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Abstract

The increase in employment polarization observed in several high-income economies has coincided with a reduction in inter-generational mobility. This paper argues that the disappearance of middling jobs can drive changes in mobility, notably by removing a stepping stone towards high-paying occupations for those from less well-off family backgrounds. Using data from two British cohorts who entered the labour market at two points in time with very different degrees of employment polarization, we examine how parental income affects both entry occupations and occupational upgrading over careers. We find that transitions across occupations are key to mobility and that the impact of parental income has grown over time. At regional level, using a shift-share IV-strategy, we show that the impact of parental income has increased the most in regions experiencing the greatest increase in polarisation. This indicates that the disappearance of middling jobs played a role in the observed decline in mobility.

JEL-Codes: J210, J240, J620, O330, R230.

Keywords: British cohort, inter-generational mobility, job polarization, parental income, occupational transition.

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1 Introduction

Over the last few decades a number of countries have witnessed a decline in income and social mobility that has strengthened the link between individuals' origins and their socio-economic outcomes. At the same time, the shares in total employment of low- and high-paying occupations have increased at the expense of that of middling occupations, transforming the availability of jobs for workers. Existing work has proposed several explanations for the reduction in mobility, but little attention has been paid to the role of the changing structure of employment despite the fact that both phenomena have taken place roughly simultaneously.[1] Yet the timing of the two trends raises the question of whether individuals from less well-off backgrounds can still climb the social ladder as the middle rungs become scarce.

This paper bridges the gap between the literature on social mobility and that on employment polarization. The question has recently been addressed in two closely related papers, Guo (2022) and Hennig (2022), which focus on the impact that the structure of employment has on education decisions in the US. Their conceptual frameworks maintain that, when higher education is costly and borrowing to finance it is not possible, the disappearance of middling jobs results in a polarization of education which in turn leads to lower income mobility. We explore an alternative mechanism that does not rely on costly education, making it applicable to a broader range of economies. Our key hypothesis is that occupational transitions during an individual's career are an essential aspect of inter-generational mobility. In fact, the UK data we employ indicate that about 30% of those starting in middling occupations and 40% of those starting in low-paying occupations experience upwards occupational mobility between their mid-20s and their early-40s. Our analysis hence focuses on the role of middling jobs as stepping stones in the occupational ladder.

We start by developing a model aimed at illustrating a simple mechanism through which polarization may affect occupational mobility. We consider a setup with two employment periods and three occupations, low-paying, middling, and high-paying. Individuals differ in parental income, which can be either low or high, and which determines first-period human capital, so that when individuals are young those with low parental income are randomly allocated to either low-paying or middling jobs, and those with high parental income to middling or high-paying jobs. During the first period, individuals may increase their human capital through on-the-job learning, which occurs with a given probability that depends on the occupation. In the second period, firms observe the human capital of mature workers and reallocate them across occupations.

[1] See, for example, Blanden et al. (2007), Chetty et al. (2014a), and Bell et al. (2022) on the decline in mobility, and Autor et al. (2003), Goos and Manning (2007), and Goos et al. (2009) on the extent of polarization.

We make two crucial assumptions: first, that the probability of on-the-job learning is higher for middling than for low-paying occupations; second, that on-the-job learning is sufficiently strong for an individual from a low-income household to potentially have higher human capital than some individuals from high-income backgrounds. In this context, the availability of middling jobs is the key element determining the extent of mobility. When middling jobs are scarce, the majority of those from low-income backgrounds will start their careers in low-paying occupations. As a result, few of them have learning opportunities and thus only a few individuals with low-income parents will be promoted to high-paying jobs. Moreover, this implies that since few positions are left vacant in middling occupations, few of those who started in high-paying occupations will be demoted, even if they failed to learn. As a result, there is a lower degree of mobility when middling jobs are scarce than when they are plentiful.

The core of our analysis is an empirical assessment of occupational mobility using data from two mature British cohorts, the National Child Development Study (NCDS58) and the British Cohort Study (BCS70). The surveys cover individuals born in, respectively, 1958 and 1970 for whom we have full activity histories along with parental income. These data have been widely used to examine the extent of mobility in the UK and existing work indicates that parent-child income mobility has declined for the younger cohort as compared to the older one.[2] We depart from existing work in two respects. First, because we are interested in the structure of employment, mobility is not defined in terms of income, as economists tend to do; rather, we focus on occupations and define occupational categories in line with the employment polarization literature.[3] Second, while existing work on inter-generational mobility focuses on the correlation between parental characteristics and the outcomes of mature children, we argue that it is important to disentangle changes in mobility that are due to the *intra-generational* component—defined as the transition between the entry job and the job when mature—from those due to the individual's initial job. The data allow us to consider occupational outcomes both at the start of individuals' careers, i.e. in their twenties, and when workers are mature, i.e. in their forties, and hence to consider occupations held at different stages of the working life.

To disentangle changes in social mobility that are due to the *intra-generational* component—defined as the transition between the entry job and the job when mature—from those due to the *inter-generational* component, we proceed in two steps, estimating first the impact of parental income on the child's first-period occupation and then the effect of first-period

[2]See for example Blanden et al. (2007), Nicoletti and Ermisch (2007), and Blanden et al. (2013).

[3]A few studies in economics have considered occupational mobility, notably Long and Ferrie (2013) who take a three-generation perspective, and Bell et al. (2022) who use recent British data. The occupational categories used are however not the same as those found in the employment polarization literature.

occupation and parental income on occupation at age 42.[4] We hence ask whether the decline in mobility observed over the period is due to a greater impact of parental background on entry jobs or if the change has occurred mainly through differences in transition probabilities over the child's lifetime.

Our focus is the comparison between the 1958 cohort and the 1970 cohort. Our data indicate that the polarization that has been observed at the aggregate level in prior work also appears when we consider the employment structure for each cohort. The change in the structure of employment has been particularly marked regarding first-period occupations. Those born in 1958 entered the labour market when middling jobs were plentiful, while those born in 1970 faced greater employment polarization, raising the question of whether intra-generational mobility was lower for the cohort who faced a lower share of middling jobs.

To understand the relationship between polarization and mobility, we measure both at the regional level. We consider differences in the impact of parental income on occupational outcomes across large regions, and construct for each region a measure of employment polarization for each cohort. This measure is constructed as a shift-share based on national level changes, the intuition being that the regions where middling jobs were more prevalent before the period of analysis were also the regions where the increase in employment polarization has been the largest. We then regress regional changes in mobility on regional changes in polarization, using an IV approach in which we instrument changes in the share of the various occupations in the UK with those observed in other European economies.

Our analysis provides three main results. The first concerns the fact that intra-generational mobility is an essential aspect of the observed correlation between parent and child outcomes. For both cohorts, we find that individuals face a large likelihood of changing occupational category over their career. Notably, around 23% (30%) of those initially in low-paying (middling) occupations are in high-paying occupations when they are 42. In fact, for those who started in low-paying and middling occupations, less than half remain in the same occupation as mature workers, with the probabilities both of moving upwards and downwards being large. Persistence is much higher for those starting in the best-paid jobs, but nevertheless, a third of them experience downwards mobility. Our results hence imply that it is important to understand career dynamics in order to explain the transmission of economic outcomes across generations.

Second, we find that the increased impact of family background on children's incomes

[4]Existing work on mobility has taken two approaches, either focusing on the correlation between the child's income or social status at around 40-years of age and that of the parent, or examining lifetime dynamics independently of parental background; see Jäntti and Jenkins (2015) for a review.

identified in previous work also appears when we focus on occupations. Moreover, the reduction in mobility is apparent at all the stages that determine an individual's occupation when mature. The effect of parental income on first-period occupation and that on the job when mature—controlling for initial occupation—have both become stronger for the younger cohort. These results raise the question of what are the implications of the disappearance of middling jobs for mobility. On the one hand, fewer individuals have access to those jobs when young, and those who do tend to come from better-off backgrounds; on the other, whether or not those in middling jobs move to high-paying occupations is more dependent on parental income for the younger than for the older cohort. The overall outcome are increased differences in intra-generational mobility according to family background. For those at the top of the parental-income distribution, upwards mobility during the working life has risen by about 5 percentage points, both for those starting in low-paid or middling jobs; in contrast, it has declined by around 8 percentage points for those from less well-off families, irrespective of the job initially held. That is, we observe that the possibility of career progression has become more dependent on parental background.

Lastly, the regional dimension of our data indicates that employment polarization tends to decrease mobility. Using a shift-share IV strategy we show that a decline in the regional share of middling employment increased the impact of parental income on the child's occupational outcome, indicating that mobility declined most in regions with greater polarization. This conclusion is supported by the finding, when using individual data, that the effect of parental income on occupational outcomes is stronger for individuals who—when young—lived in areas with greater job polarization.

Our work is related to three strands of literature. First, it contributes to the literature on the determinants of inter-generational mobility which has extensively documented the parent-child dynamics in income and social class.[5] Much of the focus has been on how individual characteristics affect income dynamics across generations, notably education, non-cognitive skills, personality traits, and quality of the neighbourhood.[6] Yet, little attention has been paid to the importance of early labour market experiences. This paper thus provides a bridge between the literatures on *inter-generational* and *intra-generational* mobility by focusing on access to jobs at the beginning of the career and the subsequent career dynamics, and shows that understanding *intra-generational* mobility is essential to understand

[5] See, for example, Nicoletti and Ermisch (2007), Kopczuk et al. (2010), Blanden et al. (2013), Long and Ferrie (2013), Chetty et al. (2014b), Chetty et al. (2017), and Güell et al. (2018) for work on inter-generational income mobility and Erikson and Goldthorpe (1992), Chan and Goldthorpe (2007), Goldthorpe and Jackson (2007), and Erikson and Goldthorpe (2010) on social class.

[6] See Björklund and Jäntti (2012), Blanden and Macmillan (2014), Blanden and Macmillan (2016), Crawford et al. (2016), and Neidhöfer et al. (2018) on education, Chetty et al. (2020) on race, and Heckman et al. (2006), Blanden et al. (2007), Heckman et al. (2013), and Chetty et al. (2014a) on other childhood outcomes.

an individual's outcome when mature.

The idea that lifecycle dynamics are important when examining inter-generational mobility has been explored by a body of work focusing on the bias resulting from the fact that we generally only have a snapshot of the child's outcomes rather than their lifetime income; see Jenkins (1987).[7] This literature has explored the relationship between point-in-time and lifetime earnings and found that the estimated effect of parental background is larger the later in the lifecycle the child's outcome is measured, as shown, for example, by Haider and Solon (2006). Similar results are obtained for the UK by Gregg et al. (2017) using the same cohort data as we do. Our paper makes two contributions to this literature. Existing work has compared the impact of parental background on income at different stages of the child's lifecycle, and we show that a similar result appears when we focus on occupations, which are usually deemed to be more stable than incomes. Moreover, our results help understand the source of the lifecycle bias as they highlight that parental income affects occupational transitions during the child's early working years.

Second, our paper is part of the recent literature in economics that has identified a decline in income mobility, notably in the US and the UK, and our contribution lies in showing that the increased importance of parental income also appears when we focus on the child's occupational outcome. In doing so, we build a bridge between the approach followed by economists and that used by sociologists. The former have focused on the relationship between parent and child incomes, while the latter have examined the transmission of social class, itself based on occupations. The decline in income mobility identified by economists is less apparent when focusing on social class, as argued by Goldthorpe (2013) who maintains that when looking at the effect of parental class on the child's class the main change in the late 20th century is a levelling out of the increasing rates of upwards absolute mobility observed in earlier decades. Our framework follows the sociology literature in seeking to explain the child's occupational outcome, yet we use parental income as our key measure of family status, and when doing so we observe a decline in absolute mobility. Our results can be reconciled with the findings by sociologist if within an occupational group the children of those with higher incomes have become more likely to experience upwards occupational mobility than they were in the past.

The literature on the increased influence of parental income on children's income in the

[7] The two other sources of bias are measurement error concerning parental income, which has been documented as leading to an attenuation bias, and bias due to spells of non-employment, which has received less attention; see Gregg et al. (2017). Blanden et al. (2013) have examined in detail the problem of measurement of parental income and shown that the observed decline in income mobility across cohorts is not driven by the poor measurement of family income in the older cohort. We also follow their suggestion and for the younger cohort average over the two observations we have for parental income. The second concern does not arise in our analysis as we include out-of-work as a possible outcome; see below for details.

UK has found that this effect operates largely through educational attainment. For example, Blanden et al. (2007), using the same data as us, find that the increase in the effect of parental income is mainly due to a strengthening of the effect of family background on educational attainment and on non-cognitive skills.[8] Our analysis complements this approach in two ways. On the one hand, we emphasize the importance of the structure of employment for mobility. As is well-established, both greater educational attainment and non-cognitive skills lead to better-paid occupations, which in turn determines incomes. We argue that the availability of employment opportunities is essential in order to turn these skills into higher incomes. On the other hand, such work has emphasized the growing importance of parental income for the acquisition of skills, which can be acquired at home or in the classroom; our analysis highlights the importance of initial occupations, which are themselves an additional potential source of learning and skill acquisition.

