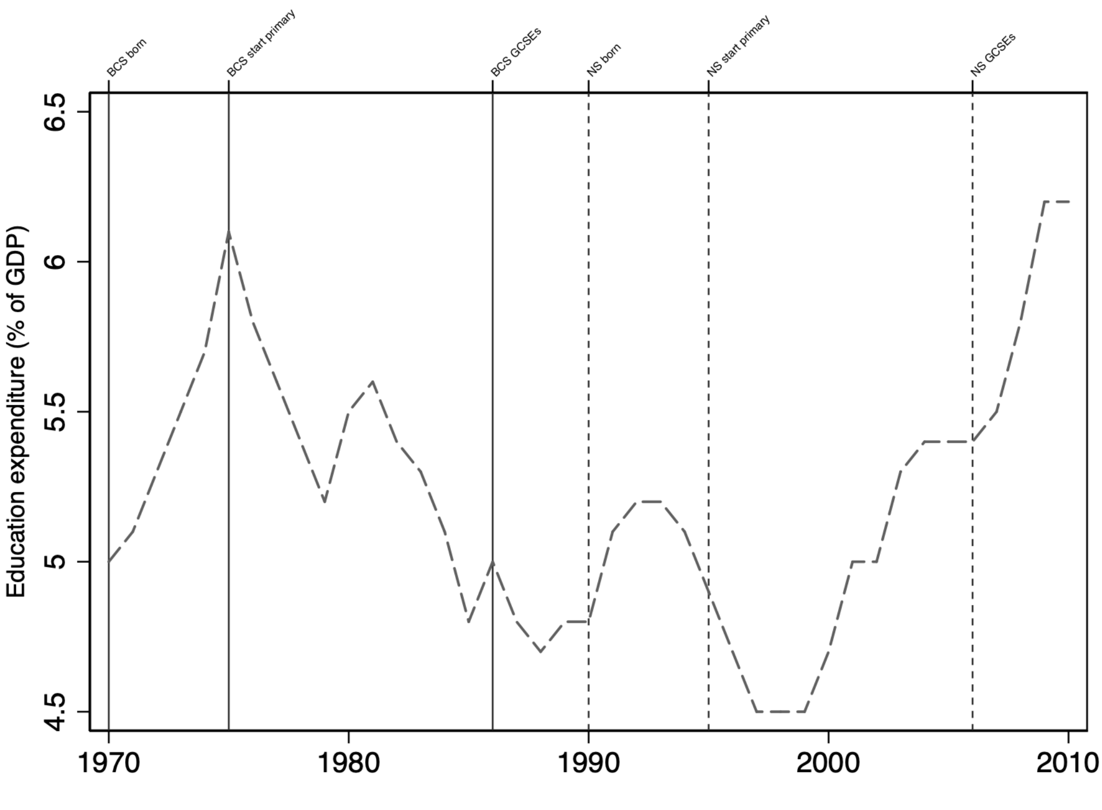
Figure 2.2 Income inequality in the UK, 1970-2020



Source: Bourquin et al. (2020)

Education has been playing an important role in driving social mobility in the UK. To explore how the trend in social mobility is affected by education policy changes and spending levels, we investigate the total public expenditure on education in the UK (% of GDP) from 1970 to 2015. Figure 2.3 shows that education expenditure as a proportion of GDP peaked at around 6.1% in 1975 before gradually declining to 4.8% in the late 1980s. Then it went to in the early 1990s before dropping to a recent low of 4.5% in the late 1990s. The first decade of the 21st century saw a rising trend in the total public expenditure on education as a proportion of GDP, from 4.5% in 1999 to 6.2% in 2010. Previous research has shown that educational attainment in a country is positively associated with its public expenditure on education (French et al., 2015; Park, 2008). In the UK, the largest share of education expenditure is on secondary education. Although the BCS cohort and the Next Steps cohort have witnessed opposite trends in public expenditure on education as a proportion of GDP, the education expenditure proportions during the secondary-school years for both cohorts were at a similar level (4.8-5.5%).

Figure 2.3 Total public expenditure on education in the UK (% of GDP), 1970-2015



Source: Table 4.2 of HM Treasury, Public Expenditure Statistical Analyses (PESA) (2015). Previous editions of PESA. Office for National Statistics, United Kingdom National Accounts, The Blue Book 1997.

2.5. Predictions

As we have discussed in Section 2.3.1, using early adult earnings is likely to underestimate true lifetime earnings indicating a downward bias in the estimated IGE at age 25. Children from more affluent backgrounds are more likely to have higher educational attainment, yet the returns to education, especially higher education, cannot fully unfold at such a young age. Table 2.10 presents the returns across the lifecycle in the BCS, showing that the returns to a degree are not statistically significant until age 30 in the BCS, and the returns tripled from age 30 to 42. In this section, we use the returns to education, and direct parental income impact across the lifecycle in the BCS combined with the associations between parental income and educational attainment in Next Steps to project the IGE from age 30 to 42 in the Next Steps cohort.

Intergenerational income persistence is determined by two factors: educational inequality, which can be measured by the association between parental income and educational attainment and returns to education. To predict lifecycle intergenerational elasticity for the Next Steps cohort, we need to make a few assumptions. First, we assume that associations between parental income and educational attainment are fixed from age 25, which means that the Next Steps cohort members have obtained all their qualifications, including GCSEs, A-levels, and university degrees, by the age of 25. According to Organisation for Economic Co-operation and Development (OECD) (2022), 86% of males who obtained a bachelor's degree in the UK in 2015 were aged 25 or younger. Thus, it is plausible to assume that qualifications obtained later in life have a limited impact on our results. Second, we assume that the returns to education are consistent over time so that we can use the returns to education component across the lifecycle in the BCS to predict the IGE in the Next Steps at each age. Table 2.9 presents the returns to qualifications over time for all full-time employed males aged 24-65 using the Labour Force Survey (LFS) from 1996 until 2016. We regress the log of monthly earnings on all qualifications obtained, controlling for age, age squared, and region-fixed effects. The results suggest that the returns to degree and A-levels are broadly stable over the 20-year period, while the returns to GCSEs show a gradually diminishing trend.

Table 2.9 The returns to qualifications over time for all full-time employed males aged 24-65 from the Labour Force Survey, 1996-2016

	1996	1998	2000	2002	2004	2006	2008	2010	2012	2014	2016
Higher degree	0.0341	0.0512***	0.0853***	0.0773***	0.0741***	0.0860***	0.0998***	0.107***	0.121***	0.117***	0.111***
	(0.0209)	(0.0125)	(0.0126)	(0.0119)	(0.0142)	(0.0122)	(0.0122)	(0.0126)	(0.0131)	(0.0130)	(0.0137)
First degree	0.251***	0.250***	0.249***	0.264***	0.242***	0.260***	0.268***	0.274***	0.236***	0.231***	0.248***
	(0.0153)	(0.00904)	(0.00922)	(0.00888)	(0.0105)	(0.00949)	(0.00952)	(0.0100)	(0.0105)	(0.0105)	(0.0111)
Other HE	0.333***	0.358***	0.356***	0.363***	0.215***	0.227***	0.102***	0.130***	0.108***	0.0990***	0.0806***
	(0.0242)	(0.0173)	(0.0171)	(0.0187)	(0.0529)	(0.0442)	(0.0342)	(0.0264)	(0.0275)	(0.0284)	(0.0283)
HE Diploma	0.0778***	0.0754***	0.0719***	0.0627***	0.0744***	0.0631***	0.0655***	0.0760***	0.0581***	0.0581**	0.0847***
	(0.0259)	(0.0188)	(0.0184)	(0.0190)	(0.0205)	(0.0192)	(0.0199)	(0.0195)	(0.0224)	(0.0237)	(0.0242)
A-levels	0.0993***	0.0570***	0.0496***	0.0630***	0.0734***	0.0759***	0.0664***	0.0828***	0.0778***	0.0919***	0.0768***
	(0.0135)	(0.00824)	(0.00840)	(0.00824)	(0.00983)	(0.00889)	(0.00906)	(0.00968)	(0.00994)	(0.00999)	(0.0106)
A/S levels	0.193*	-0.0609	0.0529	0.000948	-0.0523	-0.0389	-0.00204	-0.0913***	0.00109	-0.0540**	-0.0245
	(0.103)	(0.0445)	(0.0405)	(0.0366)	(0.0423)	(0.0345)	(0.0320)	(0.0292)	(0.0239)	(0.0228)	(0.0220)
5+GCSEs A*-C	0.307***	0.307***	0.311***	0.289***	0.271***	0.252***	0.250***	0.238***	0.219***	0.221***	0.189***
	(0.0114)	(0.00681)	(0.00701)	(0.00694)	(0.00838)	(0.00769)	(0.00788)	(0.00845)	(0.00881)	(0.00907)	(0.00940)
1-4 GCSEs A*-C	0.163***	0.174***	0.162***	0.150***	0.126***	0.120***	0.116***	0.118***	0.0906***	0.0853***	0.0677***
	(0.0110)	(0.00678)	(0.00708)	(0.00713)	(0.00912)	(0.00810)	(0.00839)	(0.00910)	(0.00983)	(0.0102)	(0.0109)
Observations	11,255	30,047	26,865	25,845	17,221	21,348	21,353	18,869	17,220	17,110	15,434
R-Squared	0.316	0.315	0.325	0.333	0.308	0.309	0.307	0.317	0.299	0.298	0.278

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: Northern Ireland Statistics and Research Agency, Central Survey Unit, Office for National Statistics, Social and Vital Statistics Division (2008a, 2008b, 2008c, 2008d, 2008e, 2008f, 2008g, 2009, 2014a, 2014b, 2014c, 2014d, 2014e, 2014f, 2014g, 2016a, 2016b), Northern Ireland Statistics and Research Agency, Central Survey Unit, Office for National Statistics, Social Survey Division (2014, 2015, 2019a, 2019b, 2019c), Office for National Statistics, Social and Vital Statistics Division, Northern Ireland Statistics and Research Agency, Central Survey Unit (2008a, 2008b, 2008c, 2008d, 2014a, 2014b, 2014c, 2014d, 2015), Office for National Statistics, Social Survey Division, Northern Ireland Statistics and Research Agency, Central Survey Unit (2014a, 2014b, 2014c, 2014d, 2019a, 2019b, 2019c, 2019d, 2019f, 2019g, 2021), and Office for National Statistics, Social Survey Division, Northern Ireland Statistics and Research Agency (2019a, 2019b).

Before predicting the IGE over the lifecycle for the Next Steps, we explore the changes in returns across the lifecycle and IGE decomposition in the BCS at ages 26, 30, 34, 38, and 42. Table 2.10 illustrates the evolution of returns across ages up to 42, indicating the strengthening of returns to a degree across ages. Table 2.11 shows the full decomposition for the BCS cohort at each age. The results suggest that both the contribution of education and the direct component of parental income on earnings, conditional on education, have been growing from age 26 to 42 in the BCS.

Table 2.12 shows a simulation of Next Steps IGEs, assuming the returns to education are the same as in the BCS at each age. Here we are also assuming that the direct component is the same as in the BCS. As the direct impact of parental income on sons' earnings is lower in the Next Steps cohort than that in the BCS cohort at age 25/26, we suggest the results in Table 2.12 provide 'upper bound' estimates for the Next Steps IGEs across the lifecycle and that mobility patterns in Next Steps remain similar or a little lower than in BCS. Table 2.13 shows a simulation of Next Steps IGEs assuming the same as Table 2.12, but making the additional assumption that the direct component starts at the level witnessed in Next Steps at age 25 and then grows at the same rate as that seen in the BCS. Thus, the results in Table 2.12 offer 'lower bound' estimates, suggesting that the IGE at age 42 for the Next Steps cohort is approximately eight percentage points below that for the BCS cohort.

Table 2.10 Returns across the lifecycle in the BCS

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Age 26	Age 30	Age 34	Age 38	Age 42
Av. parent income	0.105	0.158	0.158	0.184	0.174
	(0.018)***	(0.019)***	(0.021)***	(0.024)***	(0.025)***
Maths at 10 / KS2	0.028	0.031	0.023	0.026	0.012
	(0.015)*	(0.013)**	(0.016)	(0.019)	(0.019)
Reading at 10 / KS2	-0.009	0.007	0.011	-0.009	0.032
	(0.015)	(0.013)	(0.015)	(0.019)	(0.018)*
Application at 10/Academic self-concept	0.016	0.026	0.025	0.015	0.024
	(0.012)	(0.011)**	(0.014)*	(0.016)	(0.015)
Anxious at 10 / GHQ-12 score	-0.026	-0.020	-0.033	-0.023	-0.019
	(0.011)**	(0.010)*	(0.011)***	(0.014)*	(0.013)
Number of GCSEs	0.018	0.021	0.028	0.037	0.043
	(0.004)***	(0.003)***	(0.004)***	(0.005)***	(0.005)***
Number of A-levels	0.008	0.036	0.031	0.021	0.008
	(0.009)	(0.010)***	(0.011)***	(0.013)	(0.014)
Degree	-0.010	0.093	0.155	0.190	0.281
	(0.028)	(0.027)***	(0.032)***	(0.037)***	(0.035)***

Observations	2,128	2,970	2,513	1,852	2,437
R-squared	0.095	0.198	0.217	0.251	0.254

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: University of London, Institute of Education, Centre for Longitudinal Studies (2021b).

Table 2.11 Decomposition across the lifecycle in the BCS

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Age 26	Age 30	Age 34	Age 38	Age 42
Maths at 10 / KS2	0.009	0.010	0.007	0.008	0.004
Reading at 10 / KS2	-0.003	0.002	0.003	-0.003	0.009
Application at 10/Academic self-concept	0.003	0.005	0.005	0.003	0.004
Anxious at 10 / GHQ-12 score	0.003	0.002	0.004	0.003	0.002
Number of GCSEs	0.036	0.042	0.056	0.073	0.085
Number of A-levels	0.005	0.020	0.018	0.012	0.005
Degree	-0.002	0.017	0.028	0.034	0.050
Total through education	**0.051**	**0.098**	**0.120**	**0.131**	**0.160**
Total direct from parental income	**0.105**	**0.158**	**0.158**	**0.184**	**0.174**
Total through missing dummies	**0.009**	**0.014**	**0.022**	**0.007**	**0.020**
Total intergenerational elasticity	**0.165**	**0.270**	**0.300**	**0.322**	**0.354**

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: University of London, Institute of Education, Centre for Longitudinal Studies (2021b).

Table 2.12 Projecting intergenerational elasticities using Next Steps family income gradients, BCS returns, and BCS 'direct component'

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Age 26	Age 30	Age 34	Age 38	Age 42
Maths at 10 / KS2	0.008	0.009	0.007	0.008	0.004
Reading at 10 / KS2	-0.004	0.003	0.004	-0.004	0.013
Application at 10/Academic self-concept	0.002	0.003	0.003	0.002	0.003
Anxious at 10 / GHQ-12 score	0.000	0.000	0.000	0.000	0.000
Number of GCSEs	0.035	0.041	0.055	0.072	0.084
Number of A-levels	0.001	0.003	0.003	0.002	0.001
Degree	-0.001	0.013	0.021	0.026	0.038
Total through education	**0.041**	**0.072**	**0.093**	**0.106**	**0.142**
Total direct from parental income	**0.105**	**0.158**	**0.158**	**0.184**	**0.174**
Total through missing dummies	**0.009**	**0.014**	**0.022**	**0.007**	**0.020**
Total intergenerational elasticity	**0.155**	**0.244**	**0.273**	**0.297**	**0.336**

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: University of London, Institute of Education, Centre for Longitudinal Studies (2021a, 2021b, 2022).

Table 2.13 Projecting intergenerational elasticities using Next Steps family income gradient, BCS returns, and scaling Next Steps 'direct component' by BCS 'direct component' trajectory

VARIABLES	(1) Age 26	(2) Age 30	(3) Age 34	(4) Age 38	(5) Age 42
Maths at 10 / KS2	0.008	0.009	0.007	0.008	0.004
Reading at 10 / KS2	-0.004	0.003	0.004	-0.004	0.013
Application at 10/Academic self-concept	0.002	0.003	0.003	0.002	0.003
Anxious at 10 / GHQ-12 score	0.000	0.000	0.000	0.000	0.000
Number of GCSEs	0.035	0.041	0.055	0.072	0.084
Number of A-levels	0.001	0.003	0.003	0.002	0.001
Degree	-0.001	0.013	0.021	0.026	0.038
Total through education	**0.041**	**0.072**	**0.093**	**0.106**	**0.142**
Total direct from parental income	**0.068**	**0.102**	**0.102**	**0.119**	**0.113**
Total through missing dummies	**0.009**	**0.014**	**0.022**	**0.007**	**0.020**
Total intergenerational elasticity	**0.118**	**0.188**	**0.217**	**0.233**	**0.275**

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: University of London, Institute of Education, Centre for Longitudinal Studies (2021a, 2021b, 2022).

2.6. Conclusion

This chapter uses a rich set of Next Steps data to provide a picture of income persistence across generations for those born in 1989-90 in England and examine the role of educational attainment and non-cognitive traits in generating intergenerational persistence.

In the first part of the chapter, we first estimate the IGE by regressing sons' earnings at age 25 on average parental income at ages 14-17, conditional on average parental age and age-squared. Our estimated IGE is 0.125 in the Next Steps, considerably lower than that in the BCS (0.165). To minimise the influence of measurement errors and lifecycle bias, we also estimate rank-rank coefficients for both cohorts. The results suggest that the intergenerational income persistence remains stable between the 1970 cohort and the 1989-

90 cohort when we focus purely on the ranks of income across generations. However, we acknowledge that by using the rank measure, we lose the scale measurement across generations. Moreover, the results of the robustness checks suggest that our estimates for the Next Steps cohort are robust to different sample restrictions and specifications of average parental income.

Another aim of this paper is to explore the role of early cognitive skills, non-cognitive traits, and later educational attainment in driving social mobility. We first explore the relationship between parental income and the mediating factors, including cognitive skills, non-cognitive traits, and educational attainment, and then regress these mediating factors on sons' earnings, conditional on parental income. Our results suggest that GCSE attainment is the most important mediator of intergenerational persistence in the Next Steps cohort. Although non-cognitive traits have a small influence on the association between parental income and sons' earnings in the BCS cohort, they do not have any statistically significant results in the Next Steps cohort. For both cohorts, especially Next Steps, education accounts for a significant part of the persistence.

As sons' earnings are only measured at age 25 when returns to later education have not yet been fully realised, our estimates are likely to underestimate the true intergenerational income persistence due to the existence of the lifecycle bias. Thus, in the final part of this chapter, we also provide a prediction of the IGE across the lifecycle for the 1989-90 cohort using the returns to education in the 1970 cohort. Our results suggest that the IGE for the Next Steps cohort is similar to or slightly lower than that in the early cohort.

As education plays an increasingly important role in driving mobility over the decades, policymakers should provide more resources to underperforming public schools and children from deprived backgrounds to improve their educational attainments. However, our estimates tend to understate the true intergenerational income persistence as we use sons' earnings at a relatively young age. Thus, in order to alleviate the problem of lifecycle bias, further work should use future waves of Next Steps to estimate the IGE at older ages.

Chapter 3.

The medium-term impact of a conditional cash transfer on educational outcomes

3.1. Introduction

The socio-economic gap in post-compulsory education in the UK has been widely discussed in the existing literature (Otero, 2007; Thomas, 2005; Thompson and Simmons, 2013). Although the gap seems to be closing in recent years (Crawford, 2012; Higher Education Funding Council for England, 2013; Iannelli, 2007; Murphy et al., 2017), socio-economic differences in higher education participation remain substantial (UCAS, 2021). Using the 2008 GCSE cohort, Crawford and Greaves (2015) find that students from the highest socio-economic quintile group are approximately three times more likely to participate in higher education and seven times more likely to enrol in a selective university than those from the lowest group. Disadvantaged students are, however, more likely to go to further education rather than higher education, studying courses at NVQ Level 3 and below (Department of Education, 2020).

With regard to degree completion, the socio-economic gap is even more significant. Previous studies have shown that disadvantaged students have higher chances of dropping out of university than students from wealthier backgrounds, even after controlling for personal characteristics, prior attainment and university characteristics (Crawford et al., 2016; Johnes and McNabb, 2004; Quinn et al., 2005; Vignoles and Powdthavee, 2009), thus leading to the socio-economic gap in degree completion. Moreover, socio-economic differences also exist in degree classification as students from higher socio-economic backgrounds are more likely to be awarded a first or 2:1 degree than those from lower socio-economic backgrounds (Crawford, 2014; McNabb et al., 2002; Smith and Naylor, 2001).

Therefore, what motivates this work is that the long-existing socio-economic gap in education remains and continues to pose a challenge for policymakers despite a range of policy measures to close it. This chapter evaluates the medium-term impact of a conditional cash transfer, the Education Maintenance Allowance (EMA), on the higher education participation and attainments of young people from low-income families eight to nine years after receiving it. The EMA provided a maximum payment of £30 a week, depending on annual household income, as well as a retention bonus to encourage 16-to 19-year-olds to stay in certain further education courses beyond compulsory education. Despite the fact that, in England, EMA was discontinued in 2011[6] , and students have to stay in education until age 18[7], it is still worth examining the impact of EMA on educational outcomes over a longer term. Thus, this chapter conducts a retrospective empirical analysis to ask whether offering EMA is an effective way of narrowing the socio-economic gap in post-compulsory education by incentivising young people from disadvantaged backgrounds to participate in higher education and to improve their performance.

There are a range of barriers young people from disadvantaged backgrounds may face in continuing to pursue education, including information asymmetry and present bias, low prior attainment, and financial difficulties and credit constraints, the latter of which is the focus of this chapter. A number of studies have argued that financial difficulties and credit constraints are among the most significant factors that deter disadvantaged students from staying in post-compulsory education. In the UK, tuition fees of universities were first introduced in 1998, experiencing an increase from £1,200 to £3,000 in 2006 and further raised to £9,000 in 2012 (Azmat and Simion, 2017; Belfield et al., 2017a, 2017b). Although there are income-contingent loans and means-tested grants to cover the tuition fees and part of the living expenses of low-income students, more impoverished students may still face difficulties in covering the rest of their living expenses because of imperfect credit markets (Cigno and Luporini, 2011; Lott, 1987; Wigger and von Weizsäcker, 2001). On the one hand, disadvantaged students lack collateral to secure debt and cannot borrow against their future income or intangible human capital. On the other hand, private lending companies

[6] EMA is still available in Scotland, Wales and Northern Ireland.
[7] This includes: 1) stay in full-time education; 2) start an apprenticeship or traineeship; 3) spend 20 hours or more a week working or volunteering, while in part-time education or training.

are unwilling to bear the risk for students due to adverse selection and moral hazard problems. Thus, young people from low-income families are discouraged from staying in education because they fail to obtain loans from the capital market and cannot treat their parental wealth as a substitute for the loans (Cigno and Luporini, 2011; Jacobs and Wijnbergen, 2005; Lochner and Monge-Naranjo, 2002). Empirical evidence from the US shows that a $10,000 increase in household wealth increases higher education participation by 0.7 percentage points, with a much more significant impact on children from lower-income families (Lovenheim and Reynolds, 2011). In the UK, Azmat and Simion (2017) find that the 2012 reform, which increased tuition fees in England, raised dropout rates for students from low socio-economic backgrounds; however, it had relatively little impact on enrolment for those from more impoverished families. Sa (2014) finds that the impact of the increase in fees in 2012 was smaller for ethnic minorities and disadvantaged students. The explanation for this result could be the fact that means-tested grants and government-provided student loans release credit constraints among disadvantaged students. Therefore, providing students from low-income families with financial support is a possible way to alleviate their financial constraints and encourage them to stay in education after the compulsory school leaving age.

Measures to address the barriers to post-compulsory education have been reviewed in previous literature (Burke, 2013; Deming and Dynarski, 2009; Gorard et al., 2006; Lavecchia et al., 2016; Moore et al., 2013). One of the most commonly used measures is to provide students from low socio-economic backgrounds with financial aid in order to offset their immediate costs and relax their credit constraints. Evidence from the US shows that $1,000 of grants raises years of schooling by roughly 0.16 years and the possibility of participating in higher education by four percentage points (Dynarski, 2003). Moreover, Seftor and Turner (2002) find that the Pell Grant, need-based aid focusing on students on the margin of "dropping out", raises the college enrolment rate of eligible students by 1.5 and 1.3 percentage points for men and women, respectively, while Bettinger (2004) finds that it also has a positive impact on student retention from the first to the second year of university. With regards to the impact of financial aid on degree completion, Denning et al. (2017) suggest that eligibility for additional grant aid has no significant impact on credits attempted, GPA, and re-enrolment in the following year, but it generates 0.6, and 0.8 additional credits attempted two and three years after entry respectively and increases the likelihood of graduation within four, five, and six years of university entry. In the UK, Dearden et al. (2014) use a difference-in-difference method to examine the impact of a maintenance grants reform on higher education participation. They find that a £1000 increase in maintenance grants raises higher education participation by 3.95 percentage points. As for the degree outcome, Murphy and Wyness (2016) examine the impact of the English higher education bursary scheme on university completion rates, annual course scores and degree classification using fixed effects and instrumental variable (IV) approaches. Their findings indicate that an additional £1,000 increase in the first-year financial aid raises the probability of obtaining a first- or upper second-class honours degree by 2.9 percentage points, driven by both degree completion and improvements in test scores.

Most relevant to this chapter, in order to encourage children from deprived families to stay in education, a number of countries, particularly Latin American countries, have introduced conditional cash transfer (CCT) programmes (see Table 3.1). Adato and Hoddinott (2010) and Rawlings and Rubio (2005) review the literature in Latin American and Caribbean (LAC) region and surmise that the Opportunities programme (previously called PROGRESA) in Mexico increases years of schooling by 0.5-0.7 years (Behrman et al., 2005; Schultz, 2001; Todd and Wolpin, 2003), the Red de Protecion Social (RPS) in Nicaragua boosts school attendance for all children aged 7-13 by approximately 20 percentage points (Maluccio and Flores, 2005), the Families in Action (FA) in Colombia raises secondary school enrolment rates by 14 and 5.5 percentage points in urban and rural respectively (Attanasio et al., 2004). Evidence from Turkey also suggests that the Social Risk Mitigation Project (SRMP), which aims to increase school attendance rates for disadvantaged students and for secondary-school girls, in particular, increases the overall enrolment rate for 14-17-years-olds (post-compulsory) by 9.9 percentage points and raises the secondary school completion rate for girls by 7.8 percentage points (Ahmed et al., 2006). In developing countries, conditional cash transfer programmes have become an effective way to boost the education participation of disadvantaged children.