Lastly, this paper adds to our understanding of the consequences of employment polarization. Economists have mainly focused on the distribution of earnings,[9] although there is some work on its impact on educational attainment or the labour supply (Spitz-Oener 2006; Verdugo and Allègre 2020). The task approach introduced by Autor et al. (2003) implies that biased technological change results in both the polarization of employment and a change in wages, and much work has been devoted to trying to understand to what extent polarization has driven observed increases in earnings inequality. Surprisingly, the question of whether employment polarization affects mobility has been largely ignored. To our knowledge, the only exceptions are Guo (2022), Hennig (2022), Arntz et al. (2022) and Berger and Engzell (2022).

Guo (2022) and Hennig (2022) share a focus on educational decisions and how the disappearance of routine jobs affects the incentives to invest in education, which in turn results in a polarization of education and of wages, as well as in lower inter-generational mobility. These predictions are shown to be consistent with the cross-sectional correlation between polarization and local mobility measures, where the latter are those obtained by Chetty et al. 2014a for US commuting zones. Our analysis complements their work in several ways. First, in their setup the occupation of mature workers is determined exclusively by their educational choice; we add the analysis of job-to-job transitions and show that these transitions are essential to understand inter-generational mobility. Second, since these authors rely on the cost of education as a driver of the mechanism they study, their analysis is not suitable for economies where this cost is small or null, as is often the case in Europe. We hence

[8]See also Blanden and Gregg (2004) and Gregg and Macmillan (2010).

[9]This literature has grown rapidly over the past decade. See, amongst others, Autor and Dorn (2013), Beaudry et al. (2016), Caines et al. (2017), Ross (2017), Bárány and Siegel (2018). and Longmuir et al. (2020).

provide a mechanism that is more widely applicable. Lastly, measures of income mobility pull together changes in occupational outcomes and in wages in the different occupations, yet these two have varied in different ways depending on the country. Notably, while in the US mature workers have experienced an increase in wage polarization, this has not been the case in the UK.[10] Our approach isolates the dynamics of occupations, thus providing a more direct link between the structure of employment and individuals' labour market outcomes.

Also related are Arntz et al. (2022) and Berger and Engzell (2022). The approach in Berger and Engzell (2022) is close to that in Guo (2022) and Hennig (2022). Using the same US data for commuting-zone income mobility, they find a negative correlation between the local use of robots and the extent of inter-generational income mobility. Arntz et al. (2022) focus on the wages of individuals with different parental backgrounds and how they are affected by technology. Their evidence for Germany indicates that, for individuals with higher education, an increase in the use of computer-controlled tools is associated with a smaller wage gap between those with high-income and low-income parents. This result indicates that technology can sometimes offset the effect parental background, in contrast to the results for the US, and highlights the importance of examining these questions for countries other than the United States.

The rest of the paper is organised as follows. We start by presenting a simple model of the effect of employment polarization on occupational mobility in Section 2. Section 3 presents the cohort data and describes the structure of employment for the two cohorts along with their occupational dynamics. Our empirical specification distinguishes between the effect of parental income on initial occupations and on the transition across occupations during the individual's career, and the results are presented in Section 4, examining the changes that have occurred across the two cohorts. Section 5 estimates mobility at the regional level and provides evidence on the correlation across regions between the extent of job polarization and changes in mobility. Section 6 concludes.

2 Theoretical framework

We start by developing a simple theoretical setup that relates polarization to mobility. The model illustrates how mobility changes as the share of middling jobs falls. We consider three types of jobs $j = \{1, 2, 3\}$, which can be interpreted, respectively, as low-paying, middling and high-paying occupations. Individuals live for two periods and work in both, but may

[10] Below we show that, in line with existing work, our data does not display an increase in wage polarization for mature workers. However, we find that young individual's wages have become more polarized across the two cohorts.

change jobs over their lifetime. The allocation of workers to jobs depends on their human capital. Parents transfer human capital to their children such that the allocation of entry jobs is determined by parental background. Workers may or may not increase their human capital by acquiring skills on the job, and as a consequence they may move up or down the job ladder. It is the possibility of learning that will create a relationship between the structure of jobs and mobility.

2.1 Workers' skills and family background

We suppose that there are two types of parental background, denoted low-income (L) and high-income (H). The difference between the two groups can encompass income or human capital; what is important for our purposes is that children of H-parents have more initial human capital than those of L-parents, whether through direct transmission or access to better schools or more years of education. We denote by z_i the share of parents with background $i = \{L, H\}$, with $z_H + z_L = 1$. Since parental type determines the child's initial skills, the first-period human capital is simply h_L and h_H for those with low- and high-income parents, respectively, where $h_L < h_H$ and z_L and z_H are the shares of young individuals of each type.

Second-period human capital is assumed to depend on parental background and on the amount of learning in the first-period occupation. We assume that in each sector there is a probability π_j that the worker learns on the job and accumulates human capital. We suppose that $\pi_1 = 0$, and $\pi_2 = \pi_3 = \pi$; that is, there is no learning in low-paying jobs while the probability of learning is the same in middling and high-paying jobs.

Individuals who do not learn on the job have the same human capital as when young, i.e. h_L or h_H. An individual with parent-type i who worked in occupation j when young and learnt will have human capital h_i^j in the second period. In order to rank the human capital of individuals we make the following assumption:

Assumption 1 *Second-period human capital is such that* $h_L < h_H < h_L^2 = h_H^2 < h_L^3 = h_H^3$.

This assumption captures the key hypothesis that drives our results, namely that the opportunities for human capital accumulation are greater in the better-paid sectors. To limit the number of parameters, we make the simplifying assumption that parental background is irrelevant for those who have learnt on the job and that only the sector where they initially worked matters. We can then simply denote the resulting levels of human capital of those who work in sectors 2 and 3 when young and learnt as h^2 and h^3. Our key constraint, which holds by Assumption 1, is that $h_H < h_L^2$, which ensures that the human capital gains for individuals of L background who learn in middling jobs are sufficiently large to compensate for differences in initial human capital that are due to parental background.

2.2 The allocation of labour

Denote the share of low-paying jobs by q_1, the share of middling jobs by q_2, and the share of high-paying jobs by q_3.[11] For simplicity we assume that wages depend only on occupation, and that wages in high-paying (resp. middling) jobs are greater than in middling (resp. low-paying) jobs, so that employers fill jobs of each type with the workers with the highest human capital available.[12] The model can present various allocations of individuals across occupations depending on parameter values. We focus on a particular case that illustrates the mechanism we have in mind. To do so we make two assumptions on parameter values:

Assumption 2 *We suppose that*

(i) the share of low-income parents, z_L, satisfies $1 - q_3 > z_L > q_1$,

(ii) the probability of learning, π, satisfies $\pi(1 - q_1) < q_3$.

The first part of Assumption 2 ensures that in the first period some individuals from both high- and low-income parental backgrounds are in occupation 2, while the second part characterizes second-period allocations, ensuring that some non-learning individuals from high-income background work in occupation 3.[13]

Table 1 summarises, under Assumption 2, the distributions of jobs in the first period, with each column giving the probability that an individual from parental-type i is in each of the occupations. The distributions of jobs and skills in the population are such that only workers with low-income (resp. high-income) parents are initially in low-paid (resp. high-paid) occupations, while both types of individuals are found in middling jobs.

In the second period, the allocation of individuals across jobs depends on three factors: parental background, the occupation in which the individual worked in the first period,

[11] For simplicity of exposition, we do not consider non-employment. It is possible to show that a model in which non-employment is also a possibility and there is no learning while non-employed would deliver equivalent results.

[12] This outcome can be supported by a variety of wage set-ups and extended to allow wages to also depend on the worker's human capital. An example of this is a set-up where the output of a worker with human capital h in occupation k is given by $A_k h$ where A_k is the productivity of a firm with type-k jobs, with $A_1 < A_2 < A_3$. Suppose that a constant share ρ of output is kept by the firm and a share $(1 - \rho)$ is paid to workers. Employers hence fill jobs of each type with the most skilled worker available and workers always prefer occupation 3 (2) to occupation 2 (1). Wage differences will be due to both occupation and the individual's human capital.

[13] Under different parameter values, other configurations of second-period occupations are possible. The aim of the model is not to give an exhaustive description of possible outcomes but rather to illustrate a possible mechanism.

Table 1: First-period allocation of labour

	L	H
Low-paying	$\frac{q_1}{z_L}$	0
Middling	$1 - \frac{q_1}{z_L}$	$1 - \frac{q_3}{z_H}$
High-paying	0	$\frac{q_3}{z_H}$

and whether or not they learnt. We denote by $P_i(k)$ the probability that an individual of background i will be in occupation k in the second period and report these probabilities in Table 2. Under Assumptions 1 and 2, low-paying jobs are filled with individuals from low-income households, while middling and high-paying jobs contain workers from both low- and high-income households.

Table 2: Second-period allocation of labour

	L	H
Low-paying	$\frac{q_1}{z_L}$	0
Middling	$(1-\pi)\left(1 - \frac{q_1}{z_L}\right)$	$\frac{1-q_1-q_3-(1-\pi)(z_L-q_1)}{z_H}$
High-paying	$\pi\left(1 - \frac{q_1}{z_L}\right)$	$\frac{q_3-\pi(z_L-q_1)}{z_H}$

The crucial mechanism behind Table 2 is the replacement of H-type workers who did not learn with L-type workers who were in occupation 2 and learned. The latter will move upwards and will force some of the former to move from occupation 3 to occupation 2. Changes in q_1 and q_3 hence have both direct and indirect effects. The direct effects stem from the fact that there are more or fewer jobs of type k available; the indirect ones are due to the differences in human capital accumulation across occupations.

Consider, the occupational outcomes of individuals with low-income parents. A higher value of q_1 increases the likelihood that they work in low-paying occupations simply because there are more of these positions. The share of L-workers in high-paying occupations also falls in response to a higher value of q_1 due to the indirect effect stemming from the different human capital accumulation in the various jobs. A higher value of q_1 implies that in the first period fewer L-workers were in occupation 2, hence fewer individuals increased their human capital to h_2, reducing the share of L-workers that moved into high-paying occupations.[14] The value of q_1 also affects the second-period outcome for H-type individuals, since lower

[14] These dynamics are captured in Table A.1 in the appendix, which reports the extent of intra-generational mobility.

upwards mobility of L-type workers means a lower probability of downwards mobility for those who did not learn as employers now hire fewer workers from low-income background to work in occupation 3.

The second-period allocation of workers from high-income families also depends on q_3, as the greater availability of these jobs makes it more likely that H-type individuals work in occupation 3 than in occupation 2. In contrast, an increase in q_3 does not affect the likelihood that L-workers are in high-paying occupations as their possibility to do so is limited by their extent of learning rather than by the availability of jobs. This means that an increase in the share of occupation-3 jobs available benefits exclusively those from high-income backgrounds.

2.3 The impact of polarization

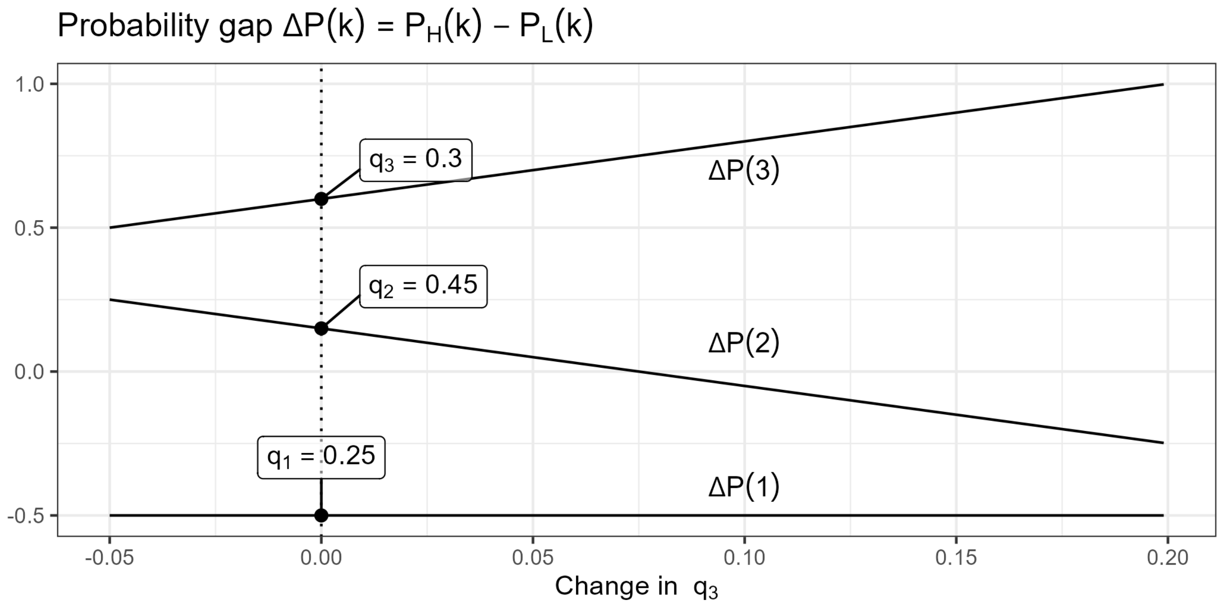
In our setup, polarization, understood as a reduction in the share of middling jobs, affects both entry jobs and transition probabilities (intra-generational mobility), which together will shape the extent of inter-generational mobility. Suppose, to start with, that polarization takes the form of an increase in q_3 at the expense of q_2, leaving q_1 unchanged. For ease of exposition, we assume that the change affects the distribution of occupations in both periods of an individual's working life.[15]

To capture inter-generational persistence in a simple way, we measure it by the advantage that parental background gives in terms of accessing the various occupations when mature. We define *inter-generational mobility* as the gap between H-type and L-type workers in the probability of being in each occupation, that is, $\Delta P(k) = P_H(k) - P_L(k)$, where the relevant probabilities are given in Table 2 and a lower value of $\Delta P(k)$ implies higher mobility.

Figure 1 presents the relationship between our measure of mobility and polarization. The baseline distribution of occupations is assumed to be such that 25% of workers are in low-paying, 45% in middling, and 30% in high-paying occupations. These figures are roughly those found in the data, as we will see below. As we move to the right along the horizontal axis q_3 increases, reducing q_2 until only 25% of workers are in middling occupations. The figure indicates that as polarization increases the advantage in accessing high-paying occupations that those from high-income backgrounds have rises. H-workers also have an advantage in being in occupation 2 for low levels of polarization, but this advantage falls as q_3 increases, and for high levels of polarization becomes negative. The reason for this is that as the share of middling jobs open to young workers falls, fewer L-type workers have learning opportunities and hence fewer manage to move to high-paying occupations. This increases the number

[15] Other scenarii are possible and would make the model richer, notably by allowing for different degrees of polarization when individuals are young and when they are mature.

Figure 1: Probability gap in second-period occupations between H and L backgrounds according to change in q_3



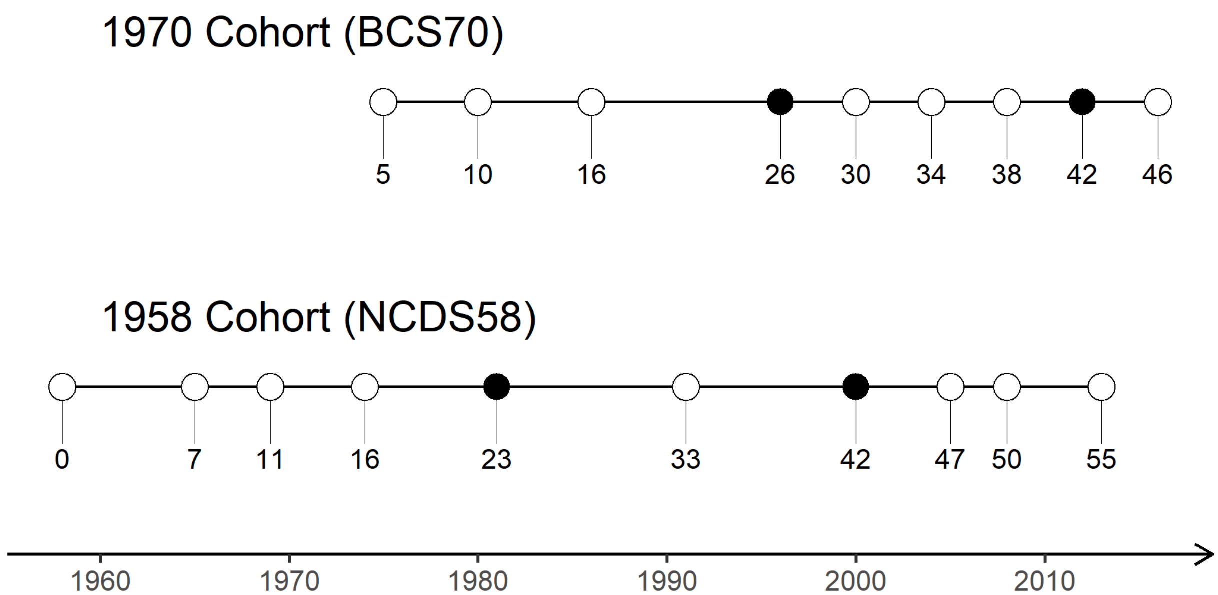
Notes: This figure presents the probability gap in second-period occupations between children from parental background H and L, i.e. $\Delta P(k)$, according to changes in the share of high-paying jobs, i.e. q_3. Parameters of the model are set such that $z_L = 0.5$, $z_H = 0.5$, and $\pi = 0.25$. The dotted line represents the baseline occupational distribution where $q_1 = 0.25$, $q_2 = 0.45$, and $q_3 = 0.30$.

of high-paying jobs available for H-type workers that did not learn. The gap in access to low-paying occupations, $\Delta P(1)$, is unchanged.

Different definitions of polarization give equivalent results. For example, in the Appendix we examine the case in which q_1 and q_3 simultaneously increase at the expense of q_2. We find that $\Delta P(3)$ increases while both $\Delta P(2)$ and $\Delta P(1)$ fall. That is, the change in the structure of occupations implies that those from low-income backgrounds are not only less likely (relative to those from high-income background) to be in high-paying occupations but also more likely to be in low-paying ones.

Our simple model hence implies a negative relationship between the extent of polarization and the degree of occupational mobility. Greater employment polarization—as measured by a reduction in q_2—reduces mobility by making the distribution of occupations of mature workers more dependent on parental background. This relationship could exist both over time or across locations. If two cohorts of workers face different degrees of polarization when they enter the labour market, we expect to find a lower degree of mobility for the one that experienced a lower share of middling jobs. Similarly, when comparing workers in two geographical areas, we expect to find lower mobility for those based in the location where polarization is greatest.

Figure 2: Dates of interviews



Notes: This figure gives the interview ages for individuals in the BCS70 and NCDS58 cohorts and the corresponding years. Black circles represent the first and second periods we consider in the analysis for both cohorts.

3 Data and employment polarization

3.1 Sample and variables

We use two mature British cohort studies that have been widely used by economists and sociologists to examine the extent of mobility in the UK. The National Child Development Study (NCDS58) is a cohort of individuals born during a given week in March 1958. The British Cohort Study (BCS70) is composed of individuals born during a given week in April 1970. Cohort members were born in England, Scotland, Wales and Northern Ireland and participated in several interviews at different points in time over their lives. Figure 2 presents all the interviews at which cohort members were interviewed and the corresponding year.

Periods. We define the first period as the year of interview closest to that in which the individual was 25 years old, the age usually considered as that of entry into the labour market. Those in the NCDS58 cohort are observed at age 23 and those in the BCS70 cohort at age 26. Both cohorts were interviewed at age 42, which we define as the second period.

Although individuals were asked to report all occupations between two interview dates, we have decided to use for our first period the occupations reported in the interviews occurring at ages 23 and 26 for the NCDS58 and the BSC70 cohorts. There are two reasons for this. First, an important difference between the two cohorts is the increase in educational attainment, so using an older age for the younger cohort implies that the two samples are more likely to be at the same stage in terms of labour market entry.[16]

Second, the data display a much higher proportion of occupational changes at the interview dates than at any time between interviews, probably capturing imperfect recollection of when an occupational change occurred. The errors in the occupational data are hence likely to be smaller in interview years than in other years. A concern is that the BCS70 the wave at age 26 was conducted via a postal survey, resulting in missing observations. We hence use information from other waves to fill in the occupation at that age 26. We also perform a robustness analysis looking at both cohorts when they were of the same age.[17]

Income and wages. We have information on parental income, provided when the child was 16 years old for both cohorts. For the BCS70 cohort, it is also available when the child was 10. Thus, when both are available, we take the average of the two observations; otherwise we use the single one we observe.[18] In order to adjust for inflation, aggregate income growth and changes in the dispersion of income, parental income is standardized, so that for both cohorts it has a mean of zero and a variance of 1.

For children, we observe wages, which are reported at each wave. We adjust for inflation using the consumer price index provided by the UK Office for National Statistics. The resulting monetary variables are all expressed in 1970 British pounds.

Occupational categories. Both cohort studies provide the full activity histories to the nearest month, from which we can derive the ISCO-88 occupations.[19] We aggregate ISCO-88 occupations into three categories: high-paying, middling and low-paying occupations. For completeness, we also include a fourth category—individuals who are out-of-work. This category groups those out of the labour force, those who are unemployed, and those in full-time study, and is included both for completeness as well as to avoid possible biases due to sample selection (Gregg et al. 2017). Our classification follows the job-polarization literature and is consistent with that used in Goos et al. (2014) and Mahutga et al. (2018), for example. Table B.1 in the Appendix presents the classification of the 26 occupations available. Goos et al. (2014) order occupations by mean wage rank in 16 European countries in 1993 and

[16] For the NCDS58 (BSC70) the population share in education is 2.2% (7.35%) at age 23 and 0.7% (2.7%) at age 26. Focusing on these interview years hence implies that roughly the same share in still in education (between 2 and 3%).

[17] Tables OA.7 and OA.8 in the Online Appendix show that when we consider the two cohorts at the same age, we find equivalent results, notably when both are considered at age 26. See Blanden et al. (2013) and Gregg et al. (2017) for further discussion of sample selection.

[18] Blanden et al. (2013) show that the observed increase in the role of parental income as a determinant of child's income is not driven by the poor measurement of permanent income in the 1958 cohort.

[19] Cohort data provide 3-digit occupations in the Standard Occupational Classification 1990 (SOC90) and the Standard Occupational Classification 2000 (SOC2000). We can derive ISCO-88 occupations by using the files from the CAMSIS project which cover both SOC occupational unit codes and translations into ISCO-88.

Table 3: Average weekly pay by occupation (in 1970£)

	First period		Second period		Annual growth (in %)	
Occupation	NCDS58	BCS70	NCDS58	BCS70	NCDS58	BCS70
High-paying	19.51	29.23	40.82	46.64	5.75	3.72
	(0.17)	(0.40)	(0.64)	(0.55)		
Middling	19.60	23.42	25.26	29.07	1.52	1.51
	(0.16)	(0.34)	(0.45)	(0.39)		
Low-paying	17.05	19.35	17.75	20.25	0.22	0.29
	(0.30)	(0.61)	(0.39)	(0.37)		
Relative pay						
High/Mid	1.00	1.25	1.62	1.60		
Mid/Low	1.15	1.21	1.42	1.44		

Notes: This table presents the average weekly pay, expressed in 1970£, in each first- and second-period occupation for the NCDS58 and BCS70 cohorts. The last two columns report the annualised growth rate of weekly pay between the first and the second period in percentages. The last two rows report the relative average weekly pay between occupations. Standard errors between parentheses. We exclude the very bottom and top of the pay distribution for each cohort, i.e. pay below £1 and above £300.

group them in three categories. We simply use their classification, with high-paying occupations including, for example, *Corporate managers* and *Teaching professionals*, middling ones include *Office clerks* and *Machine operators*, and low-paying ones those working in sales or personal services.

In our data, these occupational categories are closely related to remuneration levels. Table 3 reports the average weekly pay in the three broad occupational categories, and displays the expected correlation. Weekly pay is more concentrated for young individuals than for mature ones, as wages tend to grow faster with age for those in high-paying occupations. The last two columns report the annualised increase in weekly pay between the first and the second period. Average pay has increased for every type of occupation between both cohorts, with the change in pay across cohorts at age 42 being roughly the same for the three categories (between 14 and 15%). In contrast, for young individuals, the change across cohorts is much larger for those in high-paying occupations (50%) than for the other two groups (13 and 20%, respectively, in low-paying and middling occupations). This is reflected in the fact that while annual growth rates over the individual's lifecycle are roughly the same for the two cohorts for low-paying and middling occupations, for those in high-paying jobs entry jobs pay better for the 1970 than for the 1958 cohort, but growth is slower.

Location. Since individuals give their address at each interview, we also have their location history. We focus on the region of residence at age 16 because it is the age at which the parental income variable is defined. The classification was made prior to 1994 and thus uses the Government Offices for the Regions (GORs). We therefore rely on the Standard Statistical Regions (SSR).[20]

Once we restrict the data to those individuals for whom we have the key characteristics, i.e. parental income and occupations, our sample consists of 6,780 individuals in the NCDS58 and 7,983 in the BCS70, as reported in the Online Appendix.

The Labour Force Survey. As a complementary dataset we use the Labour Force Survey (LFS). The LFS provides data on both labour market status and region of residence. It has the advantage of containing a much larger number of observations (see Appendix B for details), and allows us to compare changes in occupational structure in the cohort data with those from a larger sample, as well as to compute measures of polarization at the regional level.