Table 3.1 Conditional cash transfer (CCT) programmes in different countries

Country	Programme	Target Population	Conditions (education-related)	Transfer size	Principal impacts	Authors
Mexico	Opportunities programme (PROGRESA)	Low-income families with children ages 8-18; age limits raised to 20 in 2001	Enrolling in primary school (grade 3 and higher) or secondary school and attending at least 85 per cent of the school days monthly and annually	For boys: varies by grades, Mex$70-225 (£5.4-16.8) per week For girls: varies by grades, Mex$70-255 (£5.4-16.8) (1998) per week	An increase of 0.5-0.7 years in years of schooling.	Behrman et al. (2005); Schultz (2001); Todd and Wolpin (2003)
Nicaragua	Red de Protecion Social (RPS)	Low-income families with children ages 6-13	Enrolling in primary school grades 1-4 and fewer than six days of unexcused school absence in a two-month cycle	School attendance transfer: C$1,440 (£70.3) per household per year School supplies transfer: C$ 275 (£13.4) per child beginning of the school year (2000)	An average attendance increase of 20 percentage points for children aged 7-13.	Maluccio and Flores (2005)
Colombia	Families in Action (FA)	Low-income families with children ages 7-17	At least 80 per cent of school attendance in a two-month cycle	Monthly payment of 14,000 pesos (£4.2) for primary school children and 28,000 pesos (£8.4) for secondary school children (2002)	An increase in secondary school enrolment of 14 percentage points in the urban area and 5.5 percentage points in the rural area.	Attanasio et al. (2004)
Turkey	Social Risk Mitigation Project (SRMP)	Low-income families with children ages 6-17	Attending at least 80 per cent of the total school days and not repeating the same grade more than once	Annual payment of 216YTL (£90) for boys and 264YTL (£110) for girls in primary school, and 336 YTL (£140) for boys and 468 YTL (£195) for girls in secondary school (2005)	An increase of 9.9 percentage points in the overall enrolment rate for 14-17 years old an increase of 7.8 percentage points in the secondary school completion rate for girls.	Ahmed et al. (2006)
Australia	Young Allowance (AUSTUDY)	Ages 16-18, with family income and assets below the threshold	Full-time higher-education students and secondary students completing their final two years of school	Maximum weekly payment of $64.15 (£26.1) for 16-17-year-olds and $77.10 (£31.3) for 18-year-olds (1992)	An increase of 3.5 percentage points in Year 11 and 12 enrolments for poor children.	Dearden and Heath (1996)

UK	Education Maintenance Allowance programme (EMA)	Ages 16-19, with family income and assets below the threshold	Attending either a full-time further education course at a school/college, a course leading to an apprenticeship or a Foundation Learning Programme	Maximum weekly payment of £30 depending on annual household income, plus a retention bonus (2006)	An increase of 4.5 percentage points in Year 11 enrolment and an increase of 6.7 percentage points in receiving two years of education.	Dearden et al. (2009)

In developed countries, there has also been a range of cash transfer programmes to boost enrolment rates in post-compulsory education. The Australian government launched an educational assistance scheme, known as the AUSTUDY Scheme, in 1987 to reduce the youth unemployment rate and to encourage students to stay in education past the minimum school-leaving age. AUSTUDY offers around £26 to 16-17-year-olds and £31 to 18-year-olds who participate in post-compulsory education, provided that their parental incomes are below a certain threshold. Walker et al. (2001) find that the proportion of AUSTUDY students among all Australians aged 15-29 years old rises by over 100 per cent during the AUSTUDY period compared with less than 50 per cent for other students, suggesting that the scheme lowers the barriers faced by disadvantaged students. Focused on secondary school particularly, Dearden and Heath (1996) use longitudinal data to estimate the impact of AUSTUDY on secondary-school retention in Australia and find that the policy contributes to a 3.5 percentage points increase in Year 11 and Year 12 participation rates among students from lower socio-economic backgrounds. In the paper, they also discuss the costs and benefits of a similar programme to be introduced in the UK, suggesting that the programme will be beneficial in the long-run because of the high returns to education.

In the UK, the Education Maintenance Allowance programme (EMA), which aims to raise the post-compulsory enrolment rate, began in pilot areas in 1999 and has been rolled out nationally since September 2004.[8] The vast majority of past studies focus on the impact of EMA on participation, retention and achievement in Years 12 and 13 during the pilot period (from 1999 to September 2004). Spielhofer et al. (2010) interviewed 2,000 Year 11 pupils to explore the barriers they experience in order to stay in education at the end of compulsory schooling. They find that approximately 12 per cent of young people who received EMA suggest that they would not have stayed in education if they had not received EMA. This result is consistent with the empirical findings from Middleton et al. (2005) that the eligibility of EMA is associated with a 5.9 percentage point increase in participation among 16-year-olds and a 6.1 percentage point increase in participation among 17-year-olds. Based on the data from the first cohort of the EMA pilot study, Dearden et al. (2009) use propensity score matching to control for the individual and local differences between pilot and control areas. They find that eligible young people are 4.5 and 6.7 percentage points more likely to stay in post-compulsory full-time education at the age of 16 and 17,

[8] In England, EMA was replaced by the 16 to 19 Bursary Fund in 2011. More information about the new bursary can be found at https://www.gov.uk/1619-bursary-fund.

respectively. Although Spielhofer et al. (2010) point out that the ‘deadweight’ of EMA is very high- about 88 per cent said their participation decisions were not affected by the receipt, EMA is still considered to be beneficial (Chowdry and Emmerson, 2010). It not only leads to higher wages that can offset the costs in the long term (Clark, 2010; Dearden et al., 2009) but also has a positive impact on wealth redistribution and crime reduction, which provides spillover benefits to the society (Feinstein and Sabatés, 2005). The impact of EMA on the retention of post-compulsory full-time education is initially evaluated by Ashworth et al. (2001). They combine one-way matching with a difference-in-difference approach and suggest that young people who receive EMA, especially those who receive full payments (£30 a week), are less likely to drop out during the academic year. Moreover, EMA raises the retention rate from Year 12 to Year 13 by 3.9 percentage points in urban areas and 6.4 percentage points in rural areas. Further, Chowdry et al. (2007) provide evidence of an impact on achievement, suggesting that the impact on Level 2 and 3 attainment rates was around 2.5 and 2.0 percentage points for females and males, respectively, when comparing the EMA pilot areas with the rest of England.

With regards to the evaluation of the EMA national roll-out, Aitken et al. (2007) conducted interviews with 375 16-19-year-olds and compared the EMA recipients with the non-recipients of similar characteristics. They find that the in-year retention rate for recipients is 2.3 percentage points higher than that for non-recipients but that recipients are 0.9 percentage points less likely to achieve the learning aims of the course they were taking than the non-recipients. Overall, the success rate of the learning aims is 1.2 percentage points higher for recipients than that for non-recipients. Moreover, O’Sullivan (2011) compares the pilot and national roll-out estimates of the impact of EMA on post-compulsory education participation and suggests that the estimated impacts of the national roll-out are smaller than the impact of the pilot.

Evidence regarding the impact of EMA on higher education is mixed. Comparing the pilot and control areas, Fitzsimons (2004) estimates a dynamic discrete choice model and finds that EMA has no impact on enrolment in higher education. However, this pilot result is challenged by later studies after the national roll-out. Valbuena (2012) uses the first seven waves of the Next Steps study and estimates a linear probability model controlling for personal characteristics, family backgrounds, attitudes and behaviours, prior educational attainment and students’ expectations of the university. He suggests that the recipients are

4.2 percentage points more likely than the non-recipients to enter higher education, but they are about 3.0 percentage points less likely to attend Russell Group universities. As the main variable of interest in Valbuena's work is the socio-economic status rather than the EMA, the sample was not restricted to individuals whose family income was below the requirement of EMA. Unlike Valbuena (2012), this chapter will exclude individuals whose family income was too high for EMA, focusing only on pupils from low-income families. Moreover, only those who have completed an NVQ level 3 or above will be included in the sample in order to reduce the influence of dropping out of age 16-18 education, which could be correlated with both receipt of, and the impact of EMA. This chapter aims to add more evidence on the medium-term effect of EMA—its impact on higher education participation and achievement—to the existing literature.

In this chapter, I estimate a multivariate regression model using the Next Steps study, controlling for a broad range of observed factors such as demographic characteristics, prior attainment, behaviours and attitudes, and school fixed effects to determine the influence of EMA receipt on higher education participation and achievement. Focusing on students from low-income backgrounds, including those with parental incomes slightly above the EMA threshold, I compare EMA recipients to non-recipients, the latter being those who either had incomes too high to be eligible for EMA, or who were eligible for EMA but did not receive it for reasons explained in Section 3.2. In order to reduce the influence of unobserved factors and have similar treatment and control groups, I use an entropy balancing approach to balance the characteristics of the treatment and control groups, those who received EMA and those who did not. In addition to the overall regression, the impact of EMA by gender is also estimated in this chapter, as existing studies have shown that male students are less likely to participate in post-compulsory education but respond better to EMA than female students (Ashworth et al., 2001; Chowdry et al., 2008; Dearden et al., 2005; Middleton et al., 2005). The results from the model indicate that EMA raises higher education participation, degree completion, and NVQ achievement among those who received the allowance for two years. The impact on higher education participation is stronger for female students, while the effect on degree completion is larger for male students.

The remainder of the chapter proceeds as follows. Section 3.2 introduces the data used in the analysis and the descriptive statistics of the sample. Section 3.3 outlines the model and methods to estimate the model. Following that, Section 3.4 discusses the results, and section 3.5 provides the concluding remarks.

3.2. Data and descriptives

The data used in this analysis comes from waves 1, 3-8 of Next Steps, previously known as the First Longitudinal Study of Young People in England (LSYPE1) (University College London, UCL Institute of Education, Centre for Longitudinal Studies, 2021a). Started in 2004, Next Steps is a large-scale and innovative panel study which documents the lives of approximately 16,000 young people born in England in 1989-90. From 2004 to 2010, the cohort members were interviewed annually until the age of 19/20 by the Department for Education (DfE). The survey mainly focuses on young people's educational and early labour market experiences but also collects information on their family, health and happiness, behaviours and attitudes, and aspirations for the future. In 2013, the management of the study was transferred to the Centre for Longitudinal Studies (CLS) at the UCL Institute of Education. The last wave, collected at the age of 25, was conducted in 2015/16 to capture the independent adult lives of the cohort members.

Next Steps adopted a two-stage probability proportional to size (PPS) sampling procedure (Department for Education, 2011a). First, schools, considered the primary sampling units (PSUs), were sampled separately for the maintained schools, the independent schools, and pupil referral units (PRUs) to obtain the sample stratum. Maintained schools were stratified based on their deprivation levels, with deprived schools oversampled by 50%. Independent schools were stratified by the proportion of pupils obtaining five or more A*-C GCSE grades in 2003 within the boarding status and gender of pupils. As for the pupil referral units (PRUs), they formed a stratum of their own. Then, within selected schools, pupils from major minority ethnic groups were oversampled to achieve 1,000 sampling units in each group. Furthermore, the sample excluded those solely educated at home, boarders and those who resided in England for education purposes only. The final issued sample for wave 1 was around 21,000 young people, with 15,770 households (74% of the target sample) and 647 schools interviewed.

3.2.1. Sample selection

As is the nature of the longitudinal survey, sample attrition is a problematic issue in Next Steps, where the available sample size reduced substantially from 15,770 in 2004 (wave 1) to 7,707 in 2015 (wave 8). Calderwood (2018) points out that attrition in Next Steps not only leads to a smaller sample size and low statistical power but also could result in sample bias if the probability of dropping out of the survey is correlated with the sociodemographic characteristics of the participants. Apart from the design weights, which adjust the sample composition to take account of the over-sampling of specific subgroups, Next Steps also constructed attrition weights as the inverse of the predicted probabilities of response. Following Calderwood (2018), this analysis will use wave 8 final weights, which combine the design weights with the attrition weights.

Young people would not be eligible to receive EMA unless their household's gross annual incomes were £30,810 or lower. In order to rule out the influence of income-related unobserved factors, such as family resources, this analysis should drop the respondents whose parental income was too high and focus only on young people who are not too dissimilar to those who have received the allowance. However, the parental income data in Next Steps is banded in waves 3 (age 16) and 4 (age 17), and thus, the exact level of the income is unknown. The cut-off point of whether eligible for EMA (£30,810) is in the income group 7 (£26,000-£31,199) in the dataset. As the household income was self-reported in Next Steps, I include income groups 1-8 (up to £36,399) instead of groups 1-7 (up to £31,199), which may introduce a small bias in the reported income, but also increases the sample size, especially for the control group. Moreover, having a more comprehensive income range also allows for a control group that consists of not only young people who did not apply to EMA but also the ones who were marginally ineligible. It also reduces the chance that eligible individuals are not in the sample because of misreporting (Britton and Dearden, 2015). In addition, I recode the missing values in explanatory variables as a separate group using missing flags to increase sample size and reduce bias. Table 3.2 shows the treatment and control groups for the analysis.

Table 3.2 Treatment and control groups for regression analysis

Overall sample			
Those whose family income was below £36,400			
Treatment groups			**Control group**
One-year EMA	*Two-year EMA*	*No information*	Not eligible* or did not apply† for both years
Eligible*, applied† and received for one year	Eligible*, applied† and received for two years	Missing values for EMA receipt status	

Notes: *Eligible here means that young people need to be enrolled in eligible courses of further education, and their family income at that time need to be below £30,810.
†In order to receive EMA, eligible young people need to fill in an EMA application form every academic year.

3.2.2. Variables

The primary outcomes of interest are higher education participation and degree attainment. Higher education participation is defined as a dummy equal to one if a young person had enrolled in any HE institution by the age of 25, while degree attainment is defined as a dummy variable for whether or not the young person achieved a first degree or higher by the age of 25. Moreover, I select the National Vocational Qualification (NVQ) as one of the outcome variables to capture the impact of EMA on the attainment of non-degree qualifications. In addition, the data also includes Russell Group University (RGU) and degree class of first degree, which are defined amongst young people who have attended an RGU and have achieved a first degree or upper second class degree (2:1), respectively. The detailed definitions of all outcome variables are listed in Appendix Table B.1. Table 3.3 shows that, in the sample, females (40.6%) are slightly more likely to participate in HE (including both degree and non-degree courses) than males (33.0%), and they are also more likely to obtain a first degree or higher (22.0% vs 19.5%) or to achieve NVQ Level 4 or above (30.2% vs 24.6%). Among those who have completed their degree, only approximately 18.9% attended a Russell Group university, but about two-thirds graduated with a first or upper second degree. However, the statistics of RGU and degree classes might not be accurate because of the small sample size.

Table 3.3 Summary of outcomes

	Gender of Young Person			
Outcome Variables	Male (%)	Female (%)	Total (%)	Observations

HE participation	33.0	40.6	36.6	3,335
Degree completion	19.5	22.0	20.7	3,335
NVQ Level 4+	24.6	30.2	27.3	3,335
Russell Group University	23.2	15.4	18.9	639
First or upper second class	66.8	67.4	67.1	643

Notes: Sample for regression analysis. Weighted using wave 8 weights.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a).

The key variable of interest is the EMA receipt status. EMA status is measured by the number of years (0, 1 or 2) a young person may have received the allowance. In order not to lose any information, young people who have no information on EMA status are included in the sample as a group on their own. Table 3.4 displays the summary statistics of EMA receipt status, both overall and separately by gender. Overall, around 57.9% of young people in the sample have ever received the EMA, and most of them have received it for two years. Males are approximately two percentage points more likely than females to receive the allowance for two years, but three percentage points less likely to receive it for one year. The proportion who have no EMA information in the sample is only 4.7% overall, indicating that missing values in EMA should not pose a large problem.

Table 3.4 Summary of EMA receipt status

	Gender of Young Person			
EMA Status	Male (%)	Female (%)	Total (%)	Observations
Never	39.7	34.7	37.4	523
One year	22.1	25.3	23.6	360
Two years	32.4	36.4	34.3	897
No information	5.8	3.6	4.7	46
Total	100	100	100	1826

Notes: Sample for regression analysis. Weighted using wave 8 weights.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a).

I would like to measure how educational attainment differs by EMA receipt status; however, young people with different EMA receipt statuses could be statistically distinguishable from each other even in the absence of the EMA, and thus the estimated impact of EMA would be biased and invalid because of the existence of other factors which are correlated with educational attainment. To get closer to causal estimates between EMA receipt and educational attainment, I use a rich set of measures to control for the demographic and non-demographic differences across groups. The control variables include personal characteristics, family background, prior attainment, and young persons' behaviours, attitudes and expectations. Furthermore, I also implemented a reweighting strategy, detailed below, to create more comparable treatment and control groups. Appendix Table B.1 describes all variables used in the analysis.

3.2.3. Descriptive statistics

It is instructive to explore the unconditional relationship between educational attainments and EMA receipt status before accounting for the control variables. Table 3.5 shows that about 26.2% of those who received EMA for one year attended university, 13.0% completed their degree, and 20.3% achieved at least NVQ Level 4, compared to 27.8%, 15.9%, and 22.3% of those who never received EMA. In contrast, young people who received EMA for two years are more likely to participate in higher education (56.3%), obtain a degree (33.0%) and achieve at least NVQ Level 4 (39.3%) than those who never received the allowance. However, both one-year and two-year EMA recipients are less likely to attend an RGU or graduate with a first or upper second class degree than the non-recipients. Overall, there are considerable raw gaps in educational attainments between one-year and two-year EMA recipients. It is hard to know why some recipients only receive the allowance for one year since the answers in the surveys are unclear[9]. Dropout might be one of the main reason here as those who did not stay in full-time education would become ineligible for EMA. Another possible explanation is that those who received EMA for one year were the less motivated pupils who did not bother to apply for EMA or university in the last year of school. Moreover, pupils can only receive EMA once their family income drop below the threshold. Those who received EMA only in Year 13 might have suffered some family financial crisis, which encouraged them to find a job rather than attend higher education. Furthermore, pupils will lose their allowance if they enrol in courses that are ineligible for the allowance. Some young people who want to work after school might attend more career-focused programmes in the last year of school and become ineligible for EMA. However, it is unfortunately not possible to test any of the above hypotheses with the data.

Table 3.5 Educational attainments by EMA receipt status

	EMA Receipt Status					Observations
	Never	One year	Two years	No information	Total	

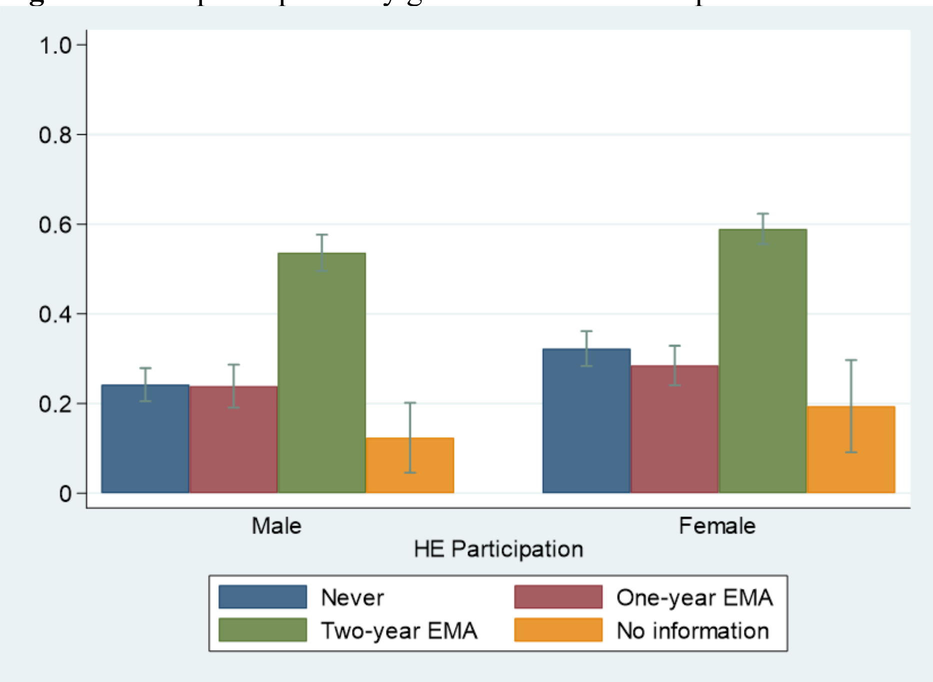
[9] The answers to "why young persons' EMA application was unsuccessful?" include unclear responses such as "was turned down", "did not take up", "was accepted", "other", "no answer", and "do not know".

Outcome Variables	(%)	(%)	(%)	(%)	(%)	
HE participation	27.8	26.2	56.3	14.9	36.6	3,335
Degree completion	15.9	13.0	33.0	7.41	20.7	3,335
NVQ Level 4+	22.3	20.3	39.3	14.4	27.3	3,335
Russell Group University	24.3	19.0	16.6	0	18.9	639
First or upper second class	70.0	65.7	66.2	59.6	67.1	643

Notes: Sample for regression analysis. Weighted using wave 8 weights.
Source University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a).

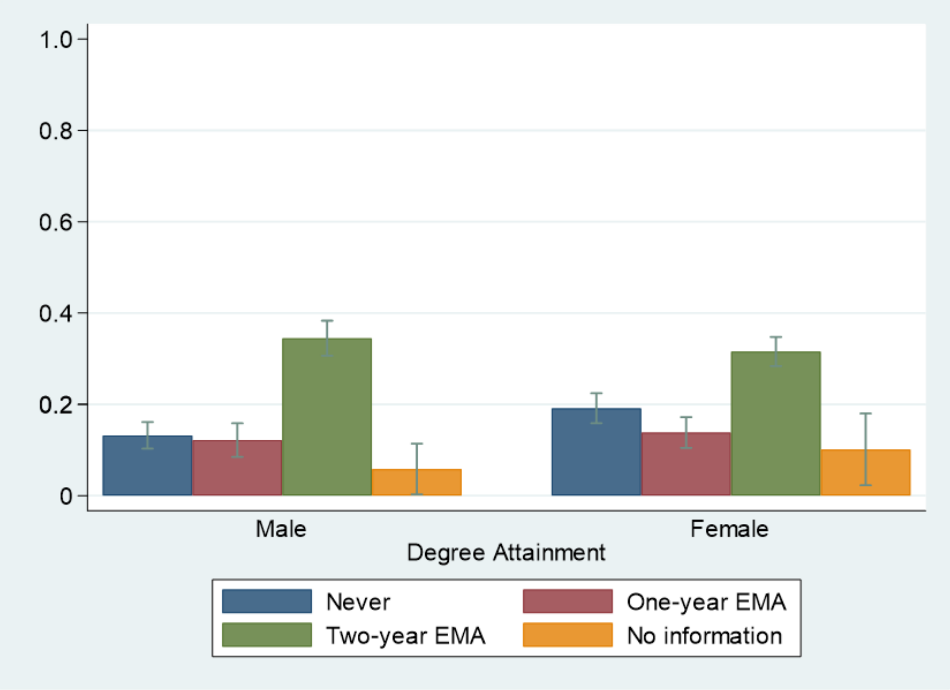
Figures 3.1-3.3 presents the gender differences in the effects of EMA on educational attainments. While there are notable gender gaps in HE participation and degree attainment, the impact of EMA on these two outcome variables shows a similar pattern for both males and females. HE participation and the chance of obtaining a degree or achieving at least NVQ Level 4 are highest for those who received EMA for two years, and those who never received the allowance are more like to attend higher education and graduate with a degree than those who received the allowance for one year. Focusing only on those who received EMA for two years, it can be concluded from the descriptive statistics that female students have higher chance of participating in higher education but low chance of obtaining a degree than male peers.

Figure 3.1 HE participation by gender and EMA receipt status



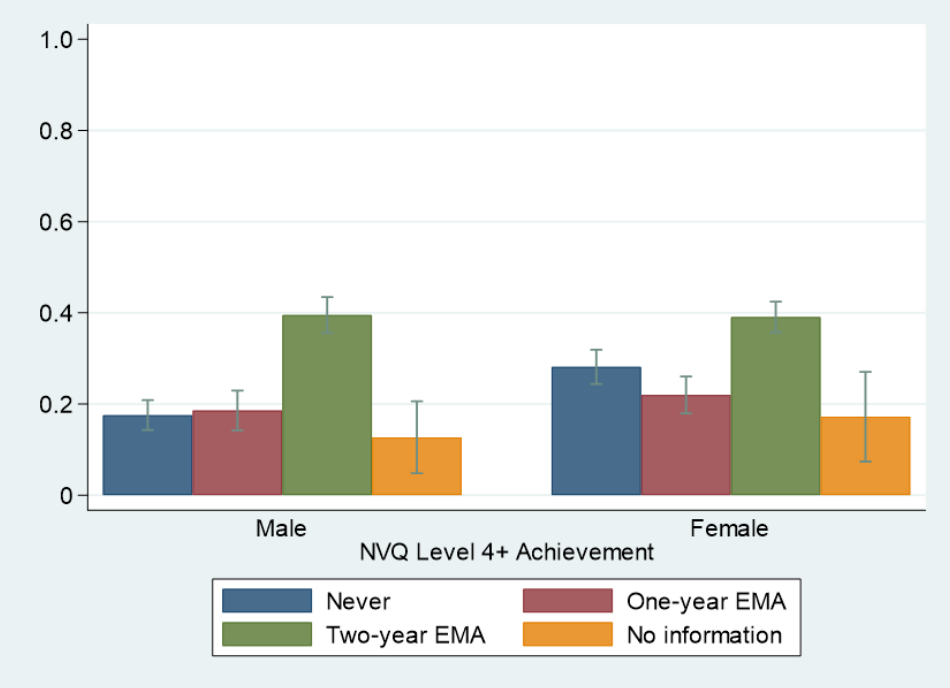
Notes: Sample for regression analysis. Weighted using wave 8 weights. Number of observations =1,826.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a).

Figure 3.2 Degree attainment by gender and EMA receipt status



Notes: Sample for regression analysis. Weighted using wave 8 weights. Number of observations =1,826. Source University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a).

Figure 3.3 NVQ Level 4+ achievement by gender and EMA receipt status



Notes: Sample for regression analysis. Weighted using wave 8 weights. Equivalent N=1,826. Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a).