3.2 The structure of employment

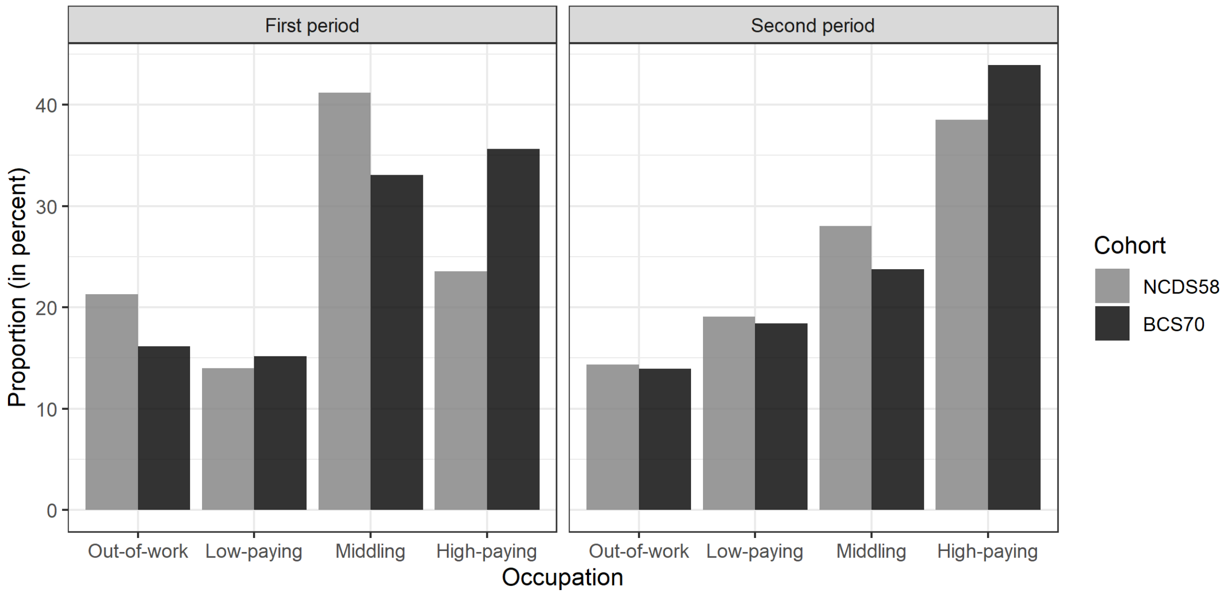
Before proceeding to our empirical analysis, we consider the extent to which the two cohorts experienced different degrees of polarization. We start by looking at changes in the distribution of occupations at ages 23/26 and 42 for both cohorts, reported in Figure 3.[21] In the first period there is an increase across cohorts in the probability of working in a high- or low-paying occupation and a decline in the likelihood of working in a middling occupation. At age 42, the changes are of smaller magnitude, and the main difference across the two cohorts is a reduction in the share of middling jobs that has been offset by high-paying ones. These changes are consistent with the literature on polarization in the UK, which shows a considerable decline in middling jobs, and an increase in the other two categories, which is particularly large for high-paying jobs (see Figure B.2 in the Appendix, which shows the extent of job polarization at the national level using the LFS data for both relevant-age cohorts, as well as Goos and Manning 2007 and Jin 2022).

Figure 4 illustrates the change in employment using the finer occupational categories. The left panel depicts the change in the share of individuals in each occupation when young and plots it against the average pay in that occupation (for young individuals of the 1970 cohort). The occupations are depicted by both their code and a geometric symbol, indicating whether they are in our category of low-paying (circle), middling (triangle) or high-paying

[20] For England, this is the highest sub-national division, while other countries in Britain consists of a single region each. The regions are (in alphabetical order): East Anglia, East Midlands, North, North West, Scotland, South East, South West, Wales, West Midlands, and Yorkshire and Humberside.

[21] We report the proportion of individuals in each occupation for the two cohorts in Table B.2; see also the Online Appendix for more details. Figure B.4 in the Appendix reports the equivalent distribution of occupations using the LFS data and shows similar patterns.

Figure 3: Occupational distribution across cohorts



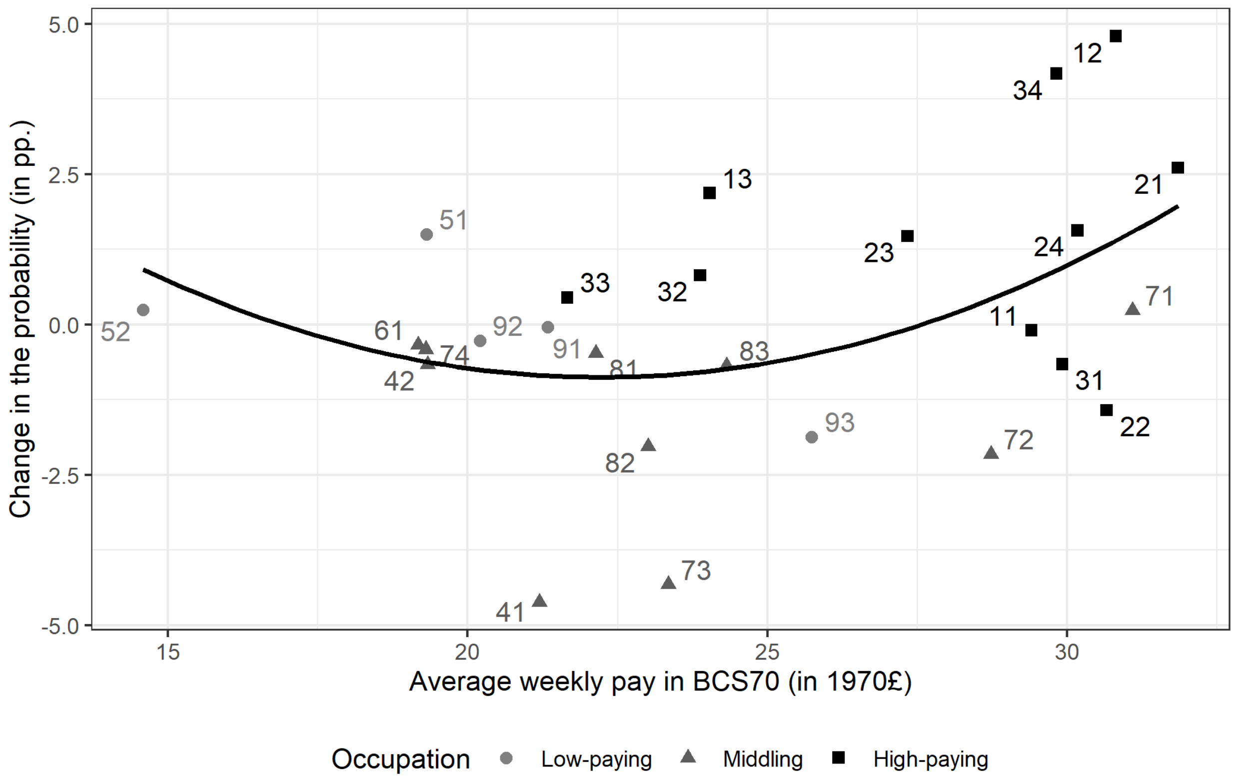
Notes: This figure reports the percentage of individuals in each type of occupation (out-of-work, low-paying, middling, high-paying) for the NCDS58 and BCS70 cohorts by period. Figure B.4 in the Appendix reports the equivalent distribution of occupations using the LFS data, and shows similar patterns.

(square) occupations. As can be seen from the fitted curve, there is a U-shaped relationship between weekly pay and the change in the share of the occupation, with both those with low and those with high remuneration gaining employment shares at the expense of those in the middle.[22]

The evidence in this section thus indicates that the strong polarization identified in cross-sectional data by previous work is also present when we focus on two specific cohorts. The differences between the first and second period distributions are interesting for our purposes, raising the question of whether polarization in the first period matters even when the changes in the distribution of employment are moderate for mature individuals. Moreover, these differences seem to mirror the pattern observed in Table 3 concerning wages. In contrast to the US, in the UK employment polarization has been argued not to have been accompanied by greater wage polarization; see, for example, Jin (2022). Our data seems to indicate that this is the case for mature workers, as can be seen in the bottom panel of Table 3, where we report the average pay of those in high-paying occupations relative to those in the other two categories. The figures indicate that there has been no change in relative wages *for mature workers*. In contrast, for young workers we find an increase in wage polarization across cohorts as the pay of those in high-paying jobs relative to those in middling jobs went

[22]See also Figure B.1 in the Appendix.

Figure 4: Change in the probability of being in each ISCO-88 occupation in the first period



Notes: The figure shows the positive relationship between the change in probability, expressed in percentage points, of members of the NCDS58 and BCS70 cohorts being in each ISCO-88 occupation in the first period and average weekly pay, expressed in 1970£, in this occupation for the BCS70 cohort.

from being the same to being 25% higher.

3.3 Occupational dynamics

While the literature on inter-generational mobility has traditionally focused on the outcomes of the child when mature, we are interested in the occupational dynamics through which individuals reach a particular outcome. To illustrate why this is important, Table 4 reports the conditional probabilities of switching occupations between age 23/26 and age 42.[23]

The table shows that there is a considerable degree of mobility across occupations over the individual's lifetime, i.e. of intra-generational mobility. Individuals who start their

[23]To understand why the probability of moving from being out-of-work into a high-paying occupation is so high, recall that the former category includes those in education. Conditional probabilities in which we consider those in education as a separate category, hence not included in out-of-work, are reported in the Online Appendix, Table OA.2, and display the expected (large) difference between those in education and the rest of those out-of-work.

Table 4: Conditional probabilities of changing occupations

	BCS70				NCDS58			
Occupation	Out	Low	Mid	High	Out	Low	Mid	High
Out-of-work	33.8	25.3	14.5	26.4	27.4	24.7	20.7	27.3
Low-paying	13.6	45.1	17.5	23.8	16.3	40.0	20.3	23.4
Middling	10.5	13.8	44.9	30.8	10.4	15.4	43.4	30.8
High-paying	8.3	8.2	11.0	72.6	8.5	8.1	12.3	71.2

Notes: This table reports the probability, expressed in percent, of being in each second-period occupation (columns) conditional on the first-period occupation (rows) for individuals in the NCDS58 and BCS70 cohorts.

careers in low-paying and middling occupations have roughly a 40% probability of staying there and a substantial likelihood of moving upwards. Notably, 30.8% of those initially in middling occupations have a job in high-paying occupations by age 42 in both cohorts. In contrast, persistence is high for those who start in high-paying occupations, over 70%. The transition probabilities are remarkably similar across cohorts, in particular those of moving into a high-paying occupation. The most significant differences come from the outcomes of those who start either out of work or in low-paying occupations. In both cases, those in the younger cohort face a lower probability of being in a middling occupation when mature (lower by 5.8 and 2.5 pp., respectively) which translates into higher odds of remaining in the occupation of origin.

These figures indicate that the occupational outcomes of mature individuals depend both on their initial occupations and on transitions across occupations, raising the question of whether a reduction in the share of middling jobs can be a break to mobility. If mobility occurs partly through individuals climbing the income ladder during their careers, the disappearance of middling jobs can have important consequences. A large proportion of those who are in high-paying occupations at age 42 started their careers in middling occupations. If fewer individuals start in such occupations, as indicated by Figure 3, then there will be fewer individuals that can move into high-paying jobs. Moreover, with middling jobs scarce, those who start out in low-paying occupations are more likely to stay in their initial occupations. The impact of such changes on mobility will depend on the extent to which parental background matters for entry into each occupation and for the subsequent dynamics.

4 Patterns of mobility

Our analysis proceeds in two steps. First, we examine how an individual's occupation is affected by parental background, differentiating between the impact on the child's initial occupation and her occupation when mature. Our second step, presented in the next section, consists in considering regional patterns of mobility to assess the extent to which regional differences in polarization are correlated with observed mobility patterns at the regional level.

4.1 The determinants of individual mobility

In order to understand the effect of parental income on occupational dynamics we start by estimating its impact on the child's probability of starting out in each occupation, where the possible occupations are out-of-work (O), low-paying (L), middling (M) and high-paying (H). We define out-of-work as the baseline occupation category. Let p_j be the probability of starting in occupation $j \in \{L, M, H\}$ which is given by the following multinomial logistic model:

$$\log\left(\frac{p_j}{p_O}\right) = \alpha_{1j} + \beta_{1j} Y^p + \gamma_{1j} X, \tag{1}$$

where Y^p is parental income, and X are individual characteristics (in our baseline specifications simply gender). Parental income is log-standardised. All terms will be interacted with a dummy that equals one for those in the 1970 cohort (BCS70) and zero otherwise. Cross-term coefficients hence represent the change across cohorts in the effect of the variable on the child's initial occupation.

We next consider the determinants of the probability of being in occupation $k \in \{L, M, H\}$ at age 42. We start by considering a specification of the form

$$\log\left(\frac{p_k}{p_O}\right) = \alpha_{2k} + \beta_{2k} Y^p + \gamma_{2k} X, \tag{2}$$

which captures how parental income determines the child's occupational outcome when mature.[24] This expression is consistent with the approach usually found in the literature on inter-generational mobility where only the labour market outcome of the mature worker is considered. In contrast, intra-generational analyses have focused on how incomes evolve over the individual's working life. We hence also consider the following specification:

$$\log\left(\frac{p_k}{p_O}\right) = \alpha_{3k} + \sum_j \eta_{kj} \mathbb{1}_j + \beta_{3k} Y^p + \gamma_{3k} X, \tag{3}$$

where $\mathbb{1}_j$ is a dummy variable that equals one if the individual was in occupation $j \in \{O, L, M, H\}$ when young.

[24] As well as this linear specification we also tried including squared parental income and obtained equivalent results.

The expression in equation (3) shares with the literature on intra-generational mobility the idea that individuals may change position on the income ladder and that it is important to understand how such dynamics operate. It differs from existing approaches in two respects. First, we focus on occupational mobility over the lifetime, rather than income mobility; second, we control for parental income as a potential factor that could influence the extent to which the child changes occupations over time. Equation (3) then adds to the literature on intra-generational mobility by allowing parental income to have an impact on lifetime occupational changes, and to that on inter-generational mobility by allowing the effect of parental income on the occupation of mature workers to occur both through their initial occupation and through the likelihood of transition to other jobs.

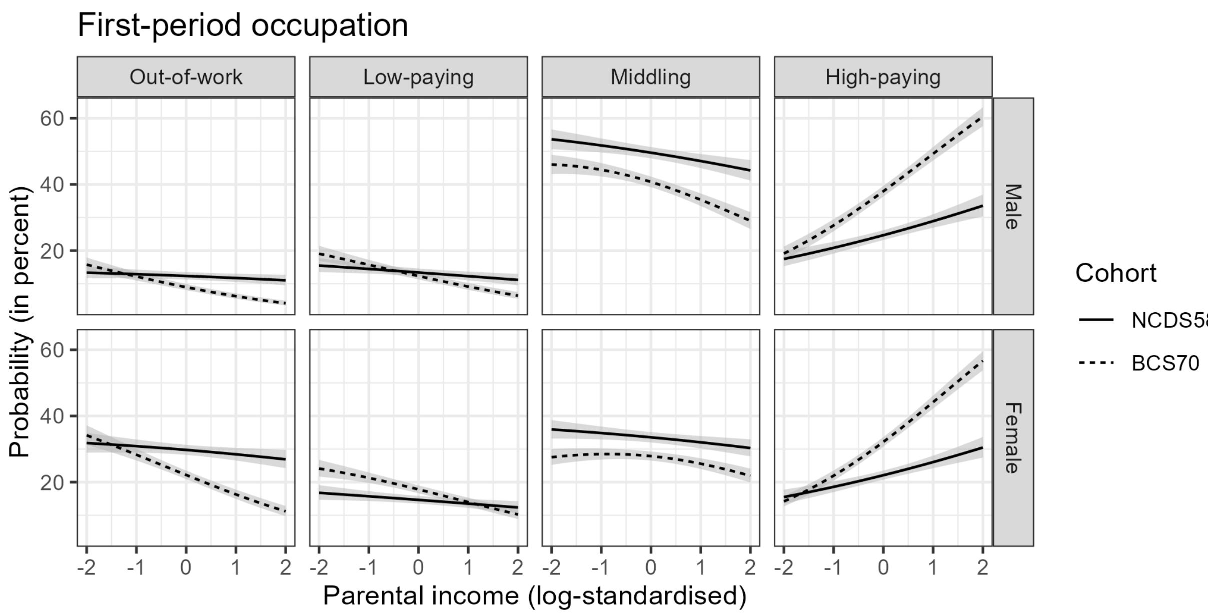
Our empirical strategy makes two important choices. The first is not to consider education decisions and to focus exclusively on the overall impact of parental income. The alternative is to consider a three-step setup in which parental income determines education, which then determines first-period occupation, which in turn determines the second-period job. Existing work has taken two approaches, with some authors focusing exclusively on parental income and others including education to examine to what extent the influence of parental background takes place through educational achievement.[25] Given the focus of our paper, we consider exclusively the two occupational outcomes and abstract from the role played by education, which is seen as one of the various channels through which background can affect outcomes. We nevertheless performed a three-step analysis which provides equivalent results.[26]

Second, we have chosen to use a multinomial logistic model considering the four possible occupational outcomes. The alternative would have been to estimate four binomial regressions, one for each occupation. Both specifications have advantages and disadvantages. In a binomial regression we compare the probability of being in occupation j relative to the other three outcomes. The interpretation of the regressions can be difficult, notably, for middling occupations as the alternative not-being-in-middling-occupations entails both better and worse outcomes than middling jobs, making it difficult to understand what the effect of parental income is. A solution to the above problem is to consider a multinomial logit, which compares the likelihood of being in each of the three employment categories to that of being in the reference group, out-of-work. Multinomial regressions have the advantage of

[25] For the latter approach see, for example, Blanden and Gregg (2004), Gregg and Macmillan (2010), Blanden and Macmillan (2014), Blanden and Macmillan (2016), and Major and Machin (2018). Harmon et al. (2003), however, point out the difficulty of differentiating between the returns to education and those to (innate or socially-acquired) ability.

[26] We find, first, that the effect of parental income on education is higher for the younger than for the older cohort and, second, that the younger cohort exhibits a stronger impact of parental income and a weaker impact of education on mature occupational outcomes (see Online Appendix F).

Figure 5: First-period occupation probability according to parental income



Notes: This figure presents the probability, expressed in percent, of being in each type of occupation (out-of-work, low-paying, middling, high-paying) in the first period according to parental income, log-standardised. Probabilities are computed for males and females in both cohorts according to the multinomial logistic regression reported in Table C.1 in the Appendix. 95% confidence intervals are indicated by grey shading.

simultaneously considering all the possible outcomes, yet they are harder to interpret as the coefficients represent odds relative to the omitted group.

Our reference outcome in the multinomial regressions is being out-of-work. It is important to note that the transition from this category into the three employment occupations occurs with roughly equal probabilities. For the NCDS58 (BSC70) the probability of transition from out-of-work to low- and high-paying occupations is, respectively, 24.7 pp. (25.3 pp.) and 27.3 pp. (26.4 pp.), i.e. of very similar magnitude. The likelihood of moving into middling occupations was somewhat lower (20.7 and 14.5 pp., respectively) but of comparable magnitude; see Table 4 above. Similar results are nevertheless obtained when we estimate binomial regressions for each of the occupations (not reported).

4.2 Initial occupations

We start by estimating the impact of parental income on the child's first-period occupations. We estimate equation (1) and report the results in the Appendix, Table C.1. Logit coefficients are hard to interpret, hence to visualize the results Figure 5 displays the estimated probability of being in each occupation when young as a function of parental income. The probabilities are computed according to the multinomial logistic regression and capture both the effect of parental income and changes in the availability of jobs. They are reported separately for each cohort and each gender; the four columns depict the four possible outcomes, starting with out-of-work occupations on the left.

Consider first the outcomes for the 1958 cohort, depicted by the continuous lines. Parental income is a key determinant of initial occupations, with high income increasing the probability of being in a high-paying occupation and reducing that of being in a middling or low-paying one. Note also that the effect of family background is particularly large for high-paying occupations. The levels vary across genders, with women being more likely than men to be out-of-work and less likely to be in any of the three types of employment.

The impact of parental income on the various probabilities for the 1970 cohort is depicted by the dashed lines. The regressions on which these results are based, reported in Table C.1 in the Appendix, display large changes across cohorts in the coefficients on the direct effect of parental income, which are captured in the figures.[27] For example, for men, the coefficient doubles for high-paying occupations, increasing from 0.21 to 0.41, a result that is reflected in the large increase in the slope of the schedule observed in the two right panels. There are various possible explanations for this. Obviously, the effect could be operating through education which has become more dependent on parental background (see Appendix F for a discussion). Other explanations are that non-cognitive skills may have become more important and that they may be positively associated with the household's income, or parental income could be a proxy for either the size or the 'quality' of the child's social network, which in turn has become more important in determining access to jobs.[28]

As expected, the probability of being in a middling occupation has fallen for all individuals, irrespective of family background. The decline has been greater the higher parental income is. Together with the previous result, this indicates that as the share of high-paying jobs increased, individuals from high-income households were more likely to go into high-paying jobs at the expense of middling ones. The probability of being in a low-paying occupation pivots around the mean, with those at the bottom (resp. top) of the parental income distribution being more (resp. less) likely to be in that occupation in the 1970 than in the 1958 cohort. The schedule for being out of work displays a steeper slope, with a decline in the probability of being in this category for all men except those at the very bottom of the parental income distribution.

[27] The regression coefficients also indicate that, for all three outcomes, the coefficient on parental income is significantly different across the two cohorts.

[28] For example, Blanden et al. (2007), using the same data as us, show a strengthening of the relationship between parental income and non-cognitive skills across the two cohorts. Major and Machin (2018) emphasize the changing role of education and the increasing importance of the "extra-investments" made by upper-middle class families. For the US, Chetty et al. (2014a) show that neighborhood characteristics are extensively correlated with mobility.

Consider now the schedules for women. Starting from the left, we can see that women experienced a large decline in the likelihood of being out-of-work, consistent with the increase in female labour force participation observed over the period. Yet, the reduction is strongly correlated to parental income, even more so than for men. The probability of being in a low-paying occupation has increased at virtually all points of the distribution—except at the very top—indicating that much of the increase in female participation occurred through access to low-paying jobs. The probability of being in middling occupations has declined for the younger cohort, as is the case for men. Interestingly, for women the schedule is roughly flat for those with parental incomes below the mean and generally less steep than for men. This indicates that parental income is less of a determinant of occupation for women than for men. As is the case for men, the slope of the schedule for high-paying occupations has increased sharply across the two cohorts.

These patterns indicate that parental income conferred a greater advantage for those born in 1970 as compared to those born in 1958. Much of the change was driven by reduced entry into middling occupations, which was offset by a greater likelihood of being in a high-paying (resp. low-paying) occupation for those coming from households at the top (resp. bottom) of the parental income distribution.

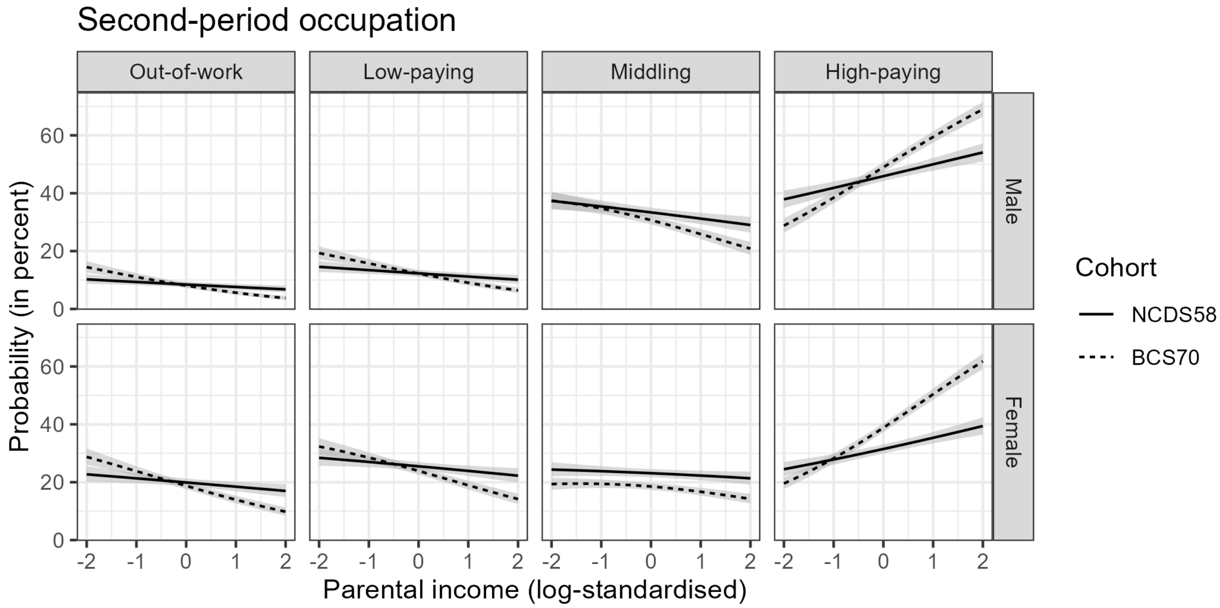
4.3 Mature occupations

We turn now to the probability of being in occupation k at age 42. Recall that we suppose that as well as depending on parental income, the occupation of mature workers depends on their initial job. We hence consider both an expression that does not include the effect of initial occupation, as given by equation (2), and one in which it is included, as in equation (3). The former specification is equivalent to those usually found in the literature.

The relationship between parental income and occupational dynamics is depicted in Figure 6 which reports the probabilities of being in each occupational category at age 42 as a function of parental income, for both genders. The probabilities are obtained from the baseline multinomial regression, which does not consider the effect of initial occupation. The regression, reported in Table C.2 in the Appendix, indicates that parental income has a large impact on occupational outcomes at age 42, with the coefficient for high-paying jobs almost doubling across cohorts. This result is in line with the extensive work that has found an increased correlation in parent-child incomes, as discussed in the introduction.