3.3. Methodology

This study adopts a regression method with a multivariate reweighting method, entropy balancing (Hainmueller, 2012), to estimate the impact of EMA on educational attainments and to explore how other factors influence the observed impact. The basic model to be estimated can be written as:

$$Y_i = \alpha + \beta EMA_i + \gamma' X_i + \eta_s + \varepsilon_i \tag{3.1}$$

where

Y_i is the educational outcome (*HE*, *Degree*, *NVQ*, *RGU*, *Class*) for individual i;

EMA_i represents the EMA receipt status, specifically, EMA_i=1 if respondents received EMA for one year, and EMA_i=2 if respondents received EMA in both 2007 and 2008, and EMA_i=0 if respondents did not receive EMA in both 2007 and 2008;

X_i denotes a vector of background characteristics (see Appendix Table 1 for a full list);

η_s is a school fixed effect;

ε_i is the error term;

and α, β and γ are the parameters, with β indicating the size effect of EMA receipt on degree outcome. The standard errors are clustered by primary sampling units (PSUs) and sample strata.

3.3.1. Model specification and estimation

I estimate equation (1) additively and sequentially to explore the potential drivers of the relationship between EMA and educational attainments. The baseline model (Model 1) includes only the variable of interest, EMA, in order to show the raw underlying gaps in educational attainments by EMA receipt status. Due to the heterogeneity between cohort members, the baseline model would fail to account for the true associations between EMA and the outcome variables, and its estimates could be biased and inefficient. Thus, I then estimate the second model (Model 2), which augments the baseline model by controlling for personal characteristics and family background, including *Gender*, *Ethnicity*, *SEN*, *Family Income*, *NS-SEC*, *Parental Qualification* and *Language*. The third model (Model 3) adds the *Key Stage 2* and *Key Stage 4 results* to examine the extent to which the impact of EMA can be explained by gaps in prior attainment. Moreover, previous studies suggest that bad behaviours in school and negative attitudes towards school and post-16 education often rule young people out of further education, especially higher education (Archer et al., 2007; Archer and Yamashita, 2003; Department for Education, 2011; Gorard et al., 2012). In the fourth model (Model 4), I further include a set of behaviour and attitude indicators, including *Truancy*, *Exclusion*, *Cannabis*, *Attitude*, and *Post16 Intention*. Furthermore, the attainments of young people tend to be clustered within schools, as those in the same school share the same facilities, curriculums, teachers and teaching methods (Chowdry et al., 2013; Crawford and Greaves, 2015; Lleras, 2008). Hence, the last model (Model 5) adds school-fixed effects to capture the variance between schools.

All the outcome variables are binary, so I use a binary response model. One crucial issue that needs to be considered is how to incorporate school-fixed effects in the final specification. Caudill (1987) and Oksanen (1986) point out that the coefficient of the group fixed effects cannot be estimated in a logit or probit model but in a linear probability model (LPM) if every member in the group has similarities. In this case, pupils in the same schools tend to have some common traits, and there are some schools in the sample containing only one pupil.[10] Thus, a logit or probit model with school fixed effects is not an optimal choice for the final specification. This anlysis uses a linear probability model with school dummies to take into account the influence of schools.

3.3.2. Entropy Balancing

A potential threat to the validity of the estimates is that young people need to come from low-income families, and apply for EMA to receive it, which means the assignment of EMA is not random. Thus, it is possible that EMA receipt status could be endogenous. As shown in Table 3.6, those who received EMA are systematically different from those who did not even though I have already restricted the sample based on household income (i.e. only individuals from households with less than £36,400). For example, EMA recipients are more likely to come from poorer and lower SES backgrounds, and their parents tend to hold lower qualifications. They also perform worse in KS2 and KS4 exams and are more likely to be excluded from school than non-recipients. However, the recipients tend to have

[10] A logit or probit model will not converge here because of the presence of schools with single sampling unit.

higher intentions to stay in full-time education after 16 and to apply for university. In order to avoid biases in the estimates, I need to balance the characteristics of the EMA recipients (treatment group) and non-recipients (control group) before running regressions for each outcome variable.

Matching methods, such as propensity score matching, are widely used to evaluate the treatment effects in education studies (Alcott, 2017; Dearden et al., 2009; McGuinness and Sloane, 2011; Nguyen et al., 2006). However, many matching methods do not focus directly on achieving covariate balance and might be unable to balance the covariate moments in finite samples (Hainmueller, 2012; Hirano et al., 2003). Thus, instead, a new pre-processing technique, entropy balancing, is used to estimate the impact of EMA. According to Hainmueller (2012), entropy balancing is an entropy maximisation method, which matches the first, second, and possibly higher moments of the covariate distributions for treatment and control groups. Unlike other methods, it directly incorporates covariate balance into the weight function and keeps valuable information in the data by choosing the weights as close to the base weights as possible. As entropy balancing only works for binary treatments, one-year and two-year EMA groups are combined as one treatment group, and those who have no information about EMA are recoded as missing. Then I use wave 8 final weights as the base weights and balance treatment and control groups with respect to the first, second and third moments[11] of all control variables, separately for the regression sample of each outcome variable[12]. Table 3.7 shows an example of the balanced sample, in which EMA recipients and non-recipients have similar characteristics after the entropy balancing.

Table 3.6 Summary statistics of control variables before entropy balancing (outcome variable: HE participation)

	EMA recipients (N=2,123)			EMA non-recipients (N=1,080)		
	Mean	Variance	Skewness	Mean	Variance	Skewness
Female	0.576	0.244	-0.308	0.444	0.247	0.227
White	0.805	0.157	-1.538	0.916	0.077	-2.990
SEN	0.177	0.146	1.696	0.284	0.203	0.960
Parental income (£)	16621	67200000	0.215	21687	97900000	-0.281
Managerial and professional occupations	0.183	0.150	1.639	0.224	0.174	1.327

[11] That is the mean, variance and skewness. For binary covariates, only their first moment will be considered.
[12] For RGU and degree classification, the treatment and control groups are balanced with respect to the first and second moments, because of the small sample size.

Parent with a degree	0.089	0.081	2.896	0.099	0.089	2.684
Non-native English	0.277	0.200	0.997	0.050	0.047	4.133
Top KS2	0.193	0.156	1.555	0.138	0.119	2.098
Top KS4	0.205	0.163	1.459	0.113	0.100	2.446
Ever played truant	0.203	0.162	1.480	0.328	0.221	0.735
Ever excluded	0.040	0.038	4.692	0.099	0.089	2.682
Ever tried cannabis	0.258	0.191	1.108	0.402	0.241	0.400
Attitude	13.77	12.56	-0.854	12.09	15.96	-0.618
Plan for post-16 education	0.937	0.059	-3.610	0.667	0.222	-0.709

Notes: Regression sample for HE participation. Weighted using wave 8 weights. Number of observations =2,231.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a, 2022).

Table 3.7 Summary statistics of control variables after entropy balancing (outcome variable: HE participation)

	EMA recipients (N=2,123)			EMA non-recipients (N=1,080)		
	Mean	Variance	Skewness	Mean	Variance	Skewness
Female	0.576	0.244	-0.308	0.576	0.245	-0.308
White	0.602	0.240	-0.419	0.603	0.240	-0.420
SEN	0.177	0.146	1.696	0.177	0.146	1.696
Parental Income (£)	16907	67300000	0.198	16921	67600000	0.199
Managerial and professional occupations	0.186	0.151	1.617	0.186	0.152	1.614
Parent with a degree	0.089	0.081	2.896	0.089	0.081	2.898
Non-native English	0.277	0.200	0.997	0.277	0.200	0.999
Top KS2	0.193	0.156	1.555	0.193	0.156	1.556
Top KS4	0.205	0.163	1.459	0.205	0.163	1.460
Ever played truant	0.203	0.162	1.480	0.203	0.162	1.480
Ever excluded	0.040	0.038	4.692	0.040	0.039	4.690
Ever tried cannabis	0.258	0.191	1.108	0.258	0.191	1.109
Attitude	13.77	12.56	-0.854	13.77	12.56	-0.855
Plan for post-16 education	0.937	0.059	-3.610	0.937	0.059	-3.585

Notes: Regression sample for HE participation. Weighted using balanced weights. Number of observations =2,231.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a, 2022).

3.4. Results

Overall, the estimated impact of EMA in this chapter refers to the association between EMA receipt status and educational attainment rather than the causal effect of EMA on attainment. As mentioned in the previous section, young people are required to submit EMA applications before they can receive the allowance. There is the possibility that some unobserved factors are correlated with both the decision of whether to apply for EMA and educational attainments. If this is the case, the estimated impact of EMA in this section would be biased and invalid (Gertler et al., 2016; Hausman and Taylor, 1981; Khandker et al., 2010)—upward biased if the unobservables are positively correlated with both application and attainment and downward biased otherwise. Thus, the term 'impact' is used in this chapter to demonstrate only the statistical association.

3.4.1. Impact of EMA on higher education participation

Table 3.8 shows the estimated impact of EMA on higher education participation. The upper lines of the table present the estimates without matching. For the one-year recipients, the impact of EMA is statistically insignificant in all specifications except for Model 2. As for those who received EMA for both years, they are 28.5 percentage points more likely to attend higher education than non-recipients in Model 1 before controlling for any other factor. Model 2 and Model 3 indicate the importance of demographic factors and prior attainment in explaining the impact of EMA on higher education participation. The positive influence of receiving a two-year EMA decreases from 28.5 to 19.7 percentage points. The changes in the size of the impact suggest that EMA receipt status is correlated with demographic factors and prior attainment, and thus, the raw difference partly proxies the influence of demographic factors and prior attainment. Model 4 shows how the impact of EMA is mediated by including a set of behaviour and attitude indicators. The impact of receiving EMA for two years further reduces to 16.4 percentage points, indicating that the decision of whether to apply for EMA and participation in higher education is driven by young people's behaviors at school and plans for their future. Finally, the estimated impacts for two-year recipients in Model 5, where school fixed effects are included, are similar to estimates in Model 4.

The middle part of Table 3.8 shows the estimated impact of EMA on higher education participation changes after applying the entropy balancing approach. On the one hand, the impact of receiving EMA for one year becomes statistically insignificant in all specifications. On the other hand, the impact of receiving EMA for two years stays statistically significant in all models. In the final specification, two-year recipients are 19.6 percentage points more likely than the non-recipients to attend higher education. The reason behind the different impact of EMA on one- and two-year recipients could be that long-term financial aids are more effective than short-term ones. Moreover, even though entropy balancing is used and attitudes are included in Model 4, there are still some unobserved factors, such as motivation, that can affect the estimates of impact. If those who received two years of EMA were more motivated and thus more likely to apply for two years, the estimates could just indicate the difference in motivation rather than the impact of EMA.

Table 3.8 Impact of EMA on higher education participation

	EMA (base=Never received)	**Model 1** *LPM*	**Model 2** *LPM*	**Model 3** *LPM*	**Model 4** *LPM*	**Model 5** *LPM*
Without reweighting	One year	-0.0155	0.0399*	0.0106	-0.0126	-0.0181
		(0.0224)	(0.0206)	(0.0189)	(0.0194)	(0.0227)
	Two years	0.285***	0.300***	0.197***	0.164***	0.159***
		(0.0221)	(0.0213)	(0.0203)	(0.0206)	(0.0228)
	No information	-0.128***	-0.0657**	-0.0629**	-0.0686**	-0.0788**
		(0.0327)	(0.0316)	(0.0309)	(0.0316)	(0.0377)
Observations		3,335	3,335	3,335	3,335	3,335
With entropy balancing	One year	-0.0497	-0.0262	0.0192	0.0250	-0.00649
		(0.0321)	(0.0256)	(0.0230)	(0.0228)	(0.0247)
	Two years	0.261***	0.250***	0.226***	0.223***	0.196***
		(0.0307)	(0.0258)	(0.0256)	(0.0253)	(0.0252)
Observations		3,203	3,203	3,203	3,203	3,203
Demographic factors			✓	✓	✓	✓
Prior attainment				✓	✓	✓
Behaviours and attitudes					✓	✓
School fixed effects						✓

Notes: Average marginal effects are reported (cluster-robust standard errors in parentheses). *** indicates p<0.01, ** p<0.05, * p<0.1.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a, 2022).

3.4.2. Impact of EMA on degree completion

The estimated impact of EMA on degree completion among all participants is presented in Table 3.9. The raw difference in degree completion by EMA receipt status is shown in Model 1— one-year EMA recipients are 2.8 percentage points less likely, while two-year EMA recipients are 17.2 percentage points more likely to obtain a first degree than the non-recipients. Models 2 and 3 show that the negative impact of receiving a one-year EMA on degree completion decreases gradually from 2.8 to 1.0 percentage points and becomes statistically insignificant, while the positive influence of receiving a two-year EMA drops from 17.2 to 11.2 percentage points. In Model 4, the impact of receiving EMA for two years further reduces to 9.1 percentage points. Moreover, for one-year recipients, the inclusion of behaviour and attitude indicators raises the negative impact of EMA to 2.4 percentage points, though not significant, as the EMA recipients tend to have higher intentions to attend post-16 education. In the final model, including school fixed effect only slightly reduces the impact to 8.4 percentage points. As for those who received the allowance for only one year, they are 3.6 percentage points less likely to obtain a first degree than those who never received EMA, and this result is significant at the 5% level.

After entrophy balancing, the impact of receiving EMA for one year becomes statistically insignificant, which means the negative association between receiving one-year EMA and degree completion is due to the underlying difference between recipients and non-recipients. For example, EMA recipients tend to come from more disadvantaged families and thus are less likely to obtain a first degree without the intervention. As for those who received EMA for two years, the impact of receiving EMA on degree completion stays statistically significant in all models though the estimated impact drops gradually from 16.0 percentage points in Model 1 to 11.8 percentage points in Model 5. Hence, EMA can not only motivate disadvantaged students to participate in higher education, but also have an positive impact on degree completion.

Table 3.9 Impact of the EMA on whether obtained a first degree (with entropy balancing)

	EMA (base=Never received)	**Model 1** *LPM*	**Model 2** *LPM*	**Model 3** *LPM*	**Model 4** *LPM*	**Model 5** *LPM*
Without	One year	-0.0282*	0.00954	-0.0101	-0.0238	-0.0356**
reweighting		(0.0160)	(0.0160)	(0.0155)	(0.0159)	(0.0177)
	Two years	0.172***	0.183***	0.112***	0.0905***	0.0841***

		(0.0186)	(0.0182)	(0.0176)	(0.0182)	(0.0200)
	No information	-0.0844***	-0.0461*	-0.0431*	-0.0447*	-0.0414
		(0.0250)	(0.0258)	(0.0235)	(0.0236)	(0.0306)
Observations		3,335	3,335	3,335	3,335	3,335
R-squared		0.051	0.143	0.241	0.250	0.422
With entropy balancing	One year	-0.0452	-0.0301	0.00421	0.00858	-0.0192
		(0.0287)	(0.0239)	(0.0220)	(0.0219)	(0.0251)
	Two years	0.160***	0.152***	0.134***	0.132***	0.118***
		(0.0265)	(0.0232)	(0.0228)	(0.0227)	(0.0236)
Observations		3,203	3,203	3,203	3,203	3,203
R-squared		0.033	0.153	0.237	0.241	0.471
Demographic factors			✓	✓	✓	✓
Prior attainment				✓	✓	✓
Behaviours and attitudes					✓	✓
School fixed effects						✓

Notes: Average marginal effects are reported (cluster-robust standard errors in parentheses). *** indicates p<0.01, ** p<0.05, * p<0.1.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a, 2022).

3.4.3. Impact of EMA on National Vocational Qualifications (NVQs) completion

As EMA supports children from low-income families who are more likely to choose a vocational pathway after compulsory education (Department of Education, 2017), it is important to see whether EMA has an impact on both academic qualifications and vocational qualifications. The first panel of Table 3.10 shows the estimated impact of EMA on NVQ Level obtained without matching. While EMA has a negative and statistically insignificant impact on one-year recipients, it does influence those who received it for two years. Specifically, the gap in the possibility of obtaining NVQ Level 4 or above (including a degree) between two-year recipients and non-recipients narrows gradually from 17.0 to 8.0 percentage points once demographic factors, prior attainment, and behaviours and attitudes, and school fixed effects are considered.

The second panel of Table 3.10 shows the estimates of the impact of EMA on NVQ Level 4 completion with entropy balancing. Similar to the result without reweighting, there is no statistically significant impact of EMA on one-year recipients. However, for those who received the allowance for two years, they are 12.1 percentage points more likely to obtain at least NVQ Level 4 after controlling for all other factors.

Table 3.10 Impact of the EMA on whether obtained NVQ Level 4 or above (with entropy balancing)

	EMA (base=Never received)	**Model 1** *LPM*	**Model 2** *LPM*	**Model 3** *LPM*	**Model 4** *LPM*	**Model 5** *LPM*
Without reweighting	One year	-0.0193	0.0184	-0.000886	-0.0185	-0.0232
		(0.0198)	(0.0198)	(0.0193)	(0.0200)	(0.0219)
	Two years	0.170***	0.182***	0.112***	0.0847***	0.0799***
		(0.0205)	(0.0208)	(0.0208)	(0.0209)	(0.0227)
	No information	-0.0792**	-0.0392	-0.0374	-0.0371	-0.0467
		(0.0342)	(0.0340)	(0.0319)	(0.0319)	(0.0409)
Observations		3,335	3,335	3,335	3,335	3,335
R-squared		0.039	0.127	0.204	0.215	0.401
With entropy balancing	One year	-0.0280	-0.0162	0.0175	0.0228	0.00405
		(0.0299)	(0.0250)	(0.0236)	(0.0235)	(0.0264)
	Two years	0.159***	0.153***	0.136***	0.133***	0.121***
		(0.0278)	(0.0241)	(0.0239)	(0.0237)	(0.0248)
Observations		3,203	3,203	3,203	3,203	3,203
R-squared		0.027	0.151	0.221	0.227	0.471
Demographic factors			✓	✓	✓	✓
Prior attainment				✓	✓	✓
Behaviours and attitudes					✓	✓
School fixed effects						✓

Notes: Average marginal effects are reported (cluster-robust standard errors in parentheses). *** indicates p<0.01, ** p<0.05, * p<0.1.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a, 2022).

3.4.4. Impact of EMA on Russell Group university attendance and degree classification

So far, the analysis has focused on participation and completion of higher education. It is also worth knowing whether EMA has an impact on achievement in higher education because attending a high-status institution and obtaining a first or upper-second degree have been shown to be associated with higher returns in the labour market (see, for example, Hussain et al. (2009) for university quality and Walker and Zhu (2011) for degree classification). Among the university graduates, I find that EMA has no impact on obtaining a degree from a Russell Group university (see Appendix Table B.2). Furthermore, receiving EMA for two years seems to have a negative and statistically significant impact before controlling for the school fixed effects, approximately 12.2 percentage points in Model 4, on obtaining a first or upper second class degree (see Appendix Table B.3). These results are not surprising because EMA recipients are from low-income backgrounds and they are the marginal students who are less likely than the non-recipients to attend high-status institution or obtain a first or upper second degree in the first place. Moreover, the primary purpose of EMA is to encourage children from low-income families to stay in education rather than improve their performance. Before July 2008, young people were required to attend all learning sessions of their chosen programmes to receive the weekly payment, but there was no achievement requirement (Hubble, 2008).[13] Although Chowdry et al. (2008) find a positive effect of EMA on average Key Stage 5 scores, the results here suggest that EMA has no positive impact on academic performance in higher education. However, the validity and robustness of the results need to be further examined as the sample size is around 600 young people.

3.4.5. Heterogeneous Treatment Effects

As there is a gender gap in educational attainment in the sample (see Table 3.3) and different gender might respond differently to financial aid, the impact of EMA on educational attainments by gender will be examined in this section. To investigate whether males and females react differently to the allowance, I estimate the models again using Model 4 with entropy balancing, separately for males and females. Because of the small sample size after separating by gender, treatment and control groups are balanced with respect to only the first moment of all control variables.

Table 3.11 presents the estimates of the impact of EMA on educational attainments for males and females, respectively. For both males and females, receiving EMA for one year has no impact on higher education participation, degree completion and NVQ achievement.

[13] However, there are one-off payments which are based on both attendance and performance against set learning goals.

When it comes to those who received EMA for two years, the situation becomes quite different. Two-year male recipients are 14.6 percentage points more likely to attend higher education, 14.1 percentage points more likely to complete a degree, and 11.8 percentage points more likely to achieve NVQ Level 4 or above. As for two-year female recipients, the estimated impacts of EMA on higher education participation, degree completion and NVQ achievement are 22.8, 10.5, and 13.4 percentage points respectively. These results indicate that males and females respond different to financial incentives. The allowance has a larger impact on higher education participation for females but a more significant effect on degree completion for males, indicating that EMA tends to have a longer-term impact on young males than their female peers.

Table 3.11 Impact of EMA on educational attainments, by gender (with entropy balancing)

		HE		**Degree**		**NVQ**	
		Male	*Female*	*Male*	*Female*	*Male*	*Female*
EMA	One year	-0.0254	-0.0040	-0.0273	-0.0068	0.0358	0.0027
(base=Never received)		(0.0415)	(0.0368)	(0.0363)	(0.0390)	(0.0413)	(0.0378)
	Two years	0.146***	0.228***	0.141***	0.105***	0.118***	0.134***
		(0.0382)	(0.0342)	(0.0366)	(0.0348)	(0.0394)	(0.0372)
Observations		1,423	1,780	1,423	1,780	1,423	1,780

Notes: Average marginal effects are reported (cluster-robust standard errors in parentheses). *** indicates p<0.01, ** p<0.05, * p<0.1.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a, 2022).

3.5. Conclusions and recommendations

In the UK, Education Maintenance Allowance (EMA), which is a kind of conditional cash transfer programme, has been an effective way to encourage young people from low-income families to stay in education after the compulsory school-leaving age. The results in this chapter show that EMA not only influences the education-related decisions and behaviours at the time when young people were receiving the payments but also affects educational attainments later in life, i.e. degree participation and attainment. The results also imply that the allowance has different impacts on young men and women.

In this chapter, regression analysis with entropy balancing is conducted using rich longitudinal data to estimate the medium-term impact of EMA on educational attainments. It is worth noting that the finding in this paper could provide a ‘higher bound’ estimate of the impact of EMA as those who applied and obtained EMA could have been more motivated than those who never applied. The estimates suggest that receiving EMA for two years has a statistically significant impact on higher education participation, degree completion and NVQ achievement, even after controlling for demographic factors, prior attainment, behaviours and attitudes and school fixed effects. After balancing the treatment and control groups, two-year EMA recipients are 19.6 percentage points more likely to attend higher education, 11.8 percentage points more likely to complete a degree, and 12.1 percentage points more likely to achieve NVQ Level 4 or above. However, there is no statistically significant result for one-year EMA recipients. One possible explanation for this result is that long-term financial incentives are more effective than short-term ones. Young people need to receive incentives for a certain amount of time before they can change their decisions and behaviours. Moreover, this chapter finds EMA has no positive impact on attainment measures and attendance of high-status institutions. The implication is that while EMA helps disadvantaged young people to stay in education, it cannot do much about their performance. In general, the results confirm that financial difficulties and credit constraints do play important roles in education decisions among young people from low-income backgrounds. Policies targeting these disadvantaged young people, such as EMA, will be beneficial in the long run as the returns to higher education are substantial (Blundell et al., 2000; Moretti, 2004; Walker and Zhu, 2011). Furthermore, the estimated impacts of EMA have a gender heterogeneous effect. Receiving EMA for two years is associated with a larger impact on higher education participation for female students but a more significant effect on degree completion for male students. This gender difference suggests that the positive effect of the allowance lasts longer among young males than their female peers.

Nevertheless, it is important to note that there are still some limitations which need to be considered in future research. Firstly, the exact reasons why young people did not receive or why they did not apply for the EMA remain unknown. As emphasised above, the impact estimated in this chapter describes the association between EMA and educational attainments, not the causality. There could be some unobserved factors that influence their decision of whether they applied for the allowance as well as the result of whether they received it. If these unobserved factors are also correlated with educational attainments, the estimates would be biased and invalid. In addition, EMA was replaced by a new policy, the 16 to 19 Bursary Fund in England, in 2011 due to the high ‘deadweight’ cost of the previous programme. The new bursary fund provides financial support to a much smaller group of students and substantially cuts down the annual expenses from £564 million to £174 million. Britton and Dearden (2015) estimate the impact of the reform and find that the implementation of the new policy leads to falls in Year 12 and 13 participation and attainment among those who would have been eligible for EMA, especially among pupils from the lowest-income group. They also conduct a cost-benefit analysis and suggest that short-run savings from the reform are overall outweighed by the long-run losses. Therefore, in order to know whether the scrapping of EMA adversely affects social and educational mobility, further work could compare the impact of the new policy with that of the EMA on educational attainments over a longer term.

Chapter 4.

Intergenerational educational mobility and the COVID-19 pandemic

4.1. Introduction

Since the first national lockdown in March 2020, the COVID-19 pandemic has dramatically affected the economy and the labour market in the UK. Overall, gross domestic product (GDP) dropped 9.8% in 2020 (Harari et al., 2021), and although economic activity started to recover from spring 2021, GDP in September 2021 was still 0.6% below its pre-pandemic level (February 2020) (Office for National Statistics, 2021a). To minimise the effect of the pandemic on the labour market and support employers, the Coronavirus Job Retention Scheme (CJRS), also known as the "furlough scheme", was announced in March 2020, providing grants to employers to ensure that they could retain and keep to pay their staff. Even with the CJRS, the UK unemployment rate rose gradually from 4.0% before the pandemic to 5.2% between October to December 2020 (Office for National Statistics, 2021b). Moreover, UK total actual weekly hours worked also declined greatly after the first national lockdown, from 1.05 billion hours before the pandemic to 8.45 billion hours in April to June 2020 (Office for National Statistics, 2021b).

Although the COVID-19 recession affects everyone in the country, there is concern that it may have a greater impact on the disadvantaged. Several recent studies from the US and Europe provide evidence that the pandemic may have had a greater impact on those from lower socio-economic status (SES) groups. For example, examining the impact of school closures on learning loss and time spent learning, several studies (Andrew et al., 2020; Dietrich et al., 2021; Grätz and Lipps, 2021; Green, 2020; Wößmann et al., 2020) show a disproportionate effect on young people from disadvantaged backgrounds. In the labour market context, several studies have shown that workers from disadvantaged groups have suffered both larger increases in employment losses and larger reductions in earnings during the COVID-19 pandemic (Cortes and Forsythe, 2020; Dang and Nguyen, 2020; Hupkau et al., 2021). In particular, studies to date have highlighted the disadvantage of being younger, less educated, and from a poor background. Major et al.(2020) show that unemployment during the first wave of the pandemic was disproportionately higher for young people, while Eyles (2021) finds that young people who grew up in the poorest households are over twice as likely to have lost work since the pandemic began. Montenovo et al. (2020) examine job losses during the early months of the COVID-19 recession in the US and find large drops in employment among younger workers and non-college graduates. Focusing on the UK, Adams-Prassl et al. (2020) suggest that younger workers and those on low incomes are much more likely to have lost their job due to COVID-19 and are more likely to have experienced a reduction in earnings than older and higher-income workers.

Unlike recent recessions in developed economies, which disproportionately hit men's employment, the COVID-19 recession was a "shecession", which had a more significant impact on women, and especially mothers, than on men (Alon et al., 2021). Albanesi & Kim (2021) examine the real-time labour market data in the US and find that women's employment, especially the employment of married women with children, falls more than men's at every stage of the pandemic. Using a sample of 30 advanced economies and 8 emerging market economies, Bluedorn et al. (2021) show that compared with the average employment rate in 2019, the employment rate in the second quarter of 2020 fell by around 2.5 and 2 per cent for women and men, respectively. The gendered impact of the COVID-19 recession is due to women being more likely to work in contact-intensive industries (e.g. service industries) that were shut down during the pandemic or due to the so-called "motherhood penalty" where mothers assumed increased caring responsibilities as a result of school and nursery closures, resulting in them being unable to maintain unemployment (Alon et al., 2020; Andrew et al., 2020; Blundell et al., 2020; Couch et al., 2020).

While the literature on the impacts of the pandemic is rapidly growing, to date, none of this work has explored the potential differential impact of the pandemic on first-in-family or first-generation university graduates, even though there is evidence that this group has worse labour market outcomes already in early career (Adamecz-Völgyi et al., 2022). In this chapter, we examine the impact of the COVID-19 pandemic on the labour market experiences of ‘first in family’ (FiF) students. FiF is defined as individuals who attend university and obtain a university degree, but whose (step) mother and (step) father did not (Henderson et al., 2020). We use data from three waves of the Next Steps COVID-19 survey to investigate the heterogeneous labour market impacts of the COVID-19 pandemic on the FiF graduates as compared to their non-FiF peers. These young people were born in 1989/90 and were approximately age 30 by the time the pandemic began. This means they would have already completed higher education and be settled into an early career when the pandemic hit. There is evidence that the long-term scarring effects of experiencing labour market shocks early in a career can be detrimental (Arulampalam, 2001; Bell and Blanchflower, 2011; Gregg, 2001; Gregg and Tominey, 2005; Schmillen and Umkehrer, 2017), making this an issue of policy relevance.

We examine the relationship between FiF status and labour market outcomes during the pandemic using a range of outcomes across three time points from May 2020 to March 2021. We only focus on those who were “employed, self-employed, unpaid/voluntary workers or apprentices” before the outbreak. There are mainly three possible scenarios arising from the pandemic on the circumstances of workers[14]. First, they could have simply carried on working “employed and working (employed)”. Second, they could have been placed on the government’s CJRS scheme, whereby they were put on paid leave but paid up to 80% of their usual wage “employed but on furlough or paid leave[15] (on furlough)”, or third, they could have been put on unpaid leave, become unemployed, or left the workforce altogether “Unemployed, inactive or other non-employed (Non-employed)”. While some of these scenarios have advantages and disadvantages (e.g., many would prefer to be on paid leave than to keep working), this is also a plausible order of attractiveness to the individual as per the order set out above. In particular, among those who did not keep working, those who were put on furlough continued to be paid at up to 80% of their usual wage and thus were far better off in financial terms than those who became unemployed or who were put on unpaid leave.

We compare FiF graduates with their non-FiF graduate peers using linear probability regressions and controlling for a rich set of covariates, including personal and household

[14] A very small number of individuals in our sample were studying or retired after the outbreak.
[15] Paid leave here refers to any forms of statutory leave and time off, including but not limited to maternity and paternity leave, holiday entitlement and sick pay.

characteristics, pre-COVID labour market characteristics, COVID-related factors, time spent on children and caring for others, and Personal network at age 25. Based on a range of literature highlighting the differential effects of the pandemic on women, we explore these outcomes separately by gender. Since we have three waves of data collected during the pandemic, we are also able to estimate how these outcomes change over time.

Focusing on those who didn't keep working, our results highlight the disadvantage arising from the intersectionality of socio-economic background and gender. We find that FiF female graduates are more likely to stop working altogether or to be put on unpaid leave but less likely to be on furlough or paid leave than non-FiF female graduates (those whose parents have a university degree). However, we find no statistically significant difference between FiF and non-FiF male graduates.

This chapter contributes to the previous literature in several important ways. First, we provide the first analysis of the labour market outcomes for FiF graduates during the COVID-19 pandemic in England. Unlike other indicators of disadvantaged groups, using FiF status focuses on the prolonged impact of parental human capital rather than their family income or another type of disadvantage. Also, FiF status is of policy interest as it is used as a measure by universities to increase the diversity of their student intake in Widening Participation and contextualised admissions (Henderson et al., 2020). Second, we use the 'millennial' generation, a relatively young cohort facing a number of challenges during their early adulthood (Henderson, 2019). The Great Recession started when they were about to enter university at age 18, and they also faced higher university fees than any previous cohorts as higher education tuition fees increased gradually from £3,000 in 2006 to £9,000 in 2012. Previous studies have shown that younger workers are more likely to lose their job and have experienced a decrease in earnings during the pandemic than older workers (Adams-Prassl et al., 2020; Belot et al., 2020; Chatterji and Li, 2021). Thus, using this cohort enables us to reduce the influence of age heterogeneous effects and focus on the more at-risk age group. The potential long-term scarring of these effects and the scope for policymakers to intervene makes this analysis particularly important. Third, our data include three waves collected from May 2020 to March 2021. Instead of focusing on a single point in time, we analyse how our results change as the economic environment and government policies change over time. Importantly, these pandemic survey waves are linked to eight existing waves of data providing us with rich information on family background. A further contribution is that we study inequalities in access to an important labour market insurance policy – the furlough scheme (CJRS). This scheme was created during the pandemic to protect workers whose jobs were not viable during government lockdowns. Our results suggest FiF workers were less likely to benefit from the scheme, highlighting an important dimension of inequality that requires further investigation.

The rest of this chapter is organised as follows. We review evidence on the pre-existing inequalities in section 4.2 and government policy responses to the COVID-19 pandemic in England in section 4.3. Section 4.4 introduces the data and methodology used in this chapter, followed by section 4.5, where we present the descriptive statistics. Our results are presented in section 4.6 and discussed in section 4.7. Finally, section 4.7 provides conclusions with a discussion of policy implications.

4.2. Inequalities before the COVID-19 pandemic

There is a well-established body of literature focusing on socio-economic gaps in educational and labour market outcomes in the UK. Individuals from disadvantaged backgrounds tend to have lower pre-university educational attainment (Blanden and Gregg, 2004; Blanden and Macmillan, 2016; Machin et al., 2013), have less chance to attend and complete university (Boliver, 2013; Chowdry et al., 2013; Crawford, 2014) and to attend a selective university (Campbell et al., 2021), and are less likely to enter high-status occupations and earn less than their peers from more affluent families once they enter labour market (Blanden et al., 2007; Gregg et al., 2017b; Macmillan et al., 2015). Most of the existing studies use social class or family (parental) income indicators to identify who belongs to the disadvantaged group.

According to Henderson et al. (2020), a large proportion of recent university graduates in England (approximately 68%) are FiF. FiF students are less privileged than their non-FiF peers since non-graduate parents tend to have fewer economic resources to invest in their children's education and early development (Blundell et al., 2000; O'Leary and Sloane, 2005; Walker and Zhu, 2011). Moreover, potential FiF students have limited access to information about university admission and experiences from their parents (Radford, 2013; Thayer, 2000) and are more likely to enrol in vocational programmes, which impede their progress toward a university degree (Striplin, 1999), which is a stepping stone for high-status jobs. Without the social networks and family wealth of graduate parents, FiF might still be disadvantaged in the labour market even if they have achieved a university degree.

Evidence from the US has shown that FiF students are less likely to be prepared for college admission (Choy, 2001; Horn and Nunez, 2000; Lohfink and Paulsen, 2005), have a lower chance to go to college (Engle, 2007; Wilbur and Roscigno, 2016), enrol in less academically selective institutions (Berkner and Chavez, 1997; Pascarella et al., 2004), and are less likely to stay enrolled or attain a bachelor's degree than non-FiF students (Warburton et al., 2001; Wilbur and Roscigno, 2016). As for labour market outcomes, some studies find a wage gap between FiF and non-FiF students (Thomas and Zhang, 2005; Zhang, 2012), while others suggest that a university degree fills that gap (Choy, 2001; Nunez and Cuccaro-Alamin, 1998). Manzoni and Streib (2019) summarise the mixed evidence from previous studies and find that a substantial wage gap between first- and continuing-generation students remains ten years after completing college though the gap for women disappears when individual characteristics are added into the model, and the gap for men fades once labour market characteristics are controlled.

In the UK, there are limited studies focusing specifically on FiF students. Stuart (2006) uses life story methods to examine the university experience of first-generation students and suggests that friendship, as a form of social capital, plays an important role in their HE decision and success at university. The first quantitative study looking at FiF students in the England is Henderson et al. (2020), where they employ a combination of logit models and multinomial logit models to investigate who FiF students are and how parental education influences children's university access, subject studied, institution attended and risk of dropout. They find that FiF graduates tend to come from ethnic minority backgrounds and have higher prior attainment than those who match their parents without a degree. Moreover, the results suggest that FiF graduates are more likely to study 'high earning' subjects, such as Law, Economics and Management, but are less likely to attend elite universities and are at greater risk of dropout. These findings are supported by Adamecz-Völgyi et al. (2020), who explore potential FiF[16] and examine whether or not potential FiF picks up additional information beyond other indicators of disadvantaged and

[16] 'Potential FiF' refers to young people who could be the first in their family to achieve a university degree because neither of their parents has one (Adamecz-Völgyi et al., 2020).

vulnerable groups. They suggest that even after other measures of disadvantage are controlled, being FiF is still shown to be an important barrier to university participation and graduation, and this association is likely to operate through the channel of early educational attainment. The only study exploring the early career labour market outcomes of FiF in England examines the wage gap between FiF and non-FiF and estimates their returns to a degree (Adamecz-Völgyi et al., 2022). They find no wage difference for male graduates, while for females, FiF graduates earn 7.4 percent less than non-FiF, and this gap can be explained by the difference in prior academic attainment, whether they attended a prestigious institution and whether their degree is required for their job. Even though returns to a degree are higher for female FiF graduates than for female non-FiF graduates, the negative impacts of having non-graduated parents offset the high returns to their own degree.

4.3. England's policy responses to the COVID-19 pandemic

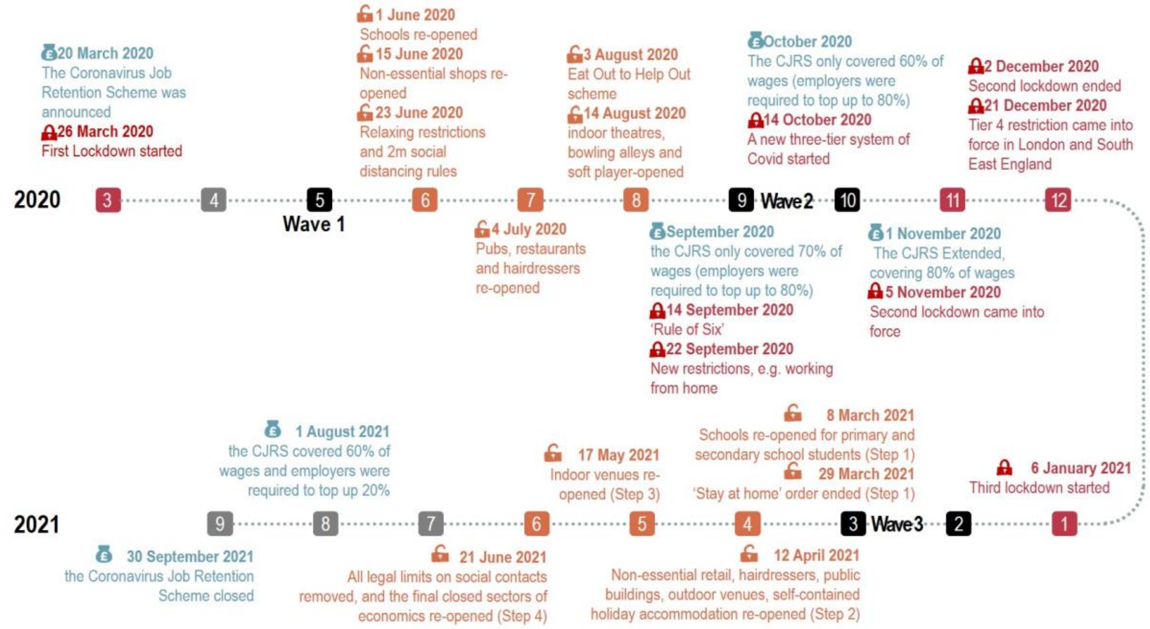
On 11 March 2020, the World Health Organisation (WHO) declared COVID-19 a pandemic, which became one of the biggest threats faced by the UK for decades.[17] In response to the pandemic, the Prime Minister urged people to work from home where they possibly can on 16 March 2020. Then, almost two months after the first two cases of coronavirus in the UK were confirmed, the Prime Minister announced the first national lockdown on 23 March 2020, with lockdown measures legally coming into force on 26 March 2020. Meanwhile, the Coronavirus Job Retention Scheme (CJRS) was announced on 20 March 2020, providing grants to employers to ensure that they could retain and keep to pay their staff (Powell et al., 2022). The CJRS initially covered 80% of an employee's wages (up to £2,500 per month)[18] as well as the Employer's National Insurance contributions (NIC) and pension contributions from 1 March to 30 June 2020. This grant was available to all businesses of all sizes, and there was no limit on funding per employer, making it easier for businesses to keep their workers during the pandemic so that they could resume speedily and efficiently after the crisis. In the meantime, these policies also protect workers from losing

[17] Due to the devolved nature of much of the policymaking around the COVID-19 pandemic and the fact that Next Steps includes only young people in England, we focus on England as opposed to the UK in this chapter.
[18] The wages of furloughed workers can be further topped up to 100% by the employer.

their incomes and welfare to avoid the negative impacts of unemployment on individuals and society.

Figure 4.1 provides an overview of the timeline of all policy developments in this area and how they relate to the waves of the survey used in this chapter. The first survey (wave one) was carried out in May 2020 when the Prime Minister was about to announce a conditional plan for lifting the first national lockdown. From 11 May 2020, those who could not work from homes, such as construction workers and those in manufacturing, were encouraged to return to their work. On 12 May, the government announced the CJRS would be extended from 1 July to 31 October, only for employees already furloughed. The CJRS still covered 80% of an employee’s wages during this period, but as the lockdown restriction eased, the NICs and pension contributions were not covered from 1 August 2020.

Figure 4.1 Timeline of England’s policy responses to the pandemic and the COVID-19 survey



Source: Authors’ own graphic. Data on lockdowns from Institute for Government (2021).

The second survey (wave two) was carried out from September to October 2020 when the CJRS only covered 70% and 60% of wages in September and October, respectively, and the employers were required to top up to at least 80%. As the cases of COVID-19 increased rapidly, a second national lockdown came into force on 5 November 2020, followed by a third lockdown which started on 6 January 2021. Due to these restrictions, the Prime Minister further extended the CJRS and employers were not required to have previously used the CJRS to be eligible. Employers should pay employees’ wages for hours worked, as well as Employer's National Insurance contributions and pension contributions, while the government contributes 80% of employees' wages for furloughed hours (up to £2,500 per month).

The most recent survey (wave three) took place from February to March 2021, when the Prime Minister published a road map for lifting the third lockdown. During that period, the initial scheme was subsequently extended from 1 November 2020 to 30 September 2021, and the level of grant available to employers under the scheme stayed the same (80% of wages) until 30 June 2021[19]. By 21 November 2021, 11.7 million jobs have been furloughed through the scheme, costing the government £70 billion (Powell et al., 2022).

4.4. Data and descriptive statistics

In this chapter, we use a series of COVID-19 surveys which link to the national longitudinal cohort study, Next Steps, formerly known as the First Longitudinal Study of Young People in England (LSYPE) (University College London, UCL Institute of Education, Centre for Longitudinal Studies, 2021a). Next Steps is nationally representative[20] and collects information on young people's family life, relationships and friends, education and employment, social participation and activities, health and happiness, and behaviour and attitudes. The cohort members, along with their parents, were first interviewed in the spring of 2004 (aged between 13 and 14) and were interviewed annually until the age of 20 in 2010. There are currently eight waves of data, and the last wave was carried out in 2015/16 when approximately 8,000 cohort members were aged 25.

The COVID-19 surveys for this cohort were created to ask about the experiences of the participants during the pandemic (and so are linked to the existing Next Steps study).

[19] From 1 July 2021, the Government contribution supported 70% of wages for hours not worked, reducing to 60% from 1 August. The scheme ended on 30 September 2021.

[20] In order to be representative of young people in England, Next Steps adopted a two-stage probability proportional to size (PPS) sampling procedure. First, schools, considered as the primary sampling units (PSUs), were sampled separately for the maintained schools, the independent schools, and pupil referral units (PRUs) to obtain the sample stratum. Maintained schools were stratified based on their deprivation levels, with deprived schools oversampled by 50%. Independent schools were stratified by the proportion of pupils obtaining five or more A*-C GCSE grades in 2003 within boarding status and gender of pupils. As for the pupil referral units (PRUs), they formed a stratum of their own. Then, within selected schools, pupils from major minority ethnic groups were oversampled to achieve 1,000 sampling units in each group. Furthermore, Next Steps excluded those solely educated at home, boarders and those who resided in England for education purposes only.

Currently, there are three waves of the survey, from May 2020 to March 2021. All three waves cover topics including physical and mental health, time, financial situation, family and household, employment, and education. In addition to these topics, wave 3 also asks questions about pay and household income.

4.4.1. Sample selection and measures of variables

Non-response and sample attrition are common in longitudinal surveys. Overall, the missing values not only reduce the reliability and efficiency of our estimates because of the smaller sample size but also affect the external validity of the study as respondents are often systematically different from non-respondents. Furthermore, it would threaten the internal validity of our results if attrition and non-response were related to being FiF. In COVID-19 surveys, the response rates of the cohort members within the target population are 11.9%, 22.9%, and 26.4% for waves one, two and three, respectively. Only a quarter of Next Step cohort members who participated in at least one wave of the COVID survey responded to all three waves. Thus, we can treat our sample as repeated cross-sectional data.

We handle missing data using weights that combine the original sample design weight of Next Steps with the survey non-response weight in the corresponding wave. The design weight is the reciprocal of the cohort member's selection probability scaled so that the weighted and unweighted achieved sample sizes are equal. As for the non-response weight, it is the inverse of the probability of response in the target population, which is modelled on a set of covariates using logistic regression. We investigate how being FiF is related to attrition and non-response in the second panel of Table 4.1 in section 4.2. Overall, non-FiF graduates tend to have a higher response rate than non-FiF graduates.

As we focus on economic activity among FiF and non-FiF graduates, non-graduates as well as those who were not employed before the pandemic, are excluded from the sample. Of the 884, 1,573 and 1,814 graduates who responded to the surveys in waves one, two and three, 779, 1,396 and 1,338 were working before the pandemic. This subset of Next Steps is our main sample for the analysis in this chapter. In order to avoid dropping cases with missing values, we use missing flags for all variables except for the outcome variables and our main variable of interest.

Our main variable of interest is FiF status, which depends on the university graduation of the cohort members and their parents. The cohort members are regarded as university graduates if they have gained a university higher degree, a first-degree level qualification, a diploma in higher education, a teaching qualification or a nursing or other medical qualification by the age of 25. Information on parental graduation is available in the first four waves, up until the cohort members were aged 17. It is possible that the parents could have gained a university degree when the cohort member was older than 17; however, we focus on the influence of growing up with parents without university degrees and therefore restrict parental degree attainment to this point.

In this chapter, we are interested in whether the pandemic affects labour market outcomes differently according to an individual's FiF status. Using those were employed and working after the outbreak as our base group, we construct binary outcome variables: whether the participant was employed but on furlough or paid leave (=1 if employed but on furlough; =0 if employed and working) and whether the participant was unemployed, inactive or other non-employed (=1 if unemployed, inactive or other non-employed; =0 if employed and working). All variables are derived from the last wave of the main surveys and the respective wave of the COVID-19 surveys. As there are very few people in voluntary jobs and apprenticeships both before and after the pandemic, we combine them with the employed and working group. *Employed and working* is defined as "employed, self-employed, unpaid/voluntary workers or apprentices", both before and during the pandemic. *Furlough or paid leave* refers to "employed, self-employed, unpaid/voluntary workers or apprentices" before the pandemic and "employed but on paid leave (including furlough)" during the pandemic. *Unemployed, inactive or other non-employed* is defined as "employed, self-employed, unpaid/voluntary workers or apprentices" before the pandemic but "employed and on unpaid leave, self-employed but not currently working, unemployed, permanently sick or disabled, looking after home or family, or doing something else" post-outbreak.

To limit the influence of confounding factors and enhance the internal validity of our study, we include four groups of control variables in this chapter:

- *Personal and household characteristics:* gender, ethnicity, whether attended a Russell Group university, marital status, having (school-aged) children, and the interaction term of gender and having (school-aged) children;

- *Pre-COVID labour market characteristics:* occupation (SOC code 2010), whether self-employed, whether on zero hours contract and pre-COVID working hours;
- *COVID-related variable:* whether has had Coronavirus;
- *Time use variables (wave one and two only)*: time on homeschooling, time on other activities with children, and time on caring for others;
- *Personal network at age 25*: whether found job through personal contacts, and whether found job by professional networking.

4.4.2. Descriptive statistics

We start our analysis by exploring the prevalence of our main variable of interest and main outcome variables. The first panel of Table 4.1 shows sample composition by FiF status. As we are focusing on those who were employed, the proportions of graduates in all three waves of the COVID-19 surveys are around 40%, higher than in the target population[21]. FiF graduates account for approximately 70% of the graduates in our sample for all waves. In order to examine the impact of growing up with non-graduate parents, we compare FiF graduates with non-FiF graduates (those who match their parents with a degree). Thus, group 2 (non-FiF graduates) is used as the baseline group in the empirical analysis.

Table 4.1 Sample used in this chapter

		Group 1: FiF graduates (parents no degree)	Group 2: non-FiF graduates (parents with degree)
Sample size		Male: N=908 (69.3%) Female: N=1,625 (73.7%)	Male: N=401 (30.7%) Female: N=579 (26.3%)
Response and non-attrition rate within the target population	Wave 1	26.5%	34.5%
	Wave 2	49.8%	55.3%
	Wave 3	56.5%	61.2%

Notes: The number of observations refers to those who were working pre-COVID. Sample size is weighted using the combined weight for each wave.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a).

Table 4.2 compares the proportions of graduates who were employed and working, were employed but on furlough or paid leave, and unemployed, inactive or other non-employed

[21] Target population includes original sample only (i.e. not ethnic minority boost sample). N=15,770

by FiF status and gender and wave. In general, both male and female graduates were less likely to have kept working in the first wave compared to their status before the pandemic (when they were all in work). With the lifting of the first national lockdown, the probability that graduates kept working increased in wave two for both males and females, but it dropped for females in wave three during the third national lockdown. Among all three waves, the rate of unemployed, inactive or other non-employed is highest in wave two, while the probability of being on furlough or paid leave is highest in wave one and much more than the probability in wave two when the CJRS was reduced to cover 60 to 70% of wages. When comparing FiF and non-FiF graduates, we find that both male and female FiF graduates were less likely to keep working than their non-FiF peers in all three waves. The gap is most significant in wave one for males (15.7 percentage points) and wave three for females (7.1 percentage points). Among those who did not keep working, FiF males were more likely to be put on furlough or paid leave than non-FiF males in all three waves, whereas FiF females were more likely to be unemployed, inactive or other non-employed than their non-FiF peers in all waves. Specifically, FiF males were 13.5 percentage points more likely to be on furlough or paid leave than non-FiF males in wave one, and this gap narrows in the following two waves as the probability of being on furlough or paid leave decreases greatly from 17.2% in wave one to just 3% and 5% in wave two and three respectively for FiF male workers. Although FiF female workers were slightly less likely to be on furlough or paid leave than their non-FiF peers, they were much more likely to become unemployed, inactive or other non-employed, especially in wave two.

Table 4.2 Labour market status by FiF status and gender and wave

		Male			Female		
Outcome		Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3
Whether kept working	FiF	0.783	0.867	0.897	0.677	0.829	0.772
		(0.414)	(0.340)	(0.305)	(0.468)	(0.377)	(0.420)
	non-FiF	0.940	0.881	0.910	0.716	0.835	0.843
		(0.239)	(0.324)	(0.287)	(0.452)	(0.372)	(0.364)
	Total	0.826	0.872	0.900	0.688	0.830	0.791
		(0.380)	(0.335)	(0.300)	(0.464)	(0.375)	(0.407)
Whether on furlough or paid leave	FiF	0.172	0.030	0.050	0.170	0.035	0.068
		(0.378)	(0.172)	(0.218)	(0.377)	(0.183)	(0.253)
	non-FiF	0.037	0.006	0.039	0.232	0.111	0.084
		(0.189)	(0.079)	(0.194)	(0.424)	(0.315)	(0.278)
	Total	0.134	0.022	0.047	0.188	0.053	0.073
		(0.341)	(0.148)	(0.211)	(0.391)	(0.225)	(0.260)

Whether stopped working	FiF	0.046	0.099	0.050	0.152	0.136	0.155
		(0.210)	(0.299)	(0.218)	(0.360)	(0.344)	(0.362)
	non-FiF	0.024	0.113	0.046	0.052	0.046	0.085
		(0.152)	(0.317)	(0.211)	(0.223)	(0.210)	(0.280)
	Total	0.040	0.104	0.049	0.124	0.115	0.130
		(0.196)	(0.305)	(0.216)	(0.330)	(0.319)	(0.336)

Notes: Standard errors in parentheses. Weighted using the combined weight for each wave.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a).

Table 4.3 and Figure 4.2 show how the amount of time spent on children and caring for others varies by FiF status, gender and wave. For example, about 78% of male FiF graduates were employed and working in wave one. As time use variables are not available in wave three, we impute missing values in time use variables in wave three using the average of the first two waves. If the variable is missing in one of the two waves, we just use the value in the other wave instead of the average. In general, female workers spent more time on children and caring for others than male workers in all three waves. Focusing on the FiF status, we find that both male and female FiF graduates spent more time on children and caring for others than their non-FiF peers.