Coming from a better-off background increases the probability of being in a high-paying occupation and reduces all others. This effect has strengthened across cohorts. For example, while a one-standard-deviation increase in parental income used to raise the odds of being

Figure 6: Second-period occupation probability according to parental income



Notes: This figure presents the probability, expressed in percent, of being in each type of occupation (out-of-work, low-paying, middling, high-paying) in the second period according to parental income, log-standardised. Probabilities are computed for both genders in both cohorts according to the multinomial logistic regression reported in Table C.2 in the Appendix. 95% confidence intervals are indicated by grey shading.

in a high-paying occupation by 21% for the older cohort, this same increase raises the odds by 73% for the younger one.[29]

The main difference from our results for initial occupations is the crossing of several of the probability schedules. Consider the probability of being in a high-paying occupation; we can ask whether individuals from all backgrounds have benefited from the increase in the share of such jobs across cohorts. Figure 5 indicates that, as far as initial occupations are concerned, this is the case, with even those men at the bottom of the parental-income distribution (i.e. 2 standard deviations below the average) exhibiting a larger probability of being in a high-paying job in the younger than in the older cohort. In contrast, we can see in Figure 6 that by age 42 only those from sufficiently well-off households have reaped the benefits of the expansion in high-paying jobs. Men whose parents had an income 0.5 standard deviations below the average had the same probability in both cohorts of being in a high-paying occupation; those with low parental income, had a lower probability if born in 1970 than if born in 1958.

Figure 6 is reminiscent of the analysis in Major and Machin (2018), who show, using the

[29]These coefficients are obtained from Table C.2 by taking the exponential of the change in log odds, i.e. $\exp(0.19) = 1.209$ and $\exp(0.19 + 0.36) = 1.733$.

same data, that the effect of parental income on the probabilities of being in the various quintiles of the income distribution has increased across the two cohorts (see Major and Machin 2018, Figures 0.1 and 0.2). Our findings indicate, not surprisingly, that occupational structure is behind the observed changes in income mobility and echo theirs in terms of the probabilities of being in each of the four occupations all along the income distribution.

4.4 From initial to mature occupations

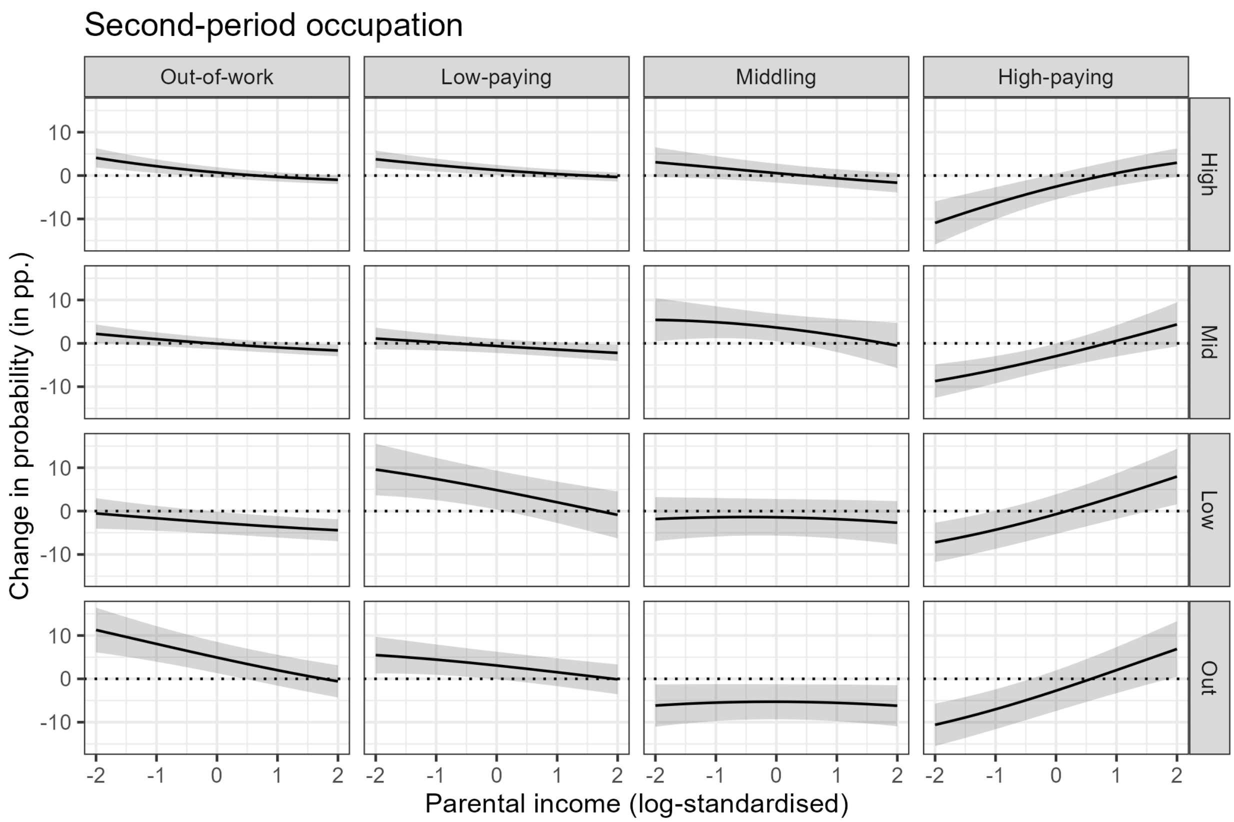
The marked change in the overall effect of parental income across the two cohorts can be due to changes either in how parental income impacts initial occupations or in its effect on mobility during the child's career, i.e. on intra-generational mobility. As we have seen above, the influence of parental background on the former has become stronger; we turn next to whether coming from a better-off background also changes the extent to which, given their initial occupation, an individual progresses over their career.

Figure 7 figure displays the difference between the BCS70 and the NCDS58 cohorts, expressed in percentage points, in the probability of being in each second-period occupation (out-of-work, low-paying, middling, high-paying) conditional on first-period occupation; see Table C.2 in the Appendix for the regression results. Each panel represents the gap across cohorts in a given transition probability for various levels of (standardised) parental income, with positive values implying that the younger cohort has a greater probability of moving from occupation j to occupation k, and vice versa. The reported changes are for men; the equivalent figure for women is provided in Appendix D, Figure D.1.

For individuals at the mean of the distribution, the probability of being in a middling occupation in late career has increased by almost 3.7 pp. if initially in a middling occupation, but has declined if initially in low-paying occupations or out of work. This indicates a reduction in upwards mobility for those starting their careers in the least well-paid categories. For example, for those who were initially out-of-work, the probability of remaining there has increased by 4.92 pp. and this has occurred at the expense of a large decline in the likelihood of moving into low-paying or middling jobs. The fourth column of graphs, reporting changes in the probability of being in a high-paying occupation, indicates that this has fallen for individuals with mean parental income irrespective of initial job. The change is small for those starting in low-paying occupations (-0.71 pp.) but larger for the other three initial occupations, with values between -2.5 and -2.9 pp. This is a surprising finding given that the share of such jobs rose by 5.4 pp.

These changes hide large differences depending on parental background. Consider the changes in the probability of being in a high-paying occupation across cohorts. For those

Figure 7: Change in second-period occupation probability conditional on first-period occupation and parental income (male only)



Notes: This figure presents the difference, expressed in percentage points, between the BCS70 and NCDS58 cohorts in the probability of being in each type of second-period occupation (out-of-work, low-paying, middling, high-paying), conditional on first-period occupation, according to parental income, log-standardised. Probabilities are computed for males in both cohorts according to the multinomial logistic regression reported in columns (2) of Table C.2. 95% confidence intervals are indicated by grey shading.

at the top and the bottom of the parental income distribution the changes are large and of opposite sign. Notably, for those with parental income 2 standard deviations below the mean there is a considerable reduction, between 7.2 and 11 pp., in the probability of attaining the top occupations, irrespective of initial occupation. Note that even those who started in high-paying occupations are now less likely to remain there if parental income is low. In contrast, when parental income is 2-standard-deviations above the mean, the likelihood of remaining at or moving to the top has increased, by as much as 8 pp. for those who started in a low-paying occupation.

The second striking pattern observed in the data is a dichotomy that appears for those who started in a low-paying occupation. Their probability of moving to a middling occupation has fallen and the alternative outcome depends on parental income. For those at the bottom of the distribution, the likelihood of remaining in a low-paying occupation has increased (by 4.8 pp. for those with average parental income and by 9.6 pp. for those at -2 standard deviations). In contrast, for those at the top of the parental income distribution the decline in mobility into middling jobs has been accompanied by a greater probability of moving into a high-paying occupation. The natural career progression from low-paying to middling occupations seems to have been partially replaced by higher probabilities of either staying in the initial occupation or jumping up to a high-paying one, with transition probabilities being strongly dependent on the individual's background. An equivalent pattern is found for those who started in middling occupations, with individuals at the top (bottom) of the parental income distribution being more likely to be in high-paying (low-paying) jobs in the younger than in the older cohort.

4.5 Intra-generational mobility and parental income

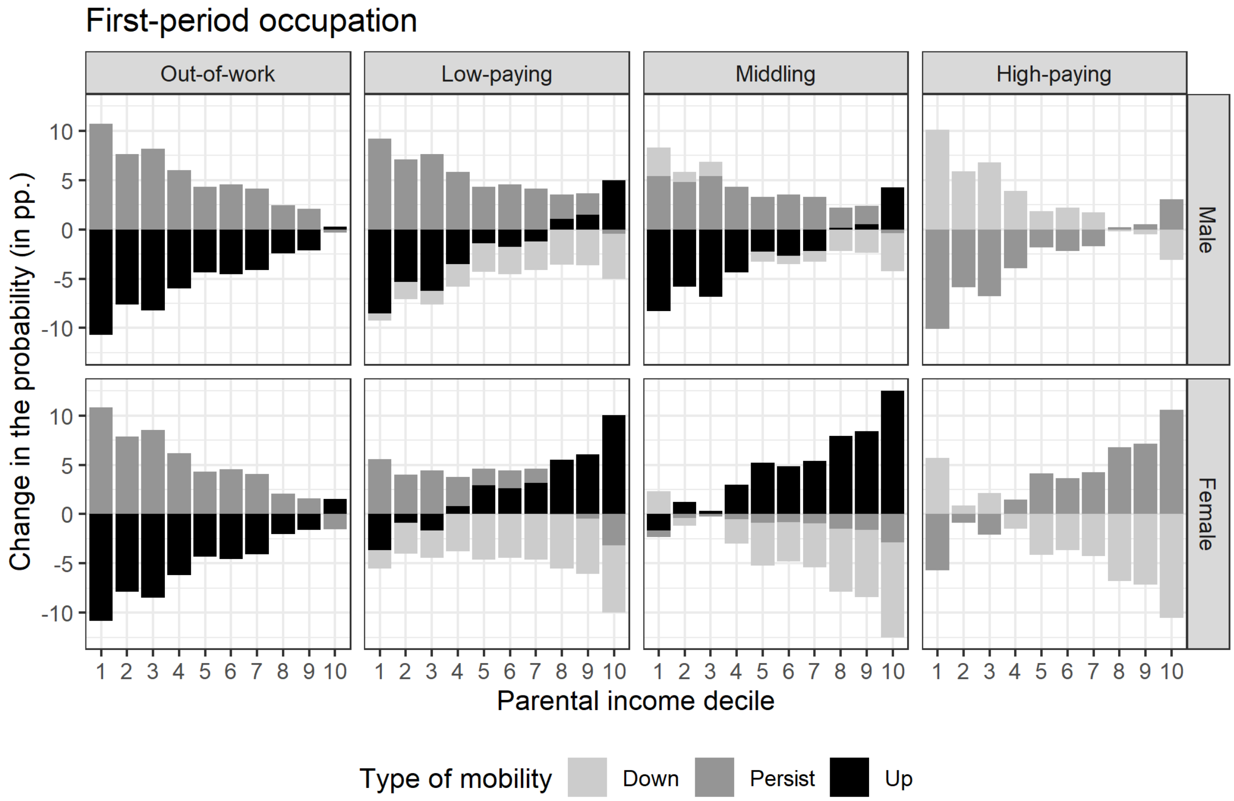
In order to provide a compact measure of mobility, we define three possible outcomes for the second period. Downward mobility is defined as ending up in a category with lower average pay than the individual's initial category; persistence consists of remaining in the same category, and upwards mobility means moving to a category with higher average pay. Hence for those starting in a low-paying occupation, downwards mobility occurs if they are out-of-work at age 42, and upwards mobility if they are in a middling or high-paying occupation.

The upwards/downwards intra-generational mobility measures are depicted graphically in Figure 8, in which we plot the *change* in the three probabilities (of moving up, staying put, and moving down with respect to the initial occupation) for different deciles of the parental income distribution.