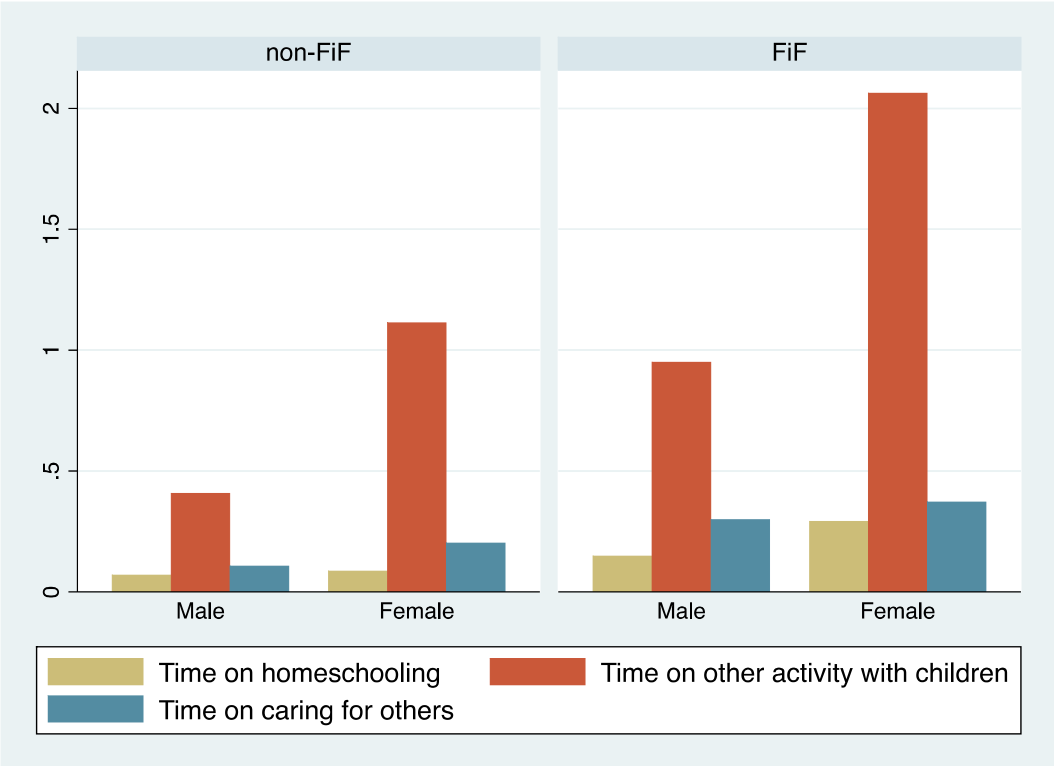
Table 4.3 Time use variables by FiF status and gender and wave

		Male			Female		
Outcome		Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3
Time on homeschooling	FiF	0.127	0.106	0.259	0.334	0.240	0.337
		(0.669)	(0.588)	(0.548)	(1.197)	(1.645)	(1.392)
	non-FiF	0.053	0.061	0.117	0.063	0.097	0.101
		(0.450)	(0.226)	(0.300)	(0.353)	(0.661)	(0.256)
	Total	0.106	0.091	0.219	0.219	0.205	0.273
		(0.617)	(0.498)	(0.495)	(0.495)	(1.468)	(1.200)
Time on other activities with children	FiF	0.586	1.019	1.235	1.772	2.314	1.952
		(1.549)	(2.519)	(1.943)	(4.146)	(4.464)	(3.885)
	non-FiF	0.328	0.387	0.556	0.730	1.387	1.148
		(1.121)	(1.028)	(1.024)	(2.610)	(2.993)	(2.397)
	Total	0.515	0.807	1.044	1.044	2.088	1.733
		(1.446)	(2.158)	(1.761)	(1.761)	(4.172)	(3.559)
Time on caring for others	FiF	0.109	0.372	0.376	0.387	0.315	0.453
		(0.418)	(2.057)	(1.548)	(2.307)	(1.968)	(2.040)
	non-FiF	0.006	0.141	0.137	0.164	0.192	0.261
		(0.059)	(0.442)	(0.350)	(0.621)	(0.949)	(0.911)

Total	0.081	0.295	0.309	0.309	0.285	0.401
	(0.360)	(1.700)	(1.330)	(1.330)	(1.775)	(1.805)

Notes: Standard errors in parentheses. Weighted using the combined weight for each wave.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a).

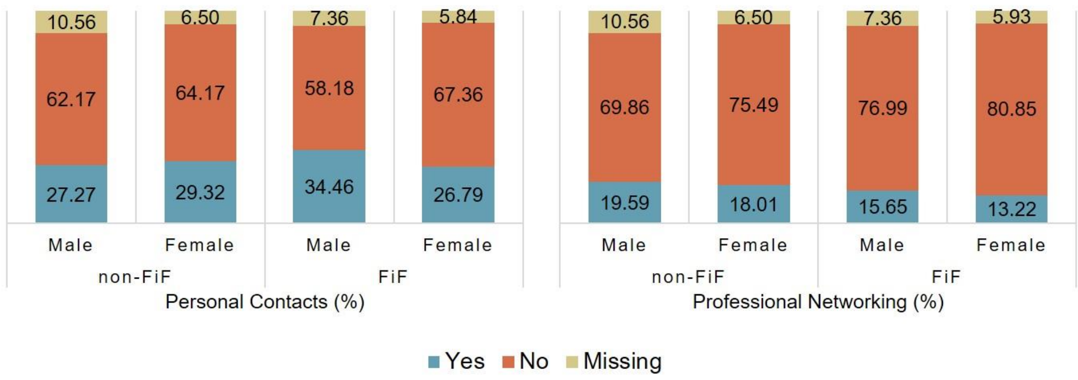
Figure 4.2 Time use variables by FiF status and gender



Notes: Standard errors in parentheses. Weighted using the combined weight for each wave.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a).

Figure 4.3 shows how graduates found their jobs at the age of 25. We find that FiF female graduates were less likely to find their jobs through personal contacts or professional networking than their non-FiF peers. For men, however, FiF men were more likely to find their jobs by personal contacts but less likely to get employed through professional networking. Thus, FiF female graduates were in a more disadvantaged place when comparing their non-FiF peers in terms of the personal network, but the difference in the personal network is not obvious between FiF and non-FiF men.

Figure 4.3 Personal network variables by FiF status and gender



Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2021). Next Steps: Sweeps 1-8, 2004-2016. [data collection]. 16th Edition. UK Data Service. SN: 5545, http://doi.org/10.5255/UKDA-SN-5545-8

4.5. Empirical strategy

In this chapter, we want to examine the relationship between FiF status and our two outcome variables: whether the participant was on furlough or paid leave and whether the participant stopped working. While our setup does not allow us to estimate the causal effects of being FiF on labour market outcomes during the pandemic, we control for a rich set of individual characteristics to reduce the selection bias and estimate a less biased association between the outcome variable and the variable of interest. We estimate linear probability models as:

$$Y_i = \alpha + \beta FiF_i + \gamma X_i + \varepsilon_i \quad (4.1)$$

where Y_i represents one of our outcome variables. FiF_i measures 'first in family' status. X_i is a vector of controls, including personal and household characteristics, pre-COVID-19 labour market characteristics, COVID-19-related variables, time use variables and personal network at age 25. i identifies the cohort member, ε_i is the error term, and α, β, and γ are the parameters we estimate. All models are weighted using the COVID-19 combined weights in the respective waves as detailed above. As men and women follow very different roles in the labour market and in the home, and the pandemic might have interacted with both, we estimate all models separately for men and women.

We start with a univariate baseline model (Model 1) to estimate the FiF gaps in labour market outcomes by gender. To minimise the influence of the heterogeneity between cohort members, we then estimate the second model (Model 2), controlling for their personal characteristics (ethnicity), educational attainment (whether graduated from a Russell Group university), and family situation (marital status, whether have child, and whether have school-aged children). In Model 3, we further control for their pre-COVID-19 labour market characteristics, including occupation (SOC code 2010), whether self-employed, whether on zero hours contract, and pre- COVID-19 working hours. As we focus on labour market outcomes during the pandemic, in the fourth model (Model 4), we add the COVID-19-related indicator, whether they had COVID. Previous work has found that time spent home-schooling and other interactive activities with children is associated with gender and employment status (Villadsen et al., 2020). Thus, the fifth model (Model 5) includes time spent on home schooling and interacting with children and caring for others. Time use variables are not available in the third wave of the COVID-19 Survey, thus we only estimate the first four models for wave three. In our final specification (Model 6), we also control for how they found out their job at age 25 as personal network could have protected them from losing their during the pandemic.

In addition, we also explore whether the associations we find are heterogenous by wave with the results available in Appendix C. As shown in Figure 4.1, the policy environment changed over time. Thus, different times and COVID-19-related policies could have an impact on the influence of the pandemic on labour market outcomes.

4.6. Results

As we mentioned before, the estimated impact of being a FiF graduate in this chapter refers to the association between FiF status and labour market outcomes rather than the causal effect of being FiF. Even though we have included a number of controls in our model, there is still a possibility that some unobserved factors are correlated with both the FiF status and labour market outcomes. Therefore, the terms, such as ‘impact’ and ‘influence’, used in this chapter demonstrate only the statistical association.

4.6.1. How does the probability of being employed but on furlough or paid leave differ by FiF status?

To compare FiF and non-FiF graduates, we use non-FiF graduates as our control group for all models. In Table 4.4, we find gender differences in terms of the relationship between being a FiF and the probability of being employed but on furlough or paid leave. Among males, the relationship between being a FiF and the probability of being employed but on furlough or paid leave is positive and significant without any controls. Once we add in personal and household characteristics, the coefficient decreases slightly from 5.4 percentage points to 4.7 percentage points but is still statistically significant. However, adding pre-COVID labour market characteristics to the model brings down the coefficient considerably to 1.5 percentage points and turns the relationship to insignificant, suggesting that FiF male graduates are more likely to be found in certain occupations where furlough was more common. Further adding COVID-19-related variables, time use variables and personal network at age 25 in Models 4, 5 and 6 has a very limited impact on both the estimated coefficients and the explanatory power of the model. Although these last three sets of controls variables could potentially be *bad controls* (i.e., might already be affected by the pandemic), controlling for them does not change our previous results.

Unlike the relationship among males, the relationship among female workers is negative and statistically significant in all models except for Model 1. The raw relationship (-4.8 percentage points) gets larger in magnitude and becomes significant when we account for personal and household characteristics in Model 2 (-6.1 percentage points) and then becomes smaller but still statistically significant after controlling for pre-COVID labour market characteristics in model 3 (-5.0 percentage points), indicating that occupations play a less important role in explaining the difference for women than for men. In our final and preferred model, we find that FiF females are 5.2 percentage points less likely than non-FiF females to be on furlough or paid leave.

Table 4.4 The probability of being employed but on furlough or paid leave by FiF status

		(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
Male							
Group	FiF	0.0538***	0.0473**	0.0153	0.0169	0.0121	0.0122
(base=non-FiF)		(0.0187)	(0.0187)	(0.0162)	(0.0163)	(0.0161)	(0.0160)
	Observations	1,239	1,239	1,239	1,239	1,239	1,239
	R-squared	0.051	0.069	0.309	0.313	0.323	0.327
Female							
Group	FiF	-0.0484	-0.0605**	-0.0498**	-0.0499**	-0.0522**	-0.0517**
(base=non-FiF)		(0.0316)	(0.0307)	(0.0225)	(0.0224)	(0.0220)	(0.0218)

Observations	2,041	2,041	2,041	2,041	2,041	2,041
R-squared	0.050	0.075	0.225	0.226	0.240	0.242
Control variables						
Personal and household characteristics		✓	✓	✓	✓	✓
Pre-COVID labour market characteristics			✓	✓	✓	✓
COVID-related variables				✓	✓	✓
Time on homeschooling and caring					✓	✓
Personal network at age 25						✓

Notes: All coefficients are estimated using ordinary least squares (OLS) regression. Missing values of the variables are controlled by using missing flags. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weighted using the combined weight for each wave.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a).

4.6.2. How does the probability of being unemployed, inactive, or other non-employed differ by FiF status?

Table 4.5 presents the estimated relationship between FiF status and the probability of being unemployed, inactive or other non-employed for males and females, respectively. Focusing on males only, we find that FiF men were less likely to be unemployed, inactive or other non-employed, but this result is small (0.2 percentage points in the final specification) and not statistically significant.

Unlike the insignificant result for their male peers, female FiF graduates are 9.9 percentage points more likely to be unemployed, inactive or other non-employed than non-FiF female graduates before we control for other factors. After controlling for personal and household characteristics in Model 2, we find that the estimated difference between FiF and non-FiF decreases slightly to 8.6 percentage points. The difference becomes much smaller (5.0 percentage points) but still significant in Model 3 once we add in pre-COVID-19 labour market characteristics, indicating that being a FiF graduate is associated with the probability of being unemployed, inactive or other non-employed partly through their pre-COVID-19 labour market characteristics. For example, compared to their FiF graduate peers, non-FiF female graduates are more likely to take managerial, directorial, professional and technical occupations, which are less likely to be affected by the pandemic. Finally, the estimated relationships in Models 4, 5 and 6, where COVID-19-related variables, time use variables and personal network at age 25 are included, are similar to estimates in Model 3.

Table 4.5 The probability of being unemployed, inactive or other non-employed by FiF status

		(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
Male							
Group (base=non-FiF)	FiF	0.00274	0.00146	-0.00192	0.000983	-0.000797	-0.00196
		(0.0410)	(0.0435)	(0.0220)	(0.0219)	(0.0220)	(0.0220)
	Observations	1,237	1,237	1,237	1,237	1,237	1,237
	R-squared	0.011	0.035	0.396	0.399	0.408	0.415
Female							
Group (base=non-FiF)	FiF	0.0990***	0.0863**	0.0495**	0.0496**	0.0480**	0.0452**
		(0.0338)	(0.0345)	(0.0200)	(0.0197)	(0.0197)	(0.0195)
	Observations	2,003	2,003	2,003	2,003	2,003	2,003
	R-squared	0.017	0.054	0.409	0.412	0.412	0.416
Control variables							
Personal and household characteristics			✓	✓	✓	✓	✓
Pre-COVID labour market characteristics				✓	✓	✓	✓
COVID-related variables					✓	✓	✓
Time on homeschooling and caring						✓	✓
Personal network at age 25							✓

Notes: All coefficients are estimated using ordinary least squares (OLS) regression. Missing values of the variables are controlled by using missing flags. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weighted using the combined weight for each wave.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a).

4.7. Discussion

This chapter focuses on the labour market outcomes of FiF and non-FiF university graduates during the COVID-19 pandemic. Our results demonstrate a differential impact of the pandemic for FiF graduates by gender when we look at what happened to those who did not keep working. The government created a brand-new means of protecting workers in industries that were forced to close during the pandemic, known as the Coronavirus Job Retention Scheme or furlough. However, we find that among women, FiF graduates became more likely to be unemployed, inactive, or other non-employed and less likely to go on a furlough or paid leave than non-FiF graduates.

Thus, our results show that FiF graduate women were more likely to have worse labour market outcomes than non-FiF female graduates whose parents attended university. Among men, however, we do not find a significant differential effect for FiF versus non-FiF graduates once we control for pre-COVID labour market characteristics.

This is consistent with the results from Adamecz-Völgyi et al. (2022) that found FiF females tend to face a penalty in the graduate labour market, while FiF males do not. They suggest that one possible explanation for this result is the gender differences in social pressure and motivation. FiF males may face more social pressure than FiF females and, thus, have a higher motivation to find higher-paid jobs. By the same reckoning, males may also have a greater motivation to negotiate with their employer to be put on furlough. Friedman (2022) also finds a “double disadvantage” for females from working-class backgrounds in the labour market than their male counterparts. He suggests that females from working-class backgrounds are less likely to talk openly about their background and this feeling of shame and inferiority tends to adversely affect their career progression. This may be a reason that they are less likely to be placed on furlough and therefore retained by their employers.

When comparing within gender, there are also several explanations for why FiF female graduates experienced worse outcomes than non-FiF female graduates. First, we have controlled for their occupations but not their specific jobs or tasks. In this chapter, we use the 3-digit Standard Occupational Classification (SOC) 2010 code, and there are 90 groups in total. It is still possible that FiF females were doing different jobs or working in different firms than their non-FiF female peers within the same SOC code. Laurison and Friedman (2016) find that individuals from non-privileged backgrounds are more likely to be employed in smaller firms and outside London.

It has also been argued that FiF females face a penalty in social networks and resources. In our sample, FiF female graduates were less likely to find their job through personal contacts and professional networking at age 25 than their non-FiF peers. A large number of previous studies have found that parental social class and networks play an important role in children’s labour market performance, especially during early adulthood (Erola et al., 2016; Härkönen and Bihagen, 2011; Skeggs, 1997; Smith, 2017). Individuals from lower socio-economic backgrounds are less likely to accumulate the same economic, cultural, and social capital as the privileged ones through family relationships. Compared with graduates with graduate parents, FiF graduates have limited occupational knowledge, information, and resources to make suitable career choices and find stable jobs. As furloughed workers are not allowed to undertake any work for their employers in the first few months when the CJRS started, it could be more attractive for employers to lay off some of the workers than keep them when no work could be done (Adams-Prassl et al., 2020). Moreover, in our sample, FiF graduates are more likely to be on a zero-hours contract that places them in a vulnerable situation where they are more likely to be laid off or put on unpaid leave when there is a shock in the economy.

4.8. Conclusion

One of the major impacts of the COVID-19 pandemic was on jobs. Entire sectors were shut down during the UK's lockdowns, and the impact of the pandemic has been felt unequally across socio-economic groups. In this chapter, we examine the impacts of the COVID-19 pandemic on labour market outcomes of first-in-family graduates. This group has received little attention in terms of how they have fared during the pandemic, despite FiF status having been shown to provide additional information over and above other measures of disadvantage. Previous research has also shown that FiF females go on to earn significantly less than those women with university-educated parents (Adamecz-Völgyi et al., 2022), and that females have been hit harder by the COVID-19 recession than in other recessions (Andrew et al., 2020; Couch et al., 2021). Hence, we explore the impact of the pandemic at the intersection of gender and FiF status.

We find that female FiF graduates experienced a higher likelihood of being unemployed, inactive or other non-employed than female graduates whose parents attended university, but no such effect for males. This result is driven by the disadvantage of both being a female and being a first in family. On the one hand, FiF females may be, on average, less motivated and less willing to express their "authentic self" than their male peers. On the other hand, they have fewer family resources to rely on and thus are less likely to find a job that is as good as their non-FiF female peers.

Despite the fact that recent recessions have usually disproportionally affected male workers, previous evidence has suggested that the COVID-19 recession is a possible 'she-cession' as women's labour market outcomes have deteriorated disproportionally during the pandemic. Our results confirm this point and further suggest that women from non-privileged backgrounds, those with non-graduate parents, are the group that has been hit the hardest by the pandemic. As the cohort members we focus on are still in their early adulthood, experiencing labour market shocks can have a long-term scarring effect on their career development.

In order to narrow gender and socio-economic gaps, the government should consider how the education system and policies can help equalise experiences across young people from different backgrounds by targeting resources to those most in need. Firstly, policymakers should ensure that affordable and reliable childcare options are available to support women’s entry into and continuance of employment. It is also important to make sure family leave is available for equitable use by males and females. Moreover, supporting policies and schemes should focus more on the poorer population through social protection measures that better preserve employment and insure workers against shocks. In addition, there should be more flexibility in working hours across sectors and occupations. Relevant policies should aim at promoting and facilitating everyone, especially low-income groups.

Chapter 5.

Conclusions

Motivated by a growing body of literature focusing on social mobility and political concerns about the worsening social inequality in England after the pandemic, this thesis investigates the intergenerational income mobility in the 1990 birth cohort in England and identifies the potential factors that drive social mobility. The three essays in this thesis contribute to the existing literature and fill in the research gap in different ways. The first essay, in the second chapter, adds more evidence on the social mobility situation in England for those born after the 1980s, with an emphasis on the drivers of social mobility. To have a closer investigation of one of the social mobility drivers—education, the second essay, the third chapter, provides a retrospective analysis of a conditional cash transfer (CCT) programme focusing particularly on its impact on higher education participation and attainment. In the third essay, the final substantive chapter, we shift our focus from schools and universities to the labour market. We enrich the literature by offering the first analysis comparing the working status of FiF graduates with their non-FiF graduate peers during the COVID-19 pandemic in England. In this concluding chapter, I will briefly review the main results and implications of each chapter and discuss the directions for future studies.

5.1. Main results and implications

As discussed in the first essay, second chapter, intergenerational income persistence is determined by two components—education inequality, which is measured by the association between parental income and children's educational outcome, and the economic returns to education. All three chapters in this thesis are closely linked in a way that the second chapter provides an overall view of the social mobility in this recent cohort while the other two chapters focus on the two components, respectively. In the third chapter, I examine how a conditional cash transfer programme, EMA, affects the first component of intergenerational income persistence (the association between parental income and children's educational outcomes). The fourth chapter explores how the COVID-19 pandemic influences the potential differences by FiF status in the second component of intergenerational income persistence (returns to education). Moreover, topics in this thesis focus on non-privileged groups, such as children from low-income families in Chapter 3 and first-in-family graduates in Chapter 4.

In Chapter 2, we examine the degree of intergenerational income persistence at age 25 among sons in England born in 1989-90 and compare our results to the estimates of persistence in the 1970 cohort using a similar sample. First, we measure the persistence by IGE, which in this thesis is represented by the association between average gross parental income at children ages 14-17 and children's gross earnings at age 25. We also estimate the rank-rank coefficient to reduce the influence of lifecycle bias and measurement error. Our estimates of intergenerational income persistence in the 1990 cohort are comparable to the estimates in the 1970 cohort, suggesting that intergenerational income persistence continues to be substantial in England and family resources during childhood play a key role in determining children's later SES as adults.

Then, the next question here is how to reduce income persistence across generations and increase social mobility in the country. To answer this question, we follow the previous studies to explore the drivers of intergenerational income persistence using a two-stage decomposition approach. We find that educational attainment, especially GCSE results, is an important mediator of intergenerational persistence in the Next Steps cohort. As the earnings of the cohort are measured at a very young age, we acknowledge that the impact of higher education has not been fully unfolded yet. Thus, in the final part of Chapter 2, we predict the IGE across the lifecycle for the 1990 cohort using the returns to education in the 1970 cohort. Our predictions suggest that the intergenerational mobility in the Next Steps cohort is similar to or slightly better than that in the 1970 cohort and that GCSE results and degree attainment are key drivers of social mobility for sons in their early 40s.

Given that educational attainment plays an important role in driving social mobility, policymakers need to ensure equal opportunities of access to education for all children and children from disadvantaged backgrounds need to be offered extra support all the way from compulsory education to higher education. As GCSE results and degree attainment are particularly important mediators of intergenerational persistence, specific policies and schemes should be proposed to raise GCSE attainment and widen higher education participation. For example, free tutorial lessons can be offered to GCSE pupils from disadvantaged backgrounds to improve their academic performance and expand their knowledge of university applications and course choices. However, socio-economic differences even exist after entering higher education. Crawford (2014) finds that children from lower SES backgrounds are 3.4 percentage points more likely to drop out, 5.3 percentage points less likely to graduate, and 3.7 percentage points less likely to graduate with a first or upper second than their peers from higher SES backgrounds on the same course. Universities, therefore, need to provide extra financial support and mentoring to vulnerable students to ensure they do not drop out of their courses because of financial difficulties and to improve their academic performance at university.

The third chapter in this thesis combines the multivariate regression model with an entropy balancing approach, which matches the mean, variance, and skewness of the covariate distributions for the EMA recipients and the non-recipients, to estimate the influence of EMA receipt on higher education participation and achievement in the Next Steps cohort. Our results suggest that EMA not only had a positive impact on participation, retention, and achievement in secondary school but also affected higher education participation and completion among children from less affluent backgrounds. After balancing the treatment and control groups, two-year EMA recipients are 19.6 and 11.8 percentage points more likely to attend higher education and obtain a first degree respectively. Thus, even though it is a costly programme, EMA could be beneficial in the long run as the lifetime returns to higher education are significant.

In 2011, the EMA was scrapped because of its high ‘deadweight’ cost—only 12% of the EMA recipients said their participation decisions were affected by the receipt. The scheme was replaced by the 16-19 Bursary Fund, which provides financial support to a much smaller group of students, with a rise in the compulsory age at which young people must be in some form of education or work-based training from 16 to 17 in 2013 and to 18 in 2015. The introduction of the new scheme reduced the annual expenses by more than two-thirds, from £560 million to £180 million. Although the combination of compulsory post-16 education and discretionary support funds is more economically favourable in the short run, it cannot keep those from low-income families on the academic track. This can pose risks to social mobility as the scrapping of EMA combined with a massive rise in higher education tuition from £3,000 to £9,000 in 2012 could discourage those from lower SES backgrounds from participating in higher education which leads to higher lifetime earnings in a longer time frame. To address the barriers to higher education, policymakers need to offer specific financial aid to those in need in order to encourage them to stay on the academic track but should also provide them with enough information to weigh the immediate costs of education and the benefits of later returns.

The final empirical chapter, Chapter 4, views the social mobility problem from a different angle, shifting the focus from educational attainment to labour market outcome. We examine the impact of the COVID-19 pandemic on the labour market experiences of FiF graduates with their non-FiF peers across three time points from May 2020 to March 2021. We find that FiF female graduates are more likely to stop working altogether or to be put on unpaid leave but less likely to be on furlough or paid leave than non-FiF female graduates. Our findings indicate an exacerbated disadvantage in the labour market arising from the intersectionality of socio-economic background and gender. Moreover, the detrimental impact of the COVID-19 recession at a young age could have potential long-term scarring effects not only on those individuals but also on social mobility issues in the country.

As the COVID-19 recession has had a greater impact on disadvantaged groups, policies need to focus on supporting workers who are female, less educated, from ethnic minorities and in lower SES backgrounds in the post-pandemic era. For example, in response to the growing popularity of remote and flexible working, policymakers should ensure that affordable and reliable childcare options are available to support women's entry into and continuance of employment, and family leave should be available for equitable use by both men and women. Moreover, supporting policies should focus not only on financial poverty but also on digital poverty, which has been playing an increasingly important role in labour market outcomes. Affordable devices and internet services should be available for all to ensure that everyone can work efficiently at home. Free training and learning platforms should be provided to the less educated and poorer population to ensure that they can have an equal opportunity to find a remote or hybrid job. Finally, social protection measures should be in place to better preserve employment and insure workers against future shocks.

5.2. Recommendations for future research

Overall, this thesis sheds new light on social mobility and inequalities in England. Although the empirical chapters in this thesis have used rich data from the 1990 cohort in 11 waves from 2004 to 2021 and have conducted a number of robustness checks, there are still limitations in this research. In this section, I will outline some potential areas for future work for each chapter.

Chapter 2 evaluates the levels of intergenerational income persistence at a relatively young age in England. Even though we try to adjust the lifecycle bias using the rank-rank coefficient and predicting the IGE across the lifecycle, our results are still likely to be biased if assumptions, such as consistent returns to education, are violated. Further research could use earnings in later waves of Next Steps to estimate less biased intergenerational income persistence in this cohort. Moreover, the Next Steps parental income is not normally distributed. For example, about 15% of cohort members had their parental income in the top income group in 2006. One possible way to make the parental income distribution in the 1990 cohort comparable to the distribution in the previous cohort is to impute those in the top income group with predicted income based on information such as parental age, ethnicity, SES status, and education. In addition, this chapter focuses on sons only to avoid the problem of female labour participation and to be comparable to the results in previous studies. There is also little existing work focusing on intergenerational income mobility among females in the UK. Thus, future work should look at the gender differences in intergenerational income mobility and explore the determinants of differences if there is a heterogeneous effect of parental income on children's earnings.

As EMA recipients were not random seleted in our sample, our analysis in Chapter 3 is likely to overestimate the impact of the allowance on higher education participation and attainment. Young people from low-income families still need to apply and stay in full-time education to get the allowance so it is likely to be the case that the the more motivated students are more likely to apply and also have higher chance to stay in education. Therefore, future work could do a mediation analysis to examine how much the impact of EMA on higher education is through participation, retention, and achievement in secondary education. Another future strand of Chapter 3 is to conduct a cost and benefit analysis of the programme by comparing the cost of the programme and the lifetime returns. Of course, the benefits of the programme are likely to be underestimated as the long-term social returns to education are hard to calculate.

In Chapter 4, we only compare the working status between FiF and non-FiF graduates during the pandemic because of the limited data (gross pay is only available in Wave 3 of the COVID-19 Survey). Future work should focus on other dimensions of labour market outcomes, such as working hours and pay. Although lives seem to be back to normal from the beginning of 2022, the impact of the COVID-19 pandemic on businesses and individuals could be long-lasting. The end of COVID-related restrictions also means the end of support, which could have a more significant influence on disadvantaged groups. Therefore, another direction of future work could be to investigate the long-term impact of the pandemic on females and those from low-SES backgrounds.

In general, this thesis provides more evidence of the trends in social mobility in England. Our findings are consistent with previous research suggesting that social mobility has stopped its worsening trend in more recent cohorts, but the COVID-19 pandemic could have exacerbated the existing inequalities and thus led to a decline in social mobility. Currently, the Next Steps Age 32 Sweep is being conducted from April 2022 to August 2023. The availability of such rich data in the near future would allow us to further explore the impact of the pandemic on the trend of social mobility as well as inequalities in education and the labour market in England.

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Appendix A. Appendix for Chapter 2

A.1. Parental income distribution

In Section 2.3.2, we suggest that differences in the variance of parental income can lead to a difference in the IGE in the two cohorts. Thus, in this appendix, we provide a detailed comparison of parental income distribution in the Next Steps and the BCS and use external sources of data to identify the time trend in the variance of parental income in order to validate our results.

Tables A1 and A2 show the distributions of annual parental income at age 16 in the BCS and the Next Steps without any sample restriction. There are 11 income groups in the BCS and 12 groups in the Next Steps. For the BCS cohort, about half of the cohort members are in the second to fourth parental income groups, while for the Next Steps, though most cohort members are also in lower middle-income groups (3-7), the group with most individuals is the top group. In order to ensure this non-normal distribution is not due to measurement errors, we check the distribution of annual gross parental income in the Family Resource Survey (FRS) in the same year, 2006. Table A3 shows that about 20% of individuals in the FRS have an annual parental income higher than £52,000. Thus, a large number of cohort members being in the top parental income group in the Next Steps is likely to be caused by bad bandings.

Table A1. Distribution of annual gross parental income at age 16 in the BCS

		N.	Percent (%)	Cumulative %
1	Under 2,600	217	3.02	3.02
2	2,600-5,199	1,222	17.01	20.03
3	5,200-7,799	1,200	16.70	36.73
4	7,800-10,399	1,241	17.27	54.00
5	10,400-12,999	992	13.81	67.81
6	13,000-15,599	783	10.90	78.71
7	15,600-18,199	507	7.06	85.76
8	18,200-20,799	306	4.26	90.02
9	20,800-23,399	276	3.84	93.86
10	23,400-25,999	127	1.77	95.63
11	26,000 or more	314	4.37	100.00
	Total	7,185	100.00	

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021b)

Table A2. Distribution of annual gross parental income at age 16 in the Next Steps

		N.	Percent (%)	Cumulative %
1	Up to 2,599	55	0.54	0.54
2	2,600-5,199	292	2.86	3.40
3	5,200-10,399	1,121	10.99	14.39
4	10,400-15,599	1,411	13.83	28.23
5	15,600-20,799	1,158	11.35	39.58
6	20,800-25,999	1,007	9.87	49.46
7	26,000-31,199	1,032	10.12	59.57
8	31,200-36,399	845	8.29	67.86
9	36,400-41,599	670	6.57	74.43
10	41,600-46,799	523	5.13	79.56
11	46,800-51,999	537	5.27	84.82
12	52,000 or more	1,548	15.18	100.00
	Total	10,199	100.00	

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a).

Table A3. Distribution of annual gross parental income (not banded) in the FRS in 2006

Percentiles	N.
10%	12,642
20%	15,996
30%	20,072
40%	24,871
50%	30,496
60%	36,068
70%	43,240
80%	52,941
90%	68,783

Notes: Sample includes parents with children, boys and girls, aged 11-19, in England.
Source: Department for Work and Pensions, Office for National Statistics, Social and Vital Statistics Division, National Centre for Social Research (2014c)

Another issue we have noticed is that the variance in the Next Steps parental income is larger than that in the BCS. Table A4 presents the variance in parental income at ages 10 and 16 for the BCS cohort and at ages 14-16 for the Next Steps cohort. Focusing on age 16, we can see that the variance in the Next Steps parental income is 0.05 larger than that in the BCS. To see whether the difference in income variance is led by time trends, we explore the variance in parental income from 1983 to 2007 using the Family Expenditure Survey (FES) and the Family Resource Survey (FES).

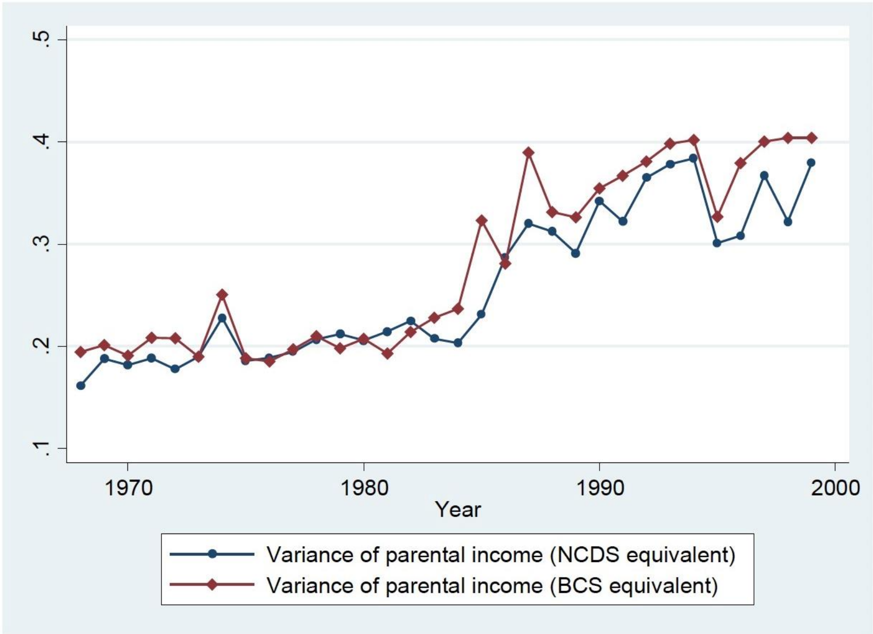
Table A4. Variance in log parental income for restricted sample (regression sample)

	BCS	Next Steps
Age 10	0.259	
Age 14		0.863
Age 15		0.569
Age 16	0.348	0.398
Age 17		0.434

Notes: Variance calculated using weighted gross parental monthly income for BCS and weighted gross parental monthly

income for NS. Sample restricted to parents with sons in England.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a, 2021b).

Figure A1. Variance in FES net parental income over time: NCDS[22] and BCS equivalent measures



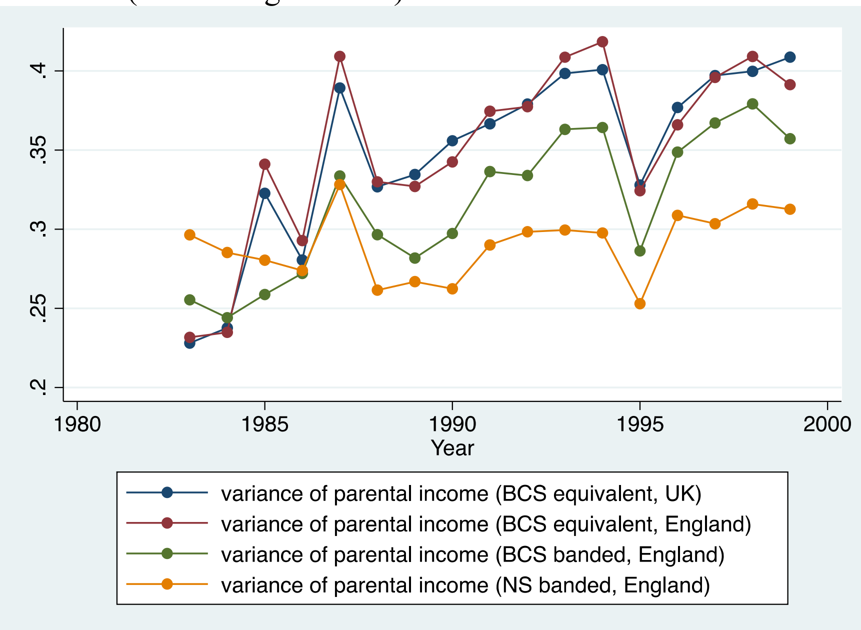
Notes: Sample is entire UK. Variance calculated using net parental weekly income. Sample includes parents with children, boys and girls, aged 10-16. All prices deflated to 2001 prices.
Source: Blanden et al. (2013)

According to Blanden et al. (2013), the variance in FES net parental income increases gradually from just above 0.2 to around 0.35 from 1980 to 1990, and then it fluctuates between 0.3 to 0.4 during the last decade of the 20th century (Figure A1). We replicate their BCS equivalent measure, which uses the income of the head of the household and the partner as parental income. Moreover, we use BCS banded measure, and Next Steps banded measures by converting FES and FRS continuous income into banded income based on the proportion of 11 income bands as in Sweep 4 of BCS and the proportion of 12 income bands as in Wave 3 of Next Steps respectively. We also restrict the sample to England, focus on children aged 11-19, and use gross parent income instead of the net income to make the variance in the external datasets more comparable to that in the BCS and the Next Steps. Figures A2-4 and Tables A5-7 show the variance in FES parental income from 1983 to 1999, while Figures A5-7 and Tables A8-10 show the variance in FES parental income from 1997 to 2007. We find that the variance in parental income rises steadily until 1994, and

[22] The 1958 National Child Development Study (NCDS) is a cohort study following lives of 17,415 people born in the UK in a single week of 1958.

the variance in parental income in 1986 is lower than that in 2006 according to various measures and sample restrictions.

Figure A2. Variance in FES net parental income over time: BCS and Next Steps equivalent measures (children aged 10-16)

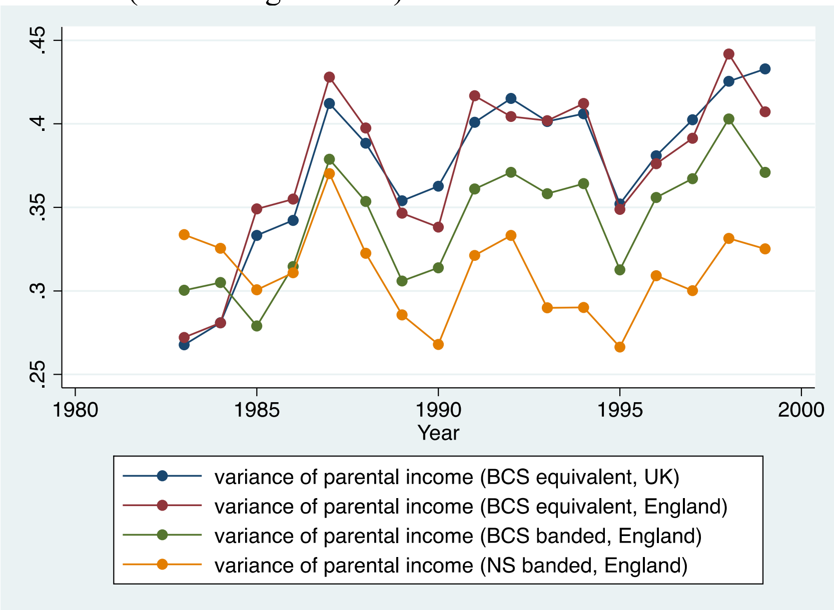


Notes: Variance calculated using net parental weekly income. Sample includes parents with children, boys and girls, aged 10-16. Prices deflated to 2001 prices. 'BCS banded' refers to the distribution of 1970 British Cohort Study income bands, which include 11 bands as in Sweep 4 of BCS. 'NS banded' refers to the distribution of Next Steps income bands, which include 12 bands as in Wave 3 of Next Steps.
Source: Family Expenditure Survey (1983-1999)[23]

[23] Data Source for Figures A2-4 and and Tables A5-7:

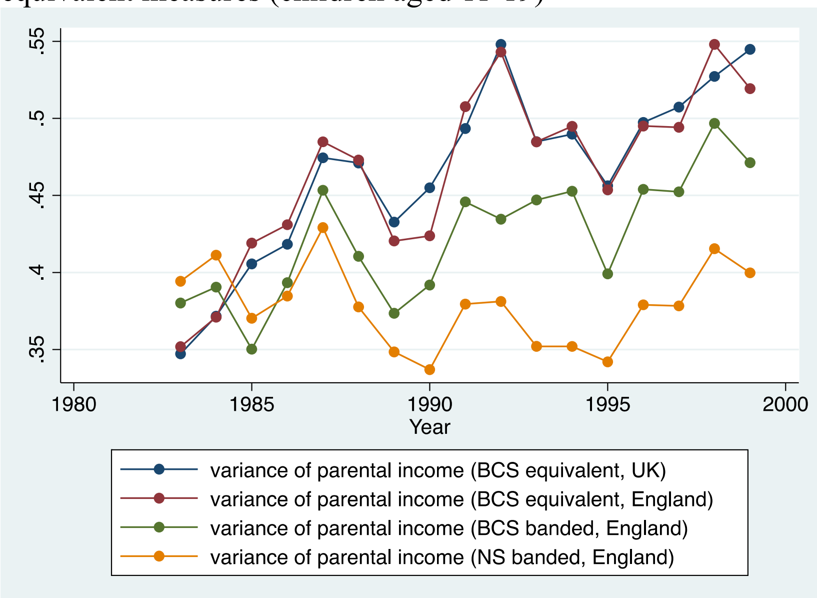
Central Statistical Office, 1992a, *Family Expenditure Survey, 1989*. [data collection]. UK Data Service. SN: 2916, DOI: 10.5255/UKDA-SN-2916-1; Central Statistical Office, 1992b, *Family Expenditure Survey, 1990*. [data collection]. UK Data Service. SN: 2918, DOI: 10.5255/UKDA-SN-2918-1; Central Statistical Office, 1992c, *Family Expenditure Survey, 1991*. [data collection]. UK Data Service. SN: 2944, DOI: 10.5255/UKDA-SN-2944-1; Central Statistical Office, 1993, *Family Expenditure Survey, 1992*. [data collection]. UK Data Service. SN: 3064, DOI: 10.5255/UKDA-SN-3064-1; Central Statistical Office, 1994, *Family Expenditure Survey, 1993*. [data collection]. UK Data Service. SN: 3242, DOI: 10.5255/UKDA-SN-3242-1; Central Statistical Office, 1995, *Family Expenditure Survey, 1993-1994*. [data collection]. UK Data Service. SN: 3280, DOI: 10.5255/UKDA-SN-3280-1; Central Statistical Office, 1996, *Family Expenditure Survey, 1994-1995*. [data collection]. UK Data Service. SN: 3478, DOI: 10.5255/UKDA-SN-3478-1; Central Statistical Office, 1997, *Family Expenditure Survey, 1995-1996*. [data collection]. 2nd Edition. UK Data Service. SN: 3635, DOI: 10.5255/UKDA-SN-3635-1; Department of Employment, 1985, *Family Expenditure Survey, 1983*. [data collection]. UK Data Service. SN: 2016, DOI: 10.5255/UKDA-SN-2016-1; Department of Employment, 1986, *Family Expenditure Survey, 1984*. [data collection]. UK Data Service. SN: 2136, DOI: 10.5255/UKDA-SN-2136-1; Department of Employment, 1987, *Family Expenditure Survey, 1985*. [data collection]. UK Data Service. SN: 2214, DOI: 10.5255/UKDA-SN-2214-1; Department of Employment, 1989a, *Family Expenditure Survey, 1986*. [data collection]. UK Data Service. SN: 2556, DOI: 10.5255/UKDA-SN-2556-1; Department of Employment, 1989b, *Family Expenditure Survey, 1987*. [data collection]. UK Data Service. SN: 2647, DOI: 10.5255/UKDA-SN-2647-1; Department of Employment, 1990, *Family Expenditure Survey, 1988*. [data collection]. UK Data Service. SN: 2683, DOI: 10.5255/UKDA-SN-2683-1; Office for National Statistics, 1999, *Family Expenditure Survey, 1997-1998*. [data collection]. UK Data Service. SN: 3963, DOI: 10.5255/UKDA-SN-3963-1; Office for National Statistics, 2000a, *Family Expenditure Survey, 1996-1997*. [data collection]. 2nd Edition. UK Data Service. SN: 3783, DOI:

Figure A3. Variance in FES net parental income over time: Next Steps and BCS equivalent measures (children aged 11-19)



Notes: Variance calculated using net parental weekly income. Sample includes parents with children, boys and girls, aged 11-19. 'BCS banded' refers to the distribution of 1970 British Cohort Study income bands, which include 11 bands as in Sweep 4 of BCS. 'NS banded' refers to the distribution of Next Steps income bands, which include 12 bands as in Wave 3 of Next Steps.
Source: Family Expenditure Survey (1983-1999)

Figure A4. Variance in FES gross parental income over time: Next Steps and BCS equivalent measures (children aged 11-19)



Notes: Variance calculated using gross parental weekly income. Sample includes parents with children, boys and girls, aged 11-19. 'BCS banded' refers to the distribution of 1970 British Cohort Study income bands, which include 11 bands as in Sweep 4 of BCS. 'NS banded' refers to the distribution of Next Steps income bands, which include 12 bands as in Wave 3 of Next Steps.
Source: Family Expenditure Survey (1983-1999)

10.5255/UKDA-SN-3783-1; Office for National Statistics, 2000b, *Family Expenditure Survey, 1998-1999*. [data collection]. UK Data Service. SN: 4071, DOI: 10.5255/UKDA-SN-4071-1.

Table A5. Variance in FES net parental income over time: BCS and Next Steps equivalent measures

Year	Variance (BCS equivalent, UK)	Variance (BCS equivalent, England)	Variance (BCS banded, England)	Variance (NS banded, England)
83	0.228	0.232	0.255	0.296
84	0.238	0.235	0.244	0.285
85	0.323	0.341	0.259	0.280
86	0.281	0.293	0.272	0.274
87	0.389	0.409	0.334	0.328
88	0.327	0.330	0.297	0.262
89	0.335	0.327	0.282	0.267
90	0.356	0.343	0.297	0.262
91	0.367	0.375	0.336	0.290
92	0.379	0.377	0.334	0.298
93	0.398	0.409	0.363	0.299
94	0.401	0.418	0.364	0.298
95	0.328	0.324	0.286	0.253
96	0.377	0.366	0.349	0.309
97	0.397	0.396	0.367	0.303
98	0.400	0.409	0.379	0.316
99	0.409	0.391	0.357	0.313

Notes: Variance calculated using net parental weekly income. Sample includes parents with children, boys and girls, aged 10-16. Prices deflated to 2001 prices. 'BCS banded' refers to the distribution of 1970 British Cohort Study income bands, which include 11 bands as in Sweep 4 of BCS. 'NS banded' refers to the distribution of Next Steps income bands, which include 12 bands as in Wave 3 of Next Steps.
Source: Family Expenditure Survey (1983-1999)

Table A6. Variance in FES net parental income over time: Next Steps and BCS equivalent measures (children aged 11-19)

Year	Variance (BCS equivalent, UK)	Variance (BCS equivalent, England)	Variance (BCS banded, England)	Variance (NS banded, England)
83	0.268	0.272	0.300	0.334
84	0.281	0.281	0.305	0.325
85	0.333	0.349	0.279	0.301
86	0.342	0.355	0.315	0.311
87	0.412	0.428	0.379	0.370
88	0.388	0.397	0.354	0.323
89	0.354	0.347	0.306	0.286
90	0.363	0.338	0.314	0.268
91	0.401	0.417	0.361	0.321
92	0.415	0.404	0.371	0.333
93	0.401	0.402	0.358	0.290
94	0.406	0.412	0.364	0.290
95	0.352	0.349	0.313	0.266
96	0.381	0.376	0.356	0.309
97	0.402	0.391	0.367	0.300
98	0.425	0.442	0.403	0.331
99	0.433	0.407	0.371	0.325

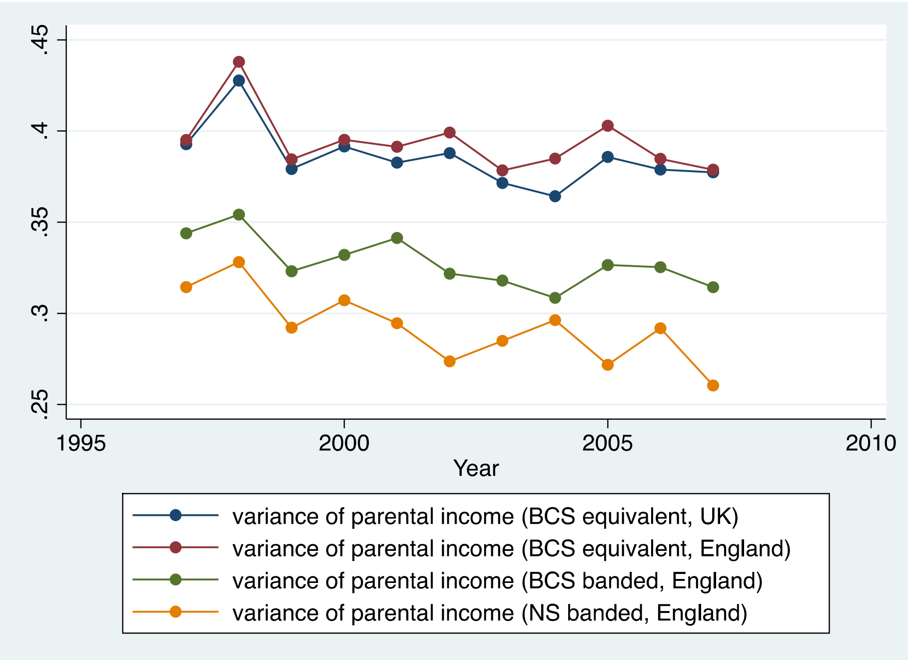
Notes: Variance calculated using net parental weekly income. Sample includes parents with children, boys and girls, aged 11-19. 'BCS banded' refers to the distribution of 1970 British Cohort Study income bands, which include 11 bands as in Sweep 4 of BCS. 'NS banded' refers to the distribution of Next Steps income bands, which include 12 bands as in Wave 3 of Next Steps.
Source: Family Expenditure Survey (1983-1999)

Table A7. Variance in FES gross parental income over time: Next Steps and BCS equivalent measures (children aged 11-19)

Year	Variance (BCS equivalent, UK)	Variance (BCS equivalent, England)	Variance (BCS banded, England)	Variance (NS banded, England)
83	0.347	0.352	0.380	0.394
84	0.372	0.371	0.390	0.411
85	0.406	0.419	0.350	0.370
86	0.418	0.431	0.393	0.385
87	0.474	0.485	0.453	0.429
88	0.471	0.473	0.410	0.378
89	0.433	0.420	0.373	0.348
90	0.455	0.424	0.392	0.337
91	0.493	0.508	0.446	0.379
92	0.548	0.543	0.435	0.381
93	0.485	0.485	0.447	0.352
94	0.490	0.495	0.453	0.352
95	0.456	0.454	0.399	0.342
96	0.497	0.495	0.454	0.379
97	0.507	0.494	0.452	0.378
98	0.527	0.548	0.497	0.415
99	0.545	0.519	0.471	0.400

Notes: Variance calculated using gross parental weekly income. Sample includes parents with children, boys and girls, aged 11-19. 'BCS banded' refers to the distribution of 1970 British Cohort Study income bands, which include 11 bands as in Sweep 4 of BCS. 'NS banded' refers to the distribution of Next Steps income bands, which include 12 bands as in Wave 3 of Next Steps.
Source: Family Expenditure Survey (1983-1999)

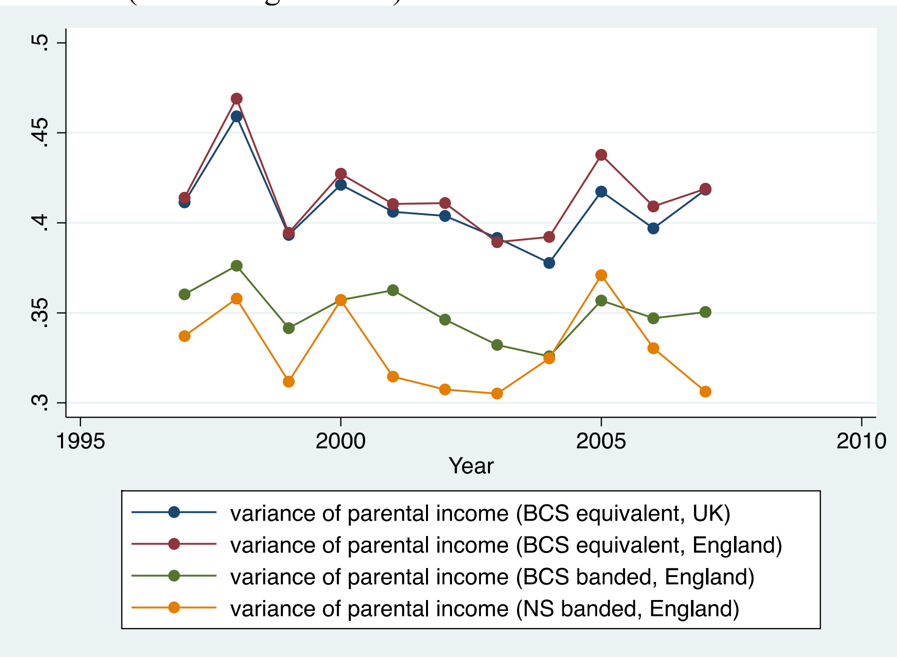
Figure A5. Variance in FRS net parental income over time: BCS and Next Steps equivalent measures