Consider first those who started in high-paying occupations. The two possible occupational dynamics are to move downwards (depicted in light grey) or to remain in a high-paying occupation (depicted in dark grey). Those born to parents in the top decile are 3 pp. more likely to stay in that occupation and 3 pp. less likely to move into a lower-income occupation in the 1970 cohort than in 1958 one. The reverse effect appears at the bottom of the parental income distribution: the bottom decile are 10 pp. more (less) likely to experience downwards mobility (remain in the occupation). Persistence drops less as we move up the parental income distribution, with the sign reversing for the 9th and 10th deciles. The figure displays what we could call a *polarization of mobility*, with only moderate changes in mobility for those in the middle of the distribution, while the changes at the two extremes of the distribution have been large and of opposite sign.

An equivalent pattern is observed for those starting out in middling occupations. At

Figure 8: Change in intra-generational mobility across cohorts



Notes: This figure plots the difference, expressed in percentage points, between the BCS70 and the NCDS58 cohorts in type of mobility (downwards, persistence, upwards) conditional on first-period occupation (out-of-work, low-paying, middling, high-paying) by decile of the parental income distribution. Probabilities are computed for males and females at each parental income decile, according to the multinomial logistic regression reported in columns (2) of Table C.2 in the Appendix.

the bottom of the parental income distribution, there have been sharp declines in upwards mobility and increases in persistence and downwards mobility, the changes becoming smaller as we move along the income distribution. The pattern is reversed from the 8th decile, with the likelihood of moving upwards increasing across cohorts for the top three deciles. The polarization of mobility is also apparent for those starting in low-paying occupations for whom the probability of moving into middling or high-paying occupations increases only for the top three deciles. Lastly, for those initially out-of-work, only at the top decile of the parental income distribution is there an increased likelihood of upwards mobility. Note that for those in the bottom decile the magnitudes of the change are large: the probability of staying has increased by 10 pp., which is offset by an equivalent decline in the probability of moving upwards. Overall these results indicate that the change in the structure of employment has been accompanied by a polarization of intra-generational mobility, with the probabilities of moving across occupations changing in opposite directions depending on whether the individual's parental income is at the top of the distribution.

Not surprisingly, the dynamics for women differ considerably from those for men. Women in the older cohort were much less likely to be in middling and especially high-paying occupations. The bottom panels of Figure 8 capture, however, the advantage of higher parental income for upwards mobility. Irrespective of parental income, younger cohort women starting in a high-paying occupation (resp. middling) have a greater probability of remaining there (moving upwards). This is not surprising in view of the occupational upgrading experienced by women in the younger cohort. In contrast, polarization arises for women who were initially in low-paying occupations, although the turning point regarding parental income is lower than for men (4th decile). This points to the tension between a general occupational upgrading of women and a decline in mobility observed for workers coming from a less well-off background. The results for those out of work broadly mimic those for men. Overall, despite the differences due to women's increased access to all occupations, these figures confirm the growing importance of parental income for intra-generational mobility.

5 Mobility and polarization at the regional level

The geography of mobility has received considerable attention over the past few years,[30] and this section explores the regional dimension of our data. We focus on two aspects both of which address the hypothesis that the observed increase in the impact of parental income on occupational outcomes is related to the polarization of employment. The next subsection considers whether the reduction in mobility that we have identified appears when we replace the cohort dummies by a measure of the extent of polarization that individuals faced in their region. It hence asks if the cohort dummies are capturing the differences in the structure of the labour market over time. Our second strategy consists in estimating the impact of parental income on occupational outcomes at the regional level in order to obtain regional measures of mobility. We then ask whether there is a correlation between the *changes* over time in regional mobility and the *increase* in polarization at the regional level.

[30]See Chetty et al. (2014a), Güell et al. (2018) and Bell et al. (2022) amongst others.

5.1 Individual outcomes and regional employment patterns

We consider again equation (2) and replace all the interacted cohort dummies BCS with the share of middling jobs in the region of origin. Thus, our specification becomes:

$$\log\left(\frac{p_k}{p_O}\right) = \alpha_{4k} + \alpha'_{4k} MidShare^r + \beta_{4k} Y^p + \beta'_{4k} MidShare^r \times Y^p \\ + \gamma_{4k} X + \gamma'_{4k} MidShare^r \times X + \psi_r, \tag{4}$$

where $MidShare^r$ is the share of middling jobs in the individual's region r, X are the control variables, and ψ_r are region fixed effects.

Our data provide information on the 10 regions that constitute the UK.[31] This allows us to identify the region of residence at each interview date, and we define an individual's region as that where they lived at age 16.[32] The cohort data have the drawback that sample sizes at the regional level are small and thus resulting measures of regional polarization may not capture well the actual changes in the structure of employment. In order to have a more representative sample, we use data from the Labour Force Survey (LFS) to build polarization measures. We compute $MidShare^r$ for the year in which the individual was 34, which is roughly half-way between the two dates chosen to examine occupational outcomes. For the NCDS58 cohort this corresponds to the year 1992, for the BCS70 cohort to 2004. Robustness analysis using, for example, the average over the entire period considered for each cohort delivered equivalent results.

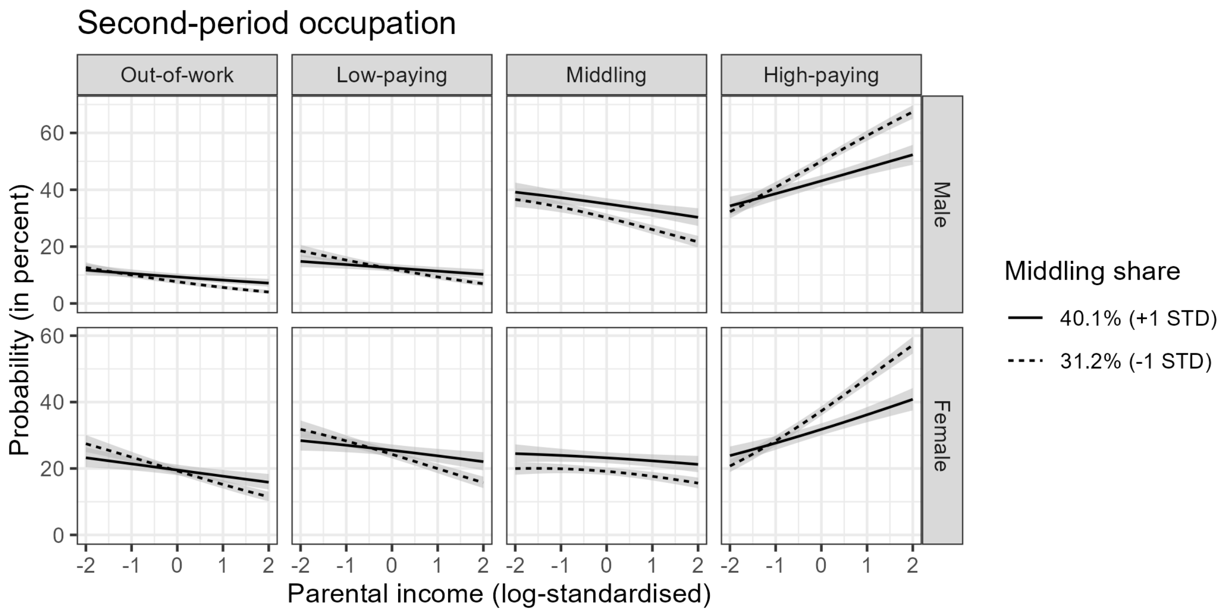
Figure 9 reports the probabilities of being in each occupational category at age 42 as a function of parental income, for both genders (see Table D.1 in the Appendix for the regression coefficients). We display the probabilities for two values of the middling share, plus and minus one standard deviation of the distribution of $MidShare^r$ across regions, respectively, 40.1% and 31.2%. The various panels display steeper slopes—i.e. a stronger impact of parental income—when the share of middling jobs is low than when it is high, in line with our core specification in Figure 6.

To gauge the magnitude of the effects, we average the (standardized) share of middling employment across regions for each cohort: for the NCDS58 (resp. BCS70) $MidShare^r$ is 0.853 standard deviations below (above) the mean. Using these figures, the regression coefficients (Table D.1) imply that a one standard deviation increase in parental income

[31] Unfortunately, these regions are relatively large and hence do not allow us to identify the very local effects that other work has observed, such as Chetty et al. (2014a) who focus on considerably smaller locations in their analysis for the US. For the UK, Bell et al. (2022) consider a dataset with the 32 NUTS2 regions; however, the drawback of their dataset is that it does not have information on parental income.

[32] The proportions of individuals that change region of residence between age 16 and age 23/26 are 10% and 11.2% for the older and younger cohorts, respectively.

Figure 9: Second-period occupation probability according to parental income and share of middling occupations at the regional level



Notes: This figure presents the probability, expressed in percent, of being in each type of occupation (out-of-work, low-paying, middling, high-paying) in the second period according to parental income (log-standardized) and the share of middling jobs available at age 34 in the region of residence at age 16. Probabilities are computed for males and females from East Anglia (reference group) according to the multinomial logistic regression reported in Table D.1 in the Appendix. 95% confidence intervals are indicated by grey shading.

raises the probability of being in a high-paying occupation by 4.6 pp. for the older cohort and by 9 pp. for the younger one. These values are close to those obtained in our core specification (Table C.2) of 4.1 and 10.5 pp. respectively, indicating that using differences in polarization across cohorts yields effects of similar magnitude to those obtained with the cohort dummy.

5.2 Regional mobility

Our final step consists in considering the correlation between regional mobility and polarization. We first estimate the impact of parental income on occupational outcomes at the regional level in order to get regional measures of mobility and then ask whether there is a correlation between the changes over time in regional mobility and the increase in polarization at the regional level. To do so we run a multinomial regression at the regional level for the determinants of the probability of being in occupation k at age 42 of the form:[33]

$$\log\left(\frac{p_k^r}{p_O^r}\right) = \alpha_k^r + \beta_k^r Y^p + \gamma_k^r X. \tag{5}$$

This regression yields estimates of 10 coefficients $\hat{\beta}_k^r$ that measure the impact of parental income on occupational outcomes in each of the regions.

Table 5 presents the coefficients on parental income obtained when we regress second-period occupations on parental income.[34] The coefficients on parental income are not always significant, which is potentially due to a lack of statistical power arising from the limited number of observations (per region and also in certain region-occupation cells; see Figure B.3 in the Appendix). Nevertheless, for the 1958 cohort, the magnitudes are often similar to those found at the national level, especially for high-paying occupations. In some cases, large and significant effects are found, notably for the West Midlands where we find an unusually large coefficient on parental income for high-paying occupations (0.63).

The results, however, clearly indicate that the changes in occupational mobility observed across cohorts at the national level also took place at the regional level and are not the result of the population reallocating across regions with different mobility patterns. Consider the effect of parental income on the likelihood of being in a high-paying occupation. Out of the 10 regions only two (South West and West Midlands) do not display a significant coefficient.[35] In all the others, the magnitude of the effect is large, with the coefficient being at least twice as large for the younger as for the older cohort and much larger in certain cases.

The estimates also imply large variations in the degree of inter-generational mobility across locations, with the coefficient on parental income for the younger cohort being twice as high in the most mobile locations as in the least mobile. When we compute the overall effect for the younger cohort (i.e. summing the two coefficients), we obtain figures ranging from 0.44 to 1.09 (the estimate obtained at the national level is 0.55).

To capture changes in mobility in region r, we focus on the between-cohort change in the role of parental income for being in occupation k, namely, $\Delta\beta_k^r$ which correspond to the "Par. Inc. $\times$ BCS" coefficients in Table 5. We thus compute the correlation between

[33] We do not compute first-period mobility and conditional second-period mobility because of sample sizes, as in many regions we have only a small number of individuals moving across certain occupations between first and second period.

[34] As before, we need to recall that these are the coefficients relative to the probability of being out-of-work. Figures D.2 and D.3 in the Appendix report the overall effect.

[35] For the former the coefficient is of similar magnitude to those found in other regions; in contrast, for the West Midlands it is close to zero, probably reflecting the fact that this region had a much higher coefficient already for the 1958 cohort than anywhere else.

mobility and polarization with the following linear regression:

$$\Delta\beta_{5k}^{r} = \delta_k + \eta_k \Delta Pol^r + \gamma_{6k} X_r + u_r, \tag{6}$$

where ΔPol^r is the change in employment polarization at the regional level, X_r are the control variables and u_r is the error term. We consider two control variables: the initial level of mobility in the region, which we proxy by the coefficient on parental income for the older cohort so that a higher value implies a greater degree of persistence, and the change in the region's unemployment rate for prime-age individuals, which captures the change in the overall economic climate.[36]

There are two concerns with our strategy. First, the regional structure of employment may have been affected by the degree of social mobility, thus implying endogeneity. Second, we have an omitted variable problem since there are aspects that we would have liked to account for, such as the quality of and access to education, for which no regional measures are available.