Notes: Variance calculated using net parental weekly income. Sample includes parents with children, boys and girls, aged 10-16. Prices deflated to 2001 prices. 'BCS banded' refers to the distribution of 1970 British Cohort Study income bands, which include 11 bands as in Sweep 4 of BCS. 'NS banded' refers to the distribution of Next Steps income bands, which include 12 bands as in Wave 3 of Next Steps.
Source: Family Resource Survey (1997-2007)[24]

[24] Data Source for Figures A5-7 and and Tables A8-10:

Figure A6. Variance in FRS net parental income over time: Next Steps and BCS equivalent measures (children aged 11-19)



Notes: Variance calculated using net parental weekly income. Sample includes parents with children, boys and girls, aged 11-19. 'BCS banded' refers to the distribution of 1970 British Cohort Study income bands, which include 11 bands as in Sweep 4 of BCS. 'NS banded' refers to the distribution of Next Steps income

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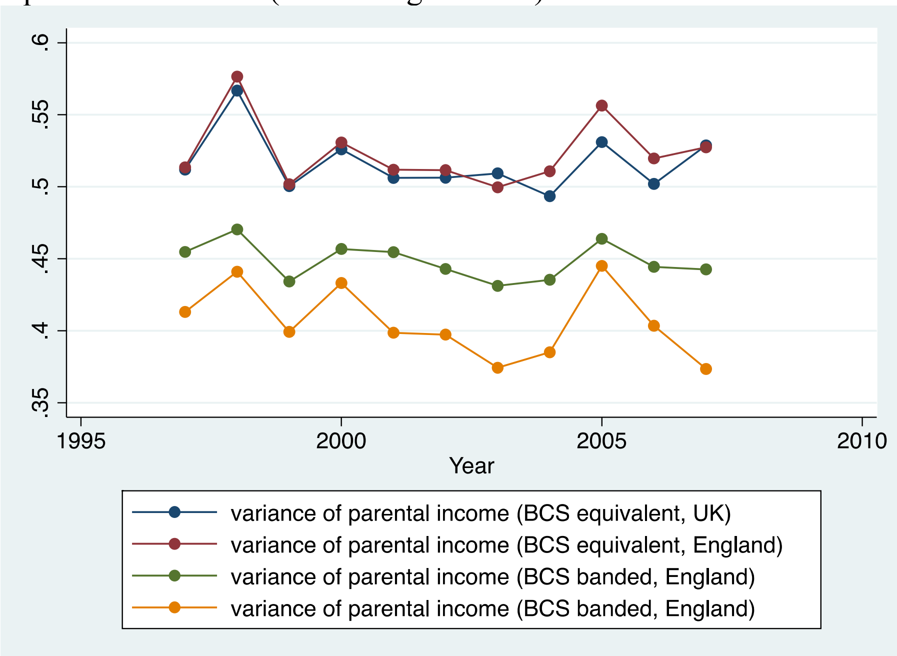
Department for Work and Pensions, National Centre for Social Research, Office for National Statistics, Social Survey Division, Department of Social Security, 2005, *Family Resources Survey, 1999-2000*, [data collection], UK Data Service, *4th Edition*. SN: 4389, DOI: 10.5255/UKDA-SN-4389-1; Department for Work and Pensions, National Centre for Social Research, Office for National Statistics, Social and Vital Statistics Division, 2014a, *Family Resources Survey, 2004-2005*, [data collection], UK Data Service, *3rd Edition*. SN: 5291, DOI: 10.5255/UKDA-SN-5291-2; Department for Work and Pensions, Office for National Statistics, Social and Vital Statistics Division, National Centre for Social Research, 2014b, *Family Resources Survey, 2006-2007*, [data collection], UK Data Service, *3rd Edition*. SN: 6079, DOI: 10.5255/UKDA-SN-6079-2; Department for Work and Pensions, Office for National Statistics, Social and Vital Statistics Division, National Centre for Social Research, 2014c, *Family Resources Survey, 2007-2008*, [data collection], UK Data Service, *2nd Edition*. SN: 6252, DOI: 10.5255/UKDA-SN-6252-2; Department for Work and Pensions, National Centre for Social Research, Office for National Statistics, Social and Vital Statistics Division, 2014d, *Family Resources Survey, 2003-2004*, [data collection], UK Data Service, *5th Edition*. SN: 5139, DOI: 10.5255/UKDA-SN-5139-2; National Centre for Social Research, Department for Work and Pensions, Office for National Statistics, Social Survey Division, Department of Social Security, 2005, *Family Resources Survey, 1998-1999*, [data collection], UK Data Service, *4th Edition.* SN: 4149, DOI: 10.5255/UKDA-SN-4149-1; National Centre for Social Research, Department for Work and Pensions, Office for National Statistics, Social and Vital Statistics Division, 2014, *Family Resources Survey, 2002-2003*, [data collection], UK Data Service, *5th Edition*. SN: 4803, DOI: 10.5255/UKDA-SN-4803-2; National Centre for Social Research, Office for National Statistics, Social Survey Division, Department for Work and Pensions, 2005, *Family Resources Survey, 2001-2002*, [data collection], UK Data Service, *3rd Edition*. SN: 4633, DOI: 10.5255/UKDA-SN-4633-1; National Centre for Social Research, Office for National Statistics, Social and Vital Statistics Division, Department for Work and Pensions, 2014, *Family Resources Survey, 2005-2006*, [data collection], UK Data Service, *2nd Edition*. SN: 5742, DOI: 10.5255/UKDA-SN-5742-2; Office for National Statistics, Social Survey Division, Department for Work and Pensions, Department of Social Security, National Centre for Social Research, 2005a, *Family Resources Survey, 1997-1998*, [data collection], UK Data Service, *6th Edition.* SN: 4068, DOI: 10.5255/UKDA-SN-4068-1; Office for National Statistics, Social Survey Division, Department of Social Security, Department for Work and Pensions, National Centre for Social Research, 2005b, *Family Resources Survey, 2000-2001*, [data collection], UK Data Service, *3rd Edition*. SN: 4498, DOI: 10.5255/UKDA-SN-4498-1

bands, which include 12 bands as in Wave 3 of Next Steps.
Source: Family Resource Survey (97-07)

Figure A7. Variance in FES parental gross income over time: Next Steps and BCS equivalent measures (children aged 11-19)



Notes: Variance calculated using gross parental weekly income. Sample includes parents with children, boys and girls, aged 11-19. 'BCS banded' refers to the distribution of 1970 British Cohort Study income bands, which include 11 bands as in Sweep 4 of BCS. 'NS banded' refers to the distribution of Next Steps income bands, which include 12 bands as in Wave 3 of Next Steps.
Source: Family Resource Survey (1997-2007)

Table A8. Variance in FRS net parental income over time: BCS and Next Steps equivalent measures

Year	Variance (BCS equivalent, UK)	Variance (BCS equivalent, England)	Variance (BCS banded, England)	Variance (NS banded, England)
97	0.393	0.395	0.344	0.314
98	0.428	0.438	0.354	0.328
99	0.379	0.384	0.323	0.292
00	0.392	0.395	0.332	0.307
01	0.383	0.391	0.341	0.295
02	0.388	0.399	0.322	0.274
03	0.372	0.378	0.318	0.285
04	0.364	0.385	0.308	0.296
05	0.386	0.403	0.327	0.272
06	0.379	0.385	0.325	0.292
07	0.377	0.379	0.314	0.260

Notes: Variance calculated using net parental weekly income. Sample includes parents with children, boys and girls, aged 10-16. Prices deflated to 2001 prices. 'BCS banded' refers to the distribution of 1970 British Cohort Study income bands, which include 11 bands as in Sweep 4 of BCS. 'NS banded' refers to the distribution of Next Steps income bands, which include 12 bands as in Wave 3 of Next Steps.
Source: Family Resource Survey (1997-2007)

Table A9. Variance in FRS net parental income over time: Next Steps and BCS equivalent measures (children aged 11-19)

Year	Variance (BCS equivalent, UK)	Variance (BCS equivalent, England)	Variance (BCS banded, England)	Variance (NS banded, England)
97	0.411	0.414	0.360	0.337
98	0.459	0.469	0.376	0.358
99	0.393	0.394	0.342	0.312
00	0.421	0.427	0.357	0.357
01	0.406	0.410	0.363	0.315
02	0.404	0.411	0.346	0.307
03	0.392	0.389	0.332	0.305
04	0.378	0.392	0.326	0.325
05	0.417	0.438	0.357	0.371
06	0.397	0.409	0.347	0.330
07	0.418	0.419	0.350	0.306

Notes: Variance calculated using net parental weekly income. Sample includes parents with children, boys and girls, aged 11-19. 'BCS banded' refers to the distribution of 1970 British Cohort Study income bands, which include 11 bands as in Sweep 4 of BCS. 'NS banded' refers to the distribution of Next Steps income bands, which include 12 bands as in Wave 3 of Next Steps.
Source: Family Resource Survey (1997-2007)

Table A10. Variance in FRS gross parental income over time: Next Steps and BCS equivalent measures (children aged 11-19)

Year	Variance (BCS equivalent, UK)	Variance (BCS equivalent, England)	Variance (BCS banded, England)	Variance (NS banded, England)
97	0.512	0.513	0.455	0.413
98	0.567	0.577	0.470	0.441
99	0.500	0.502	0.434	0.399
00	0.526	0.531	0.457	0.433
01	0.506	0.512	0.455	0.399
02	0.506	0.512	0.443	0.397
03	0.509	0.500	0.431	0.374
04	0.493	0.511	0.435	0.385
05	0.531	0.556	0.464	0.445
06	0.502	0.520	0.444	0.403
07	0.529	0.527	0.443	0.374

Notes: Variance calculated using gross parental weekly income. Sample includes parents with children, boys and girls, aged 11-19. 'BCS banded' refers to the distribution of 1970 British Cohort Study income bands, which include 11 bands as in Sweep 4 of BCS. 'NS banded' refers to the distribution of Next Steps income bands, which include 12 bands as in Wave 3 of Next Steps.
Source: Family Resource Survey (1997-2007)

A.2. A comparison with the BCS

Table A11 compares the change in intergenerational income elasticity (IGE) and relationships between mediating variables for sons in the BCS and Next Steps. Unlike in the main result section, where we include both numbers and total points of GCSEs and A-levels, we here only use the numbers to control for KS 4 and 5 attainments in order to compare our estimate for the Next Steps cohort to that for the BCS cohort.

Table A11. Comparison of intergenerational income elasticity (IGE) and relationships between mediating variables for BCS and Next Steps

		Conditional earnings regressions BCS				Conditional earnings regressions Next Steps		
	Parental income bivariate BCS	1	2	3	Parental income bivariate NS	1	2	3
Av. parent income		0.137	0.106	0.105		0.087	0.070	0.068
		(0.018)***	(0.018)***	(0.018)***		(0.020)***	(0.020)***	(0.020)***
Maths at 10 / KS2	0.318	0.048	0.028	0.028	0.298	0.051	0.022	0.021
	(0.035)***	(0.015)***	(0.015)*	(0.015)*	(0.060)***	(0.016)***	(0.016)	(0.016)
Reading at 10 / KS2	0.278	0.009	-0.009	-0.009	0.391	0.039	0.013	0.013
	(0.035)***	(0.015)	(0.014)	(0.015)	(0.052)***	(0.018) **	(0.018)	(0.018)
Application at 10/Academic self-concept	0.183	0.031	0.016	0.016	0.107	0.027	0.013	0.011
	(0.034)***	(0.012)**	(0.012)	(0.012)	(0.055)*	(0.012) **	(0.012)	(0.012)
Anxious at 10 / GHQ-12 score	-0.124	-0.025	-0.026	-0.026	-0.007	-0.001	0.000	0.000
	(0.037)***	(0.012)**	(0.011)**	(0.011)**	(0.123)	(0.005)	(0.005)	(0.005)
Number of GCSEs	1.986		0.019	0.018	1.956		0.019	0.017
	(0.139)***		(0.003)***	(0.004)***	(0.217)***		(0.003)***	(0.004)***
Number of A-levels	0.569			0.008	0.091			-0.005
	(0.053)***			(0.009)	(0.043)**			(0.009)
Degree	0.179			-0.010	0.136			0.012
	(0.017)***			(0.028)	(0.020)***			(0.024)
R^2		0.073	0.095	0.095		0.119	0.139	0.140
N	2,128	2,128	2,128	2,128	1,713	1,713	1,713	1,713

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a, 2021b, 2022)

Table A12. Decomposition of intergenerational income elasticity (IGE) for BCS and Next Steps gross income

	Decomposition BCS			Decomposition Next Steps		
	1	2	3	1	2	3
Direct Av. parent income	**0.137**	**0.106**	**0.105**	**0.087**	**0.067**	**0.068**
Total through education	**0.026**	**0.052**	**0.056**	**0.033**	**0.051**	**0.047**
Total through missings	**0.002**	**0.007**	**0.004**	**0.005**	**0.007**	**0.010**
Total intergen elasticity	**0.165**	**0.165**	**0.165**	**0.125**	**0.125**	**0.125**
Maths at 10 / KS2	0.016	0.010	0.010	0.015	0.007	0.006
Reading at 10 / KS2	0.003	-0.003	-0.003	0.015	0.005	0.005
Application at 10/ Academic self-concept	0.003	0.002	0.002	0.003	0.001	0.001
Anxious at 10 / GHQ-12 score	0.004	0.004	0.004	0.000	0.000	0.000
Total through early skills	**0.026**	**0.013**	**0.013**	**0.033**	**0.013**	**0.012**
Number of GCSEs		0.040	0.040		0.038	0.034
Total through compulsory		**0.040**	**0.040**		**0.038**	**0.034**
Number of A-levels			0.006			0.000
Degree			-0.002			0.001
Total through post-16			**0.004**			**0.001**
N	2,128	2,128	2,128	1,713	1,713	1,713

Notes: Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a, 2021b, 2022)

Table A13. Comparison of rank-rank association and relationships between mediating variables for BCS and Next Steps

		Conditional earnings regressions BCS				Conditional earnings regressions Next Steps		
	Parental income bivariate BCS	1	2	3	Parental income bivariate NS	1	2	3
Av. parent income		0.188	0.143	0.141		0.166	0.138	0.135
		(0.022)***	(0.022)***	(0.022)***		(0.030)***	(0.030)***	(0.023)***
Maths at 10 / KS2	0.115	0.192	0.111	0.108	0.006	3.834***	1.732	1.676
	(0.013)***	(0.053)***	(0.052)**	(0.052)**	(0.001)***	(1.229)	(1.229)	(1.234)
Reading at 10 / KS2	0.107	0.009	-0.066	-0.066	0.008	2.639**	0.686	0.671
	(0.013)***	(0.053)	(0.051)	(0.051)	(0.001)***	(1.296)	(1.287)	(1.289)
Application at 10/Academic self-concept	0.070	0.103	0.043	0.041	0.003	1.831**	0.811	0.708
	(0.012)***	(0.043)**	(0.043)	(0.043)	(0.001)**	(0.882)	(0.891)	(0.904)
Anxious at 10 / GHQ-12 score	-0.046	-0.104	-0.107	-0.108	-0.001	-0.135	-0.101	-0.0984
	(0.013)***	(0.037)***	(0.036)***	(0.036)***	(0.003)	(0.383)	(0.371)	(0.372)
Number of GCSEs	0.706		0.079	0.071	0.043		1.442***	1.326***
	(0.050)***		(0.010)***	(0.012)***	(0.005)***		(0.255)	(0.280)
Number of A-levels	0.202			0.012	0.002			-0.190
	(0.019)***			(0.033)	(0.001)**			(0.700)
Degree	0.065			0.105	0.003			0.538
	(0.006)***			(0.101)	(0.000)***			(1.822)
R^2		0.085	0.115	0.116		0.124	0.144	0.145
N	2,128	2,128	2,128	2,128	1,713	1,713	1,713	1,713

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a, 2021b, 2022)

Table A14. Decomposition of rank-rank association for BCS and Next Steps gross income

	Decomposition BCS			Decomposition Next Steps		
	1	2	3	1	2	3
Direct Av. parent income	**0.188**	**0.143**	**0.141**	**0.166**	**0.138**	**0.135**
Total through education	**0.039**	**0.071**	**0.074**	**0.051**	**0.081**	**0.076**
Total through missings	**-0.004**	**0.009**	**0.008**	**0.007**	**0.005**	**0.013**
Total intergen elasticity	**0.223**	**0.223**	**0.223**	**0.224**	**0.224**	**0.224**
Maths at 10 / KS2	0.022	0.013	0.012	0.024	0.011	0.010
Reading at 10 / KS2	0.001	-0.007	-0.007	0.022	0.006	0.005
Application at 10/ Academic self-concept	0.011	0.005	0.004	0.005	0.002	0.002
Anxious at 10 / GHQ-12 score	0.005	0.005	0.005	0.000	0.000	0.000
Total through early skills	**0.039**	**0.015**	**0.015**	**0.051**	**0.019**	**0.017**
Number of GCSEs		0.056	0.050		0.062	0.057
Total through compulsory		**0.056**	**0.050**		**0.062**	**0.057**
Number of A-levels			0.002			0.000
Degree			0.007			0.002
Total through post-16			**0.009**			**0.002**
N	2,128	2,128	2,128	1,713	1,713	1,713

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a, 2021b, 2022)

For the BCS, the relationship between parental income and all chosen factors is statistically significant. For the Next Step, however, there is no statistically significant relationship between parental income and GHQ-12 score and the association between parental income and academic self-concept is weaker. In the first specification, KS2 mathematic scores play an important role in explaining future earnings for both cohorts. After adding number of GCSEs into the model, the estimates for most early skills and educational attainments become statistically insignificant. Results in the final specification show that the positive relationship between number of GCSEs and earnings is statistically significant at the one per cent level for both cohorts. Moreover, sons' earnings are also associated with anxious at age 10 for the BCS. In order to have a clearer picture of how these factors contribute to the IGE, we then turn to the decomposition approach.

The results presented in Table A12 show the decomposition of the overall income persistence in the BCS and Next Steps cohorts. The income persistence is decomposed into the contribution of each factor by multiplying the coefficient of each mediating variable by its relationship with parental income. The results suggest that educational factors contribute a great part of intergenerational income persistence for both cohorts, especially for Next Steps. As we add more educational attainment variables into our models, the coefficients for average parental income and early skills drop. It suggests that parental income and early skills affect sons' earnings by influencing educational attainments. In the final specification, the direct effect of parental income accounts for 64% of the IGE for the BCS and 54% of the IGE for the Next Steps, while early skills and education are responsible for 34% and 38% for the BCS and Next Steps, respectively. The rest of the intergenerational income persistence is accounted for by variable missingness.

The results for the rank-rank association and decomposition show a similar picture. Number of GCSEs is the most important factor explaining the persistence between parental income and sons' earnings at a young age. In general, early skills and later educational attainment explain 33% and 34% of the persistence in the positions of parental income and sons' earnings in the BCS and Next Steps, respectively. Based on the decomposition results of IGE and rank-rank association for the two cohorts, we can conclude that educational attainment, especially the KS4 results, is an important driver of intergenerational income mobility in the country. It is also worth to be noted that earnings at ages 25 and 26 are still too early to be affected by degree attainment. Previous studies have found that, as the cohort member grows older, a university degree would play an increasingly important role in driving mobility.

A.3. Mediation analysis using two-year average parental income

As we have discussed in Section and Appendix A.1, the variance in parental income at ages 14 and 15, especially at age 14, in the Next Steps is considerably higher than that in the external dataset. Thus, in this appendix section, we estimate the IGE and rank-rank association using average parental income at ages 16 and 17.

Table A15 presents the results of the IGE, rank-rank association, and relationships between mediating variables using the two-year average parental income. Except for the GHQ-12 score, the relationships between all chosen factors and parental income are statistically significant at the 5% level. Similar to the results using four-year average parental income, the GCSE result plays an important role in explaining intergenerational income persistence and early skills are likely to affect earnings through later educational attainment. Focusing on the decomposition of income persistence, we find that early skills and education are responsible for 37% and 33% of the IGE and rank-rank coefficient, respectively, while 54% of the IGE and 59% of the rank-rank coefficient are explained by the direct effect of parental income (see the last specification in Table A16). These results are close to the results using four-year average parental income. Thus, we can see that, although variance in parental income is quite high at ages 14 and 15, it has a limited impact on our estimated IGE and rank-rank association and the decompositions.

Table A15. Intergenerational income elasticity (IGE), rank-rank association, and relationships between mediating variables for Next Steps

	Conditional earnings regressions IGE				Conditional earnings regressions rank-rank association			
	Parental income bivariate	1	2	3	Parental income bivariate	1	2	3
Av. parent income		0.104 (0.024)***	0.081 (0.023)***	0.079 (0.023)***		0.179 (0.034)***	0.145 (0.034)***	0.143 (0.033)***
Maths at 10 / KS2	0.314 (0.066)***	0.058 (0.018)***	0.028 (0.018)	0.027 (0.018)	0.006 (0.001)***	4.240 (1.332)***	2.040 (1.333)	1.980 (1.342)
Reading at 10 / KS2	0.412 (0.058)***	0.031 (0.020)	0.001 (0.021)	0.001 (0.021)	0.008 (0.001)***	2.220 (1.470)	0.016 (1.476)	0.009 (1.482)
Application at 10/Academic self-concept	0.137 (0.066)**	0.036 (0.013)***	0.021 (0.013)	0.020 (0.014)	0.003 (0.001)**	2.460 (0.992)**	1.336 (0.996)	1.290 (1.012)
Anxious at 10 / GHQ-12 score	-0.003 (0.017)	0.001 (0.006)	0.001 (0.005)	0.001 (0.005)	-0.001 (0.003)	-0.014 (0.422)	0.028 (0.412)	0.027 (0.414)
Number of GCSEs	2.223 (0.249)***		0.021 (0.004)***	0.020 (0.004)***	0.043 (0.005)***		1.578 (0.292)***	1.500 (0.312)***
Number of A-levels	0.115 (0.048)**			-0.009 (0.010)	0.002 (0.001)**			-0.612 (0.726)
Degree	0.155 (0.022)***			0.005 (0.026)	0.003 (0.000)***			0.064 (1.978)
R^2		0.121	0.144	0.145		0.127	0.151	0.151
N	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440

Notes: Estimated using two-year average parental income. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a, 2021b, 2022)

Table A16. Decomposition of intergenerational income elasticity (IGE) and rank-rank association for Next Steps gross income

	Decomposition IGE			Decomposition rank-rank association		
	1	2	3	1	2	3
Direct Av. parent income	0.104	0.081	0.079	0.179	0.145	0.143
Total through education	**0.033**	**0.057**	**0.053**	**0.051**	**0.086**	**0.080**
Total through missings	**0.005**	**0.007**	**0.013**	**0.021**	**0.010**	**0.018**
Total intergen elasticity	**0.145**	**0.145**	**0.145**	**0.241**	**0.241**	**0.241**
Maths at 10 / KS2	0.015	0.009	0.009	0.027	0.013	0.012
Reading at 10 / KS2	0.015	0.001	0.000	0.018	0.000	0.000
Application at 10/ Academic self-concept	0.003	0.000	0.000	0.006	0.003	0.003
Anxious at 10 / GHQ-12 score	0.000	0.000	0.000	0.000	0.000	0.000
Total through early skills	**0.033**	**0.010**	**0.009**	**0.051**	**0.016**	**0.015**
Number of GCSEs		0.047	0.044		0.070	0.067
Total through compulsory		**0.047**	**0.044**		**0.070**	**0.067**
Number of A-levels			-0.001			-0.002
Degree			0.001			0.000
Total through post-16			**0.000**			**-0.002**
N	1,440	1,440	1,440	1,440	1,440	1,440

Notes: Estimated using two-year average parental income. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a, 2021b, 2022)

Appendix B. Appendix for Chapter 3

Table B.1. A description of variables

Variable	Description	Source
Outcome Variable		
HE	1 if the young person had ever enrolled in any HE institution, 0 otherwise	Waves 6-8
Degree	1 if the young person achieved a first degree or higher, 0 otherwise	Wave 8
NVQ	1 if the young person achieved NVQ[25] Level 4 or higher, 0 otherwise	Wave 8
RGU	1 if the degree was awarded by a Russell Group[26] University, 0 otherwise	Wave 8
Class	1 if the degree achieved was a first or upper second, 0 otherwise	Wave 8
Key Explanatory Variables		
EMA	EMA receipt status	Wave 4, 5
Observed Covariates		
Gender	Gender of the Young Person (1 if female, 0 otherwise)	Wave 4
Ethnicity	Young persons' ethnic group (grouped)	Wave 4
SEN	1 if the young person had special educational needs (SEN) at age 15, 0 otherwise	Waves 3, 4
Family Income	Total gross income for both parents (banded)	Wave 4
NS-SEC	Family's current National Statistics Socio-economic classification (NS-SEC) (from household reference person)	Wave 4
Parental Qualification	Highest qualification held in the family by either main or second parent (grouped)	Wave 4
Language	1 if English was an additional language spoken at home, 0 otherwise	Wave 4
KS2	Quintiles of Key Stage[27] 2 fine graded average points	KS2, Wave 1

[25] National Vocational Qualification (NVQ) is a work-based qualification in England, Wales and Northern Ireland. It was withdrawn and replaced by the Regulated Qualifications Framework (RQF) in 2015. More informtion can be found at www.gov.uk/what-different-qualification-levels-mean/list-of-qualification -levels
[26] The Russell Group is an association of 24 UK public research universities, inclеding Oxford and Cambridge.
[27] In the UK, the national curriculum is organised in to blocks of years called 'Key Stages' (KS) and the performance of pupils will be formally assessed at the end of each KS. For example, KS2 results refer to the Standard Assessment Tests

	score	
KS4	Quintiles of total GCSE and equivalents new style point score	KS4, Wave 3
Truancy	1 if the young person played truant in Year 11, 0 otherwise	Waves 3, 4
Exclusion	1 if the young person had ever been suspended or excluded from school by Year 11, 0 otherwise	Waves 3, 4
Cannabis	1 if the young person had ever tried cannabis by Year 12, 0 otherwise	Wave 4
Attitude	Young persons' attitude to school in Year 12 (additive)	Wave 4
Post16 Intention	1 if the young person planned to stay in full-time education after 16, 0 otherwise	Waves 3, 4

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2022)

Table B.2. Impact of the EMA on whether obtained a degree from a Russell Group university

	EMA (base=Never received)	**Model 1** *LPM*	**Model 2** *LPM*	**Model 3** *LPM*	**Model 4** *LPM*	**Model 5** *LPM*
Without reweighting	One year	-0.0524	-0.0186	-0.0156	-0.0248	0.00477
		(0.0559)	(0.0562)	(0.0513)	(0.0511)	(0.0745)
	Two years	-0.0765*	-0.0456	-0.0741*	-0.0845*	-0.0200
		(0.0425)	(0.0496)	(0.0445)	(0.0434)	(0.0558)
	No information	-0.243***	-0.0939*	-0.114*	-0.113*	-0.0133
		(0.0354)	(0.0499)	(0.0582)	(0.0600)	(0.122)
Observations		639	639	639	639	639
With entropy balancing	One year	-0.0385	-0.0335	-0.00340	-0.0362	0.00807
		(0.0992)	(0.0640)	(0.0568)	(0.0555)	(0.103)
	Two years	-0.0384	-0.0229	-0.0397	-0.0822*	0.00593
		(0.0896)	(0.0556)	(0.0470)	(0.0427)	(0.0717)
Observations		627	627	627	627	627
Demographic factors			✓	✓	✓	✓
Prior attainment				✓	✓	✓
Behaviours and attitudes					✓	✓
School fixed effects						✓

Notes: Average marginal effects are reported (cluster-robust standard errors in parentheses). *** indicates p<0.01, ** p<0.05, * p<0.1.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2022)

(SATs) results at age 11 and KS4 results are the General Certificate of Secondary Education (GCSE) results at age 16.

Table B.3. Impact of the EMA on whether obtained a first or upper second degree

	EMA (base=Never received)	**Model 1** *LPM*	**Model 2** *LPM*	**Model 3** *LPM*	**Model 4** *LPM*	**Model 5** *LPM*
Without reweighting	One year	-0.0430	-0.0133	-0.0222	-0.00357	-0.0736
		(0.0658)	(0.0683)	(0.0655)	(0.0634)	(0.0956)
	Two years	-0.0375	-0.0377	-0.0722	-0.0663	-0.0317
		(0.0483)	(0.0560)	(0.0524)	(0.0523)	(0.0854)
	No information	-0.104	-0.00513	-0.0531	-0.0407	-0.0646
		(0.181)	(0.171)	(0.146)	(0.133)	(0.288)
Observations		643	643	643	643	643
With entropy balancing	One year	-0.137	-0.111*	-0.0866	-0.0718	-0.149
		(0.0847)	(0.0619)	(0.0617)	(0.0630)	(0.106)
	Two years	-0.116	-0.118**	-0.138***	-0.122***	-0.0551
		(0.0701)	(0.0465)	(0.0398)	(0.0400)	(0.0812)
Observations		631	631	631	631	631
Demographic factors			✓	✓	✓	✓
Prior attainment				✓	✓	✓
Behaviours and attitudes					✓	✓
School fixed effects						✓

Notes: Average marginal effects are reported (cluster-robust standard errors in parentheses). *** indicates p<0.01, ** p<0.05, * p<0.1.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2022)

Appendix C. Appendix for Chapter 4

C.1. Standard Occupational Classification

Table C1. Standard Occupational Classification: SOC 2010

Major groups	Minor groups
1 Managers, directors and senior officials	111 Chief executives and senior officials 112 Production managers and directors 113 Functional managers and directors 115 Financial institution managers and directors 116 Managers and directors in transport and logistics 117 Senior officers in protective services 118 Health and social services managers and directors 119 Managers and directors in retail and wholesale 121 Managers and proprietors in agriculture related services 122 Managers and proprietors in hospitality and leisure services 124 Managers and proprietors in health and care services 125 Managers and proprietors in other services
2 Professional occupations	211 Natural and social science professionals 212 Engineering professionals 213 Information technology and telecommunications professionals 214 Conservation and environment professionals 215 Research and development managers 221 Health professionals 222 Therapy professionals 223 Nursing and midwifery professionals 231 Teaching and educational professionals 241 Legal professionals 242 Business, research and administrative professionals 243 Architects, town planners and surveyors 244 Welfare professionals 245 Librarians and related professionals 246 Quality and regulatory professionals 247 Media professionals
3 Associate professional and technical occupations	311 Science, engineering and production technicians 312 Draughtspersons and related architectural technicians 313 Information technology technicians 321 Health associate professionals 323 Welfare and housing associate professionals 331 Protective service occupations 341 Artistic, literary and media occupations 342 Design occupations 344 Sports and fitness occupations 351 Transport associate professionals 352 Legal associate professionals 353 Business, finance and related associate professionals 354 Sales, marketing and related associate professionals 355 Conservation and environmental associate professionals 356 Public services and other associate professionals
4 Administrative and secretarial occupations	411 Administrative occupations: government and related organisations 412 Administrative occupations: finance 413 Administrative occupations: records 415 Other administrative occupations

	416 Administrative occupations: office managers and supervisors 421 Secretarial and related occupations
5 Skilled trades occupations	511 Agricultural and related trades 521 Metal forming, welding and related trades 522 Metal machining, fitting and instrument making trades 523 Vehicle trades 524 Electrical and electronic trades 525 Skilled metal, electrical and electronic trades supervisors 531 Construction and building trades 532 Building finishing trades 533 Construction and building trades supervisors 541 Textiles and garments trades 542 Printing trades 543 Food preparation and hospitality trades 544 Other skilled trades
6 Caring, leisure and other service occupations	612 Childcare and related personal services 613 Animal care and control services 614 Caring personal services 621 Leisure and travel services 622 Hairdressers and related services 623 Housekeeping and related services 624 Cleaning and housekeeping managers and supervisors
7 Sales and customer service occupations	711 Sales assistants and retail cashiers 712 Sales related occupations 713 Sales supervisors 721 Customer service occupations 722 Customer service managers and supervisors
8 Process, plant and machine operatives	811 Process operatives 812 Plant and machine operatives 813 Assemblers and routine operatives 814 Construction operatives 821 Road transport drivers 822 Mobile machine drivers and operatives 823 Other drivers and transport operatives
9 Elementary occupations	911 Elementary agricultural occupations 912 Elementary construction occupations 913 Elementary process plant occupations 921 Elementary administration occupations 923 Elementary cleaning occupations 924 Elementary security occupations 925 Elementary sales occupations 926 Elementary storage occupations 927 Other elementary services occupations

Source: HESA (2022) https://www.hesa.ac.uk/support/documentation/occupational/soc2010.

C.2. Full Models

Table C2. Regression results of the full model: Male

		(1) On furlough or paid leave	(2) Left work or on unpaid leave
Group	FiF	0.0122	-0.00196
(base=non-FiF)		(0.0160)	(0.0220)
Wave	Wave two	-0.127***	0.0114
(base=Wave one)		(0.0249)	(0.0195)
	Wave three	-0.137*	0.0583
		(0.0786)	(0.0482)

Ethnicity	Mixed	-0.0302	-0.101*
(base=White)		(0.0291)	(0.0535)
	Indian	0.00950	-0.00968
		(0.0282)	(0.0499)
	Pakistani and Bangladeshi	-0.0479*	-0.117***
		(0.0286)	(0.0440)
	Black	0.121**	-0.0398
		(0.0562)	(0.0379)
	Other	-0.0904***	0.00876
		(0.0307)	(0.0553)
RGU	Yes	-0.00680	-0.0448**
(base=No)		(0.0194)	(0.0202)
	Missing	-0.0518	0.196*
		(0.0459)	(0.101)
Marital status	Married	0.0839*	0.00992
(base=Single)		(0.0487)	(0.0343)
	Divorced	0.00279	0.0369
		(0.0314)	(0.0764)
	Civil Partnership	0.0389	-0.0602
		(0.0286)	(0.0389)
Child		-0.0190	-0.0591
		(0.0491)	(0.0378)
School-aged child		-0.0436	0.0413
		(0.0575)	(0.0577)
SOC2010	110	-0.0898	-0.0830
(base=Missing)		(0.0672)	(0.0565)
	112	-0.0630	-0.0406
		(0.0650)	(0.0611)
	113	-0.149**	-0.00520
		(0.0696)	(0.0511)
	115	-0.133	0.105
		(0.0876)	(0.0690)
	116	0.455**	0.336
		(0.212)	(0.255)
	119	0.234*	-0.0445
		(0.124)	(0.0600)
	122	0.105	-0.0329
		(0.167)	(0.0505)
	124	-0.225***	-0.0431
		(0.0779)	(0.0537)
	125	-0.0185	0.201
		(0.0759)	(0.158)
	211	-0.113	-0.00753
		(0.0704)	(0.0706)
	212	-0.130*	-0.0345
		(0.0705)	(0.0435)
	213	-0.131*	-0.0516
		(0.0691)	(0.0490)
	214	-0.135**	-0.0199
		(0.0632)	(0.0624)
	215	-0.168***	-0.0348
		(0.0635)	(0.0461)
	221	-0.140**	0.0274
		(0.0655)	(0.0582)
	222	0.102	-0.0308
		(0.195)	(0.0619)
	223	-0.156*	-0.0779
		(0.0842)	(0.0605)
	231	-0.156**	0.00632
		(0.0666)	(0.0448)

241	0.0369	-0.0595
	(0.167)	(0.0510)
242	-0.115*	-0.0117
	(0.0642)	(0.0494)
243	-0.156**	-0.0367
	(0.0710)	(0.0495)
244	-0.210***	0.0443
	(0.0761)	(0.0527)
245	-0.110	0.0136
	(0.0814)	(0.0609)
246	-0.157**	0.127
	(0.0633)	(0.142)
247	-0.117*	0.0295
	(0.0659)	(0.109)
311	-0.126	-0.101
	(0.0808)	(0.0623)
312	0.0759	-0.0700
	(0.206)	(0.0569)
313	-0.147**	-0.0245
	(0.0675)	(0.0438)
323	-0.110	-0.0832
	(0.0803)	(0.0591)
331	-0.147**	-0.0149
	(0.0649)	(0.0517)
341	0.0581	0.158
	(0.105)	(0.126)
342	-0.108	-0.0179
	(0.0821)	(0.0651)
344	0.0120	-0.111*
	(0.142)	(0.0634)
351	-0.204**	0.0759
	(0.0956)	(0.112)
352	-0.0971	-0.00829
	(0.0782)	(0.0469)
353	-0.150**	0.0106
	(0.0663)	(0.0613)
354	0.00972	0.0285
	(0.0905)	(0.0550)
356	-0.0273	0.0643
	(0.113)	(0.0779)
411	-0.130*	-0.0601
	(0.0714)	(0.0505)
412	-0.0950	-0.0158
	(0.0772)	(0.0501)
413	-0.170***	0.00250
	(0.0651)	(0.0527)
415	-0.112	-0.0242
	(0.0695)	(0.0592)
416	-0.106*	-0.0429
	(0.0639)	(0.0481)
511	0.0322	-0.236**
	(0.177)	(0.117)
521	-0.216***	0.0191
	(0.0753)	(0.0745)
522	-0.141*	0.0144
	(0.0770)	(0.0464)
523	-0.161*	0.612***
	(0.0866)	(0.0743)
524	-0.0488	0.336*
	(0.0792)	(0.203)

	525	-0.0991	-0.0294
		(0.0825)	(0.0591)
	531	0.0770	0.0184
		(0.0968)	(0.0650)
	543	-0.0144	-0.0557
		(0.0854)	(0.0529)
	612	-0.205***	-0.0592
		(0.0682)	(0.0453)
	614	-0.166*	-0.138*
		(0.0920)	(0.0719)
	621	0.509***	-0.117**
		(0.0627)	(0.0594)
	711	0.258	0.310
		(0.235)	(0.326)
	712	-0.162**	0.0325
		(0.0732)	(0.0643)
	713	-0.0939	0.0109
		(0.0648)	(0.0676)
	722	-0.0181	0.00643
		(0.155)	(0.0928)
	811	-0.0924	0.00195
		(0.153)	(0.0559)
	812	0.666**	0.128
		(0.259)	(0.0819)
	813	0.837***	-
		(0.0620)	
	814	-0.0303	-0.257***
		(0.0683)	(0.0847)
	821	-0.221**	-0.150*
		(0.0936)	(0.0862)
	823	-0.224***	0.106
		(0.0735)	(0.0713)
	911	-	0.967***
			(0.0421)
	912	-0.131*	0.0429
		(0.0693)	(0.0554)
	921	-0.143**	0.258
		(0.0678)	(0.258)
	923	-0.280***	-0.0193
		(0.107)	(0.0634)
	924	-0.165*	-0.188**
		(0.0945)	(0.0924)
	925	-0.140*	-0.151**
		(0.0812)	(0.0701)
	Not applicable	-0.0583	0.0155
		(0.0650)	(0.0467)
	Unable to code	-0.120*	0.0324
		(0.0647)	(0.0835)
Self-employed		-0.161***	0.272***
		(0.0459)	(0.0673)
Zero-hours contracts		-0.0316	0.294**
		(0.0535)	(0.138)
Working hours		-0.000701	-0.00511**
		(0.00111)	(0.00202)
Working hours missing		0.325	0.0830
		(0.223)	(0.210)
COVID	Yes	-0.0105	-0.00470
(base=No)		(0.0195)	(0.0265)
	Unsure	0.0376	0.00578
		(0.0231)	(0.0268)

	Missing	-0.0239	-0.107*
		(0.0488)	(0.0590)
Time on home schooling		-0.00779	-0.0219
		(0.0174)	(0.0161)
Time on other activity with children		0.0167*	0.00175
		(0.00980)	(0.0102)
Time on caring for others		-0.00624	0.0180
		(0.00477)	(0.0192)
Time use missing		0.0356	-0.0598
		(0.0740)	(0.0470)
Personal contacts	Yes	-0.0314	0.0594**
(base=No)		(0.0232)	(0.0287)
	Missing	-0.0350	0.0285
		(0.0269)	(0.0499)
Networking	Yes	0.0336	-0.0361
(base=No)		(0.0347)	(0.0362)
	Missing	-	-
	Constant	0.235***	0.240***
		(0.0900)	(0.0847)
	Observations	1,239	1,237
	R-squared	0.327	0.415

Table C3. Regression results of the full model: Female

		(1) On furlough or paid leave	(2) Left work or on unpaid leave
Group	FiF	-0.0517**	0.0452**
(base=non-FiF)		(0.0218)	(0.0195)
Wave	Wave two	-0.136***	-0.0292
(base=Wave one)		(0.0319)	(0.0270)
	Wave three	-0.0923***	-0.0122
		(0.0351)	(0.0461)
Ethnicity	Mixed	0.161***	0.0613
(base=White)		(0.0595)	(0.0453)
	Indian	-0.0215	0.185**
		(0.0268)	(0.0922)
	Pakistani and Bangladeshi	0.0736	0.0414
		(0.0493)	(0.0350)
	Black	-0.0290	0.0477
		(0.0321)	(0.0566)
	Other	-0.00400	0.0467
		(0.0404)	(0.0591)
RGU	Yes	-0.0350	-0.0191
(base=No)		(0.0286)	(0.0189)
	Missing	-0.152**	0.0329
		(0.0676)	(0.110)
Marital status	Married	0.0219	-0.0942***
(base=Single)		(0.0304)	(0.0270)
	Seperated	-0.0561	0.142
		(0.0358)	(0.0895)
	Divorced	0.0606	-0.153
		(0.0697)	(0.119)
	Civil Partnership	-0.248***	-0.0242

		(0.0832)	(0.0470)
	Missing	-0.255**	-0.283*
		(0.122)	(0.156)
Child		-0.0660*	0.0353
		(0.0341)	(0.0458)
School-aged child		0.0221	-0.0138
		(0.0530)	(0.0661)
SOC2010	112	-0.285***	-0.0120
(base=Missing)		(0.0951)	(0.0703)
	113	-0.218**	-0.0598
		(0.0909)	(0.0645)
	116	-0.253***	-0.0745
		(0.0925)	(0.0718)
	118	-0.296***	-0.0619
		(0.0997)	(0.0752)
	119	0.266	-0.0987
		(0.236)	(0.0635)
	121	-0.297***	-0.109*
		(0.0897)	(0.0641)
	122	0.0193	-0.114
		(0.123)	(0.0773)
	124	-0.0773	-0.0900
		(0.163)	(0.0669)
	125	-0.158	-0.123
		(0.104)	(0.0836)
	211	-0.261***	-0.0703
		(0.0867)	(0.0671)
	212	-0.0257	-0.00347
		(0.128)	(0.116)
	213	-0.202**	-0.116
		(0.0933)	(0.0814)
	214	-0.242**	0.172
		(0.101)	(0.173)
	215	-0.192	0.0280
		(0.145)	(0.163)
	221	-0.120	-0.0379
		(0.115)	(0.0697)
	222	-0.258***	-0.0666
		(0.0963)	(0.0644)
	223	-0.238***	-0.0969
		(0.0871)	(0.0648)
	231	-0.218**	0.0200
		(0.0894)	(0.0754)
	241	-0.233**	-0.123*
		(0.0918)	(0.0713)
	242	-0.144	0.0331
		(0.107)	(0.114)
	243	-0.245***	-0.0378
		(0.0935)	(0.0663)
	244	-0.229**	-0.113
		(0.0933)	(0.0691)
	245	-0.280***	-0.119*
		(0.0886)	(0.0622)
	246	-0.266***	-0.0635
		(0.0933)	(0.0727)
	247	-0.217**	0.106
		(0.0973)	(0.120)
	311	-0.270***	0.413*
		(0.0960)	(0.222)
	313	-0.300***	-0.138**

	(0.0868)	(0.0662)
321	-0.0608	0.227*
	(0.145)	(0.121)
323	-0.252***	-0.132**
	(0.0950)	(0.0658)
331	-0.234**	-0.0807
	(0.0919)	(0.0641)
341	-0.184*	0.0814
	(0.103)	(0.106)
342	0.363**	-0.0232
	(0.162)	(0.0739)
344	-0.200**	0.333
	(0.0946)	(0.332)
350	-0.247**	-0.0366
	(0.0959)	(0.0712)
352	-0.218**	-0.0442
	(0.0923)	(0.0745)
353	-0.235**	-0.0352
	(0.0913)	(0.0670)
354	-0.0654	-0.0360
	(0.100)	(0.0697)
356	-0.268***	-0.118*
	(0.0951)	(0.0673)
411	-0.244**	-0.142*
	(0.100)	(0.0737)
412	-0.113	0.345*
	(0.133)	(0.208)
413	-0.100	0.109
	(0.119)	(0.173)
415	-0.0240	-0.0412
	(0.154)	(0.0814)
416	-0.258***	0.193
	(0.0988)	(0.230)
421	-0.241**	-0.0380
	(0.102)	(0.0920)
541	0.696***	
	(0.0958)	
542	-0.252*	-0.437***
	(0.144)	(0.101)
543	0.179	-0.0714
	(0.323)	(0.0609)
612	0.0140	-0.0387
	(0.126)	(0.0760)
613	0.374*	-0.289**
	(0.197)	(0.133)
614	-0.124	-0.0171
	(0.105)	(0.0819)
621	0.387	-0.0288
	(0.264)	(0.0763)
622	-0.183*	0.130
	(0.109)	(0.193)
623	0.536***	
	(0.106)	
711	-0.0975	-0.119*
	(0.113)	(0.0685)
712	-0.224**	0.702***
	(0.0954)	(0.0863)
713	-0.288***	-0.0315
	(0.0881)	(0.0673)
721	-0.0302	0.138

		(0.141)	(0.161)
	722	-0.208**	-0.125*
		(0.0846)	(0.0642)
	813	0.166	-0.158
		(0.218)	(0.178)
	823	-0.226***	-0.180*
		(0.0843)	(0.102)
	921	-0.256***	-0.146**
		(0.0924)	(0.0675)
	923	0.672***	0.886***
		(0.0899)	(0.0829)
	924	0.238	-0.0848
		(0.196)	(0.0748)
	926	-0.165	-0.145
		(0.143)	(0.125)
	927	0.157	0.169
		(0.138)	(0.210)
	Not applicable	-0.142	-0.0316
		(0.0911)	(0.0635)
	Unable to code	-0.0632	0.350**
		(0.125)	(0.148)
Self-employed		-0.1000**	0.374***
		(0.0494)	(0.0725)
Zero-hours contracts		-0.120	0.105
		(0.0812)	(0.149)
Working hours		-0.00189	-0.00211
		(0.00165)	(0.00135)
Working hours missing		-0.0805**	0.462***
		(0.0329)	(0.141)
COVID	Yes	-0.0259	-0.00501
(base=No)		(0.0226)	(0.0217)
	Unsure	-0.00804	0.0273
		(0.0305)	(0.0396)
	Missing	-0.00810	-0.0918**
		(0.0429)	(0.0453)
Time on home schooling		0.00898	-0.00107
		(0.00778)	(0.00734)
Time on other activity with children		0.00937**	0.00286
		(0.00362)	(0.00283)
Time on caring for others		-0.00477	-0.00149
		(0.00363)	(0.00365)
Time use missing		-0.0334*	0.00591
		(0.0201)	(0.0349)
Personal contacts	Yes	-0.0112	-0.0153
(base=No)		(0.0247)	(0.0281)
	Missing	0.0748	0.0979
		(0.0762)	(0.0706)
Networking	Yes	0.0217	-0.0564**
(base=No)		(0.0280)	(0.0227)
	Missing	-0.114*	-0.137**
		(0.0622)	(0.0669)
	Constant	0.462***	0.154
		(0.112)	(0.0962)
	Observations	2,041	2,003
	R-squared	0.242	0.416

Notes: All coefficients are estimated using ordinary least squares (OLS) regression. Missing values of the variables are controlled by using missing flags. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weighted using the combined weight for each wave.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a)

C.3. Interaction effect between FiF status and time

As discussed in section 4.3, the changes in lockdown and furlough policies in the country could affect the impact of the pandemic on the labour market. Thus, in this section, we explore the interaction effect between FiF status and time by including an interaction term.

Table A1 shows the time-varying results. Both male and female FiF graduates are less likely to be put on furlough or paid leave in wave two. Thus, we explore the policy context during the period when the three waves were carried out (see Figure 4.1). Unlike in waves one and three, employers were required to cover part of the furloughed employees' wages (10-20%) in wave two. Moreover, the unemployment rate in the UK was higher in wave two (5.1%) than in wave one (4.1%) and wave three (4.8%). The change in the CJRS and the higher unemployment rate could be two of the reasons that there is a gap in the probability of being put on furlough or paid leave between FiF and non-FiF graduates in the second wave.

Table C4. Labour market status by FiF status and wave

		(1) On furlough or paid leave	(2) Left work or on unpaid leave
Male			
Group	FiF	0.0963***	0.0600**
(base=non-FiF)		(0.0344)	(0.0299)
Wave	Wave two	-0.0500**	0.0688*
(base=Wave one)		(0.0229)	(0.0407)
	Wave three	-0.0389	0.111**
		(0.0773)	(0.0544)
Interactions	FiF*Wave two	-0.111***	-0.0886*
		(0.0398)	(0.0498)
	FiF*Wave three	-0.131***	-0.0758**
		(0.0416)	(0.0342)
	Observations	1,239	1,237
	R-squared	0.335	0.419
Female			
Group	FiF	-0.0430	0.0424
(base=non-FiF)		(0.0512)	(0.0380)
Wave	Wave two	-0.109*	-0.0276
(base=Wave one)		(0.0564)	(0.0307)
	Wave three	-0.112**	-0.0214
		(0.0522)	(0.0481)
Interactions	FiF*Wave two	-0.0367	-0.00203
		(0.0620)	(0.0415)
	FiF*Wave three	0.0254	0.0125
		(0.0600)	(0.0471)

	Observations	2,041	2,003
	R-squared	0.243	0.416
Control variables			
Personal and household characteristics		√	√
Pre-COVID labour market characteristics		√	√
COVID-related variables		√	√
Time on homeschooling and caring		√	√
Interaction term between FiF and wave		√	√
Personal network at age 25		√	√

Notes: All coefficients are estimated using ordinary least squares (OLS) regression. Missing values of the variables are controlled by using missing flags. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weighted using the combined weight for each wave.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a)

C.4. Key worker status

Key workers have played an important role during the pandemic. Compared to non-key workers, key workers were more likely to continue working and less likely to become financially worse off after the outbreak (Wielgoszewska et al., 2020). Thus, in addition to the labour market characteristics controlled in our previous models, we further look at how the FiF difference is mediated by the key worker status of the participants.

Consistent with previous studies, both male and female key workers were less likely to be on furlough or non-employed. Non-keyworker FiF females were 10.9 percentage points more likely to be put on unpaid leave than than their non-FiF peers. However, key worker status protects FiF females from stopping working and being unpaid. Key worker status also offers protection for FiF males as being a FiF key worker is associated with a higher probability of keeping working (rathen than be put on furlough or paid leave) post-outbreak.

Table C5. Labour market status by FiF status and key worker status

		(1) On furlough or paid leave	(2) Left work or on unpaid leave
Male			
Group	FiF	0.0574**	0.0122
(base=non-FiF)		(0.0230)	(0.0317)
Keyworker	Yes	-0.0334	-0.0782***
(base=No)		(0.0209)	(0.0298)
Interactions	FiF*Keyworker	-0.124***	-0.0260
		(0.0313)	(0.0363)
	Observations	1,239	1,237
	R-squared	0.372	0.433
Female			

Group	FiF	-0.0347	0.109***
(base=non-FiF)		(0.0365)	(0.0311)
Keyworker	Yes	-0.266***	-0.138***
(base=No)		(0.0405)	(0.0286)
Interactions	FiF*Keyworker	0.000449	-0.131***
		(0.0424)	(0.0336)
	Observations	2,041	2,003
	R-squared	0.350	0.489
Control variables			
Personal and household characteristics		√	√
Pre-COVID labour market characteristics		√	√
COVID-related variables		√	√
Time on homeschooling and caring		√	√
Interaction term between FiF and wave		√	√
Personal network at age 25		√	√

Notes: All coefficients are estimated using ordinary least squares (OLS) regression. Missing values of the variables are controlled by using missing flags. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weighted using the combined weight for each wave.
Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies (2021a)