To deal with endogeneity, we construct a measure of the change in regional polarization, ΔPol^r, that is a shift-share based on national level changes. The intuition for the shift-share is that the regions in which middling jobs were more prevalent before the period of analysis should also be the regions in which the change in employment polarization has been the greatest. We hence define the change in polarization in region r as

$$\Delta Pol^r = \sum_i s_{i,1979}^r \left(s_{i,2004}^{UK} - s_{i,1992}^{UK} \right) \times 100.$$

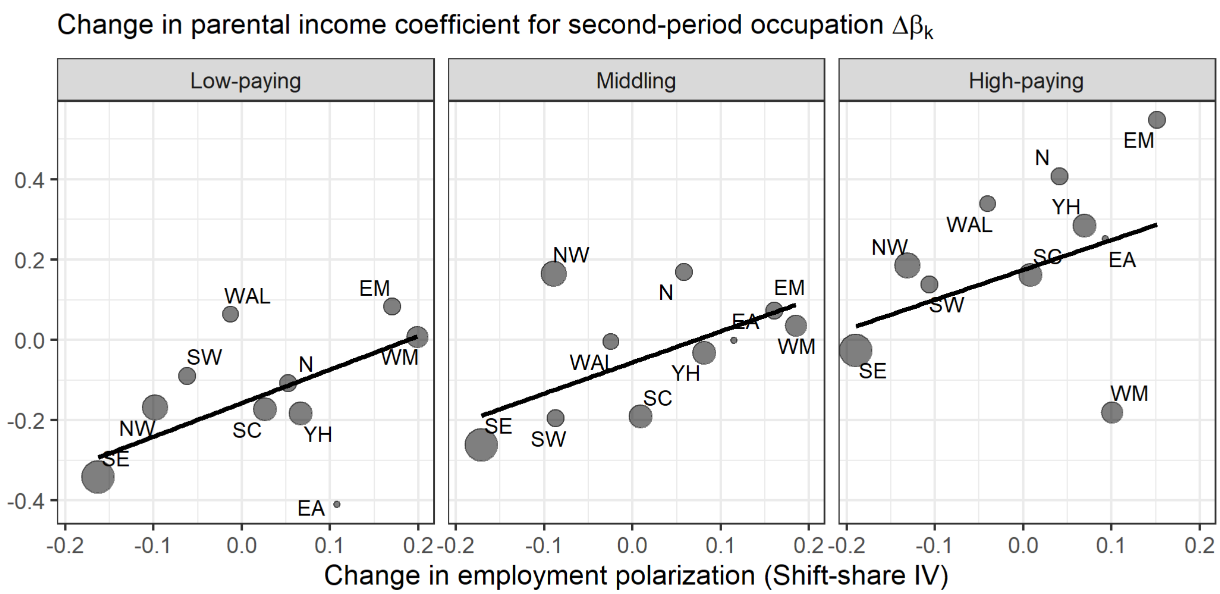
The terms $s_{i,1992}^{UK}$ and $s_{i,2004}^{UK}$ denote the shares of individuals aged 25 to 49 employed in occupation i in the UK as a whole in 1992 and 2004, respectively.[37] We then weight the change in occupational shares by the employment structure in region r before the first cohort's occupation is observed, where $s_{1979,i}^r$ is the share of individuals aged 25 to 49 which are employed in occupation i in region r in 1979, the first year for which we have data.

To account for omitted variables we use an IV strategy where we instrument the changes in occupations in the UK with the changes in these same occupations in other European countries. This choice is justified by the evidence that there has been pervasive job polarization in several Western European countries since (at least) the early 1990s; see Goos et al.

[36]We define prime-age individuals as those between 25 and 49 years of age, and compute the change in their unemployment between the years 1992 and 2004.

[37]We consider 1992 and 2004 for two reasons. First, they are the years in which, respectively, the NCDS58 and the BCS70 are aged 34 which is, roughly, halfway between the two ages at which we observe them. Second, our IV strategy (explained below) relies on EU-LFS data available from 1992.

Figure 10: Second-stage IV regression



Notes: This figure presents the second stage of the IV shift-share regression estimating the relationship between the change in the role of parental income on determining the child's occupation at age 42 and the change in employment polarization at the regional level. Both variables are represented net of the effects of the initial level of mobility in the region and of the change in the unemployment rate in the region for prime-age individuals. The x-axis is the change in employment polarization measured with a shift-share based on changes in 1-digit ISCO-08 occupations and instrumented with the average occupational changes in a set of European countries which includes Denmark, France, Germany, Italy, the Netherlands, and Spain. The y-axis measures the between-cohort change in the parental-income coefficient for the child's second-period occupation and is estimated by a multinomial logistic regression at the regional level. Each column panel refers to a second-period occupation. Each region is weighted by the inverse of the standard error of the estimated parental income coefficient.

(2009) and Goos et al. (2014). We thus estimate a just-identified 2SLS model, where the first stage predicts the change in employment polarization in UK regions with the change in employment polarization in Europe, and the second stage regresses the regional change across cohorts in the impact of parental income on the predicted change in employment polarization (in the same region) obtained from the first stage.

In order to compute our instrument, we use data from the European Labour Force Survey (EU-LFS) for Denmark, France, Germany, Italy, Netherlands, and Spain. We use broad occupational categories, at the 1-digit level. Although the EU-LFS data report the ISCO-08 categories, at the 1-digit level they are equivalent to those in ISCO-88. The instrument for region r is then the across-country average of changes in the shares of the various occupations between 1992 and 2004, weighted by the share of each occupation in region r in 1979, $s^r_{1979,i}$.

Our estimates for the first stage are reported in the Appendix (see Figure D.4), while the second-stage regression is presented in Figure 10. Since the dependent variable is a vector of estimated coefficients, we weight our observations by the inverse of the standard errors of the corresponding estimated coefficients.

The three panels present the results for the change in the coefficients on parental influence for low-paying, middling and high-paying occupations. The horizontal axis displays the change in the employment share of each occupation, ΔPol^r. We report the change in absolute value, which is negative for middling occupations; thus reporting the absolute value implies that in all three panels polarization increases as we move from left to right. The lines represent the regression lines obtained when we control for initial parental impact and the change in the unemployment rate. In all three cases we find a positive correlation between the increase in the effect of parental income and in polarization.

This section provides evidence that the increase in employment polarization is one of the causes of the reduction in occupational mobility observed across the two cohorts. When we exploit individual data, we find that differences in the extent of polarization experienced by the two cohorts result in estimates of the impact of parental income that are close to those obtained when using cohort dummies. The cross-sectional evidence, in turn, indicates that when we estimate mobility measures by regions, the declines in mobility observed are correlated with the extent of regional increases in polarization.

6 Conclusion

A vast literature has discussed the consequences of job polarization for earnings inequality. Yet, the question of whether a changing employment structure has also had an impact on social mobility has only recently been addressed. This paper explores such question focusing on the role played by middling jobs in generating occupational transitions over the individual's career that facilitate inter-generational mobility.

We start by developing a simple theoretical setup with three types of jobs and two levels of parental income. Parental background affects the child's initial human capital and determines her entry job. We suppose that in the first period there is (random) on-the-job learning, the extent of which depends on the type of job performed, with middling jobs generating more learning than low-paying ones. As workers accumulate human capital, they can move up or down the occupational ladder, creating occupational mobility. A smaller share of middling jobs implies that the possibilities for learning, and hence for upwards mobility, fall, thus leading to a greater influence of parental income on occupational outcomes.

The model highlights not only the importance of polarization for social mobility, but also the fact that transitions across occupations—i.e. intra-generational occupational dynamics—are an essential aspect of inter-generational mobility. Our empirical analysis starts by examining the importance of such transitions. We use data on two British cohorts that are particularly suited for our purposes. First, the two cohorts, born 12 years apart, entered the labour market under substantially different conditions in terms of the structure of employment, with the latter cohort facing a much more polarized labour market. Second, we have data for the children at various ages so that we can identify to what extent upwards mobility is driven by an improvement in the occupation at which children enter the labour market or by them going up the occupational ladder during their working life.

The data indicate that intra-generational occupational changes are a major source of mobility, with large shares of those starting in low-paying and middling occupations eventually moving, respectively, to middling and high-paying jobs. Comparing the two cohorts, we find that as the share of middling jobs has fallen these two sources of occupational mobility have weakened. Furthermore, our results indicate that the role of parental income in determining occupations has increased, both for first-period jobs and for the transition towards better-paid occupations. Notably, although transition probabilities across occupations have–in most cases—remained roughly constant across cohorts, for the younger one they have become more dependent on family background. For example, while the probability for those who start in low-paying jobs to move upwards has remained stable on average, this average hides a considerable increase for those with high-income parents and a decline of about 10 percentage points for those from low-income backgrounds.

When we turn to the regional analysis, our results indicate that the effect of parental background on the child's occupation is strongest where the share of middling jobs is lowest. We also examine regional changes in mobility, and our shift-share IV-strategy indicates that regions where employment polarization rose the most across the two cohorts are also those where *immobility* increased the most.

The patterns we identify suggest that as the availability of middling jobs has dwindled, parental income has become more important in determining occupational outcomes. Recent work by Güell et al. (2018) on Italy indicates that the strong regional differences in mobility identified for the US also appear in other countries, indicating that factors beyond institutional and policy differences are responsible for the variety of inter-generational mobility experiences observed. Our paper suggests that differences in the structure of employment at the regional level may be one of the causes. Moreover, Adermon et al. (2018) and Solon (2018) have emphasised the importance of *multi-generational mobility.* Our findings point to a potential transmission of polarization across generations, where the increased importance of parental background may accumulate across generations, creating a multiplier effect that over time accentuates the occupational distance across groups from different backgrounds. This is a question that we intend to pursue in future work.

Table 5: Probability of second-period occupation by region

	Multi. logit - Dep. var.: Second-period occupation		
	Low-paying	Middling	High-paying
East Anglia (N = 904)			
Par. inc.	0.04	−0.00	0.13
	(0.15)	(0.14)	(0.14)
Par. inc. × BCS	−0.10	0.31	0.57**
	(0.25)	(0.26)	(0.26)
East Midlands (N = 1066)			
Par. inc.	0.06	0.12	0.17
	(0.15)	(0.15)	(0.15)
Par. inc. × BCS	0.45**	0.44**	0.92***
	(0.22)	(0.21)	(0.21)
North (N = 1037)			
Par. inc.	−0.04	−0.08	0.02
	(0.15)	(0.14)	(0.14)
Par. inc. × BCS	0.07	0.34	0.58***
	(0.22)	(0.22)	(0.21)
North West (N = 1810)			
Par. inc.	0.12	0.06	0.32***
	(0.11)	(0.10)	(0.11)
Par. inc. × BCS	−0.01	0.32**	0.35**
	(0.16)	(0.15)	(0.15)
Scotland (N = 1489)			
Par. inc.	0.03	0.13	0.14
	(0.12)	(0.12)	(0.12)
Par. inc. × BCS	0.18	0.17	0.52***
	(0.18)	(0.18)	(0.17)
South East (N = 3718)			
Par. inc.	0.01	0.06	0.17**
	(0.09)	(0.08)	(0.08)
Par. inc. × BCS	−0.06	0.02	0.26**
	(0.11)	(0.11)	(0.11)
South West (N = 1141)			
Par. inc.	−0.10	0.05	0.17
	(0.16)	(0.16)	(0.16)
Par. inc. × BCS	0.08	−0.02	0.31
	(0.21)	(0.21)	(0.21)
Wales (N = 821)			
Par. inc.	−0.23	−0.16	−0.07
	(0.17)	(0.16)	(0.16)
Par. inc. × BCS	0.34	0.27	0.62***
	(0.24)	(0.23)	(0.22)
West Midlands (N = 1495)			
Par. inc.	0.04	0.12	0.63***
	(0.12)	(0.12)	(0.14)
Par. inc. × BCS	0.09	0.12	−0.08
	(0.17)	(0.17)	(0.18)
Yorkshire and Humberside (N = 1282)			
Par. inc.	0.03	−0.05	0.02
	(0.14)	(0.12)	(0.12)
Par. inc. × BCS	0.06	0.21	0.53***
	(0.19)	(0.17)	(0.17)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Out-of-work occupation in second period is the base outcome of the multinomial logistic regression. Male in the NCDS58 cohort is the reference group. Parental income in logarithm and then standardized at the cohort level. Control variables in all regressions include Intercept, BCS cohort, Female and Female × BCS.

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Appendix

A Model details

This appendix presents further details on the model. We start by deriving, from Table 1, the distribution of human capital in the second period which is given by

$$h = \begin{cases} h_L & \text{with probability} \quad q_1 + (1-\pi)(z_L - q_1) \\ h_H & \qquad '' \qquad\qquad (1-\pi)z_H \\ h^2 & \qquad '' \qquad\qquad \pi(1-q_1-q_3) \\ h^3 & \qquad '' \qquad\qquad \pi q_3 \end{cases}$$

Using this distribution we can obtain the allocation of labour reported in Table 2.

Table A.1 reports the transition probabilities across occupations for the two types of workers. It can be computed as the probability that an individual of parental background i and initial occupation j ends in occupation k when mature.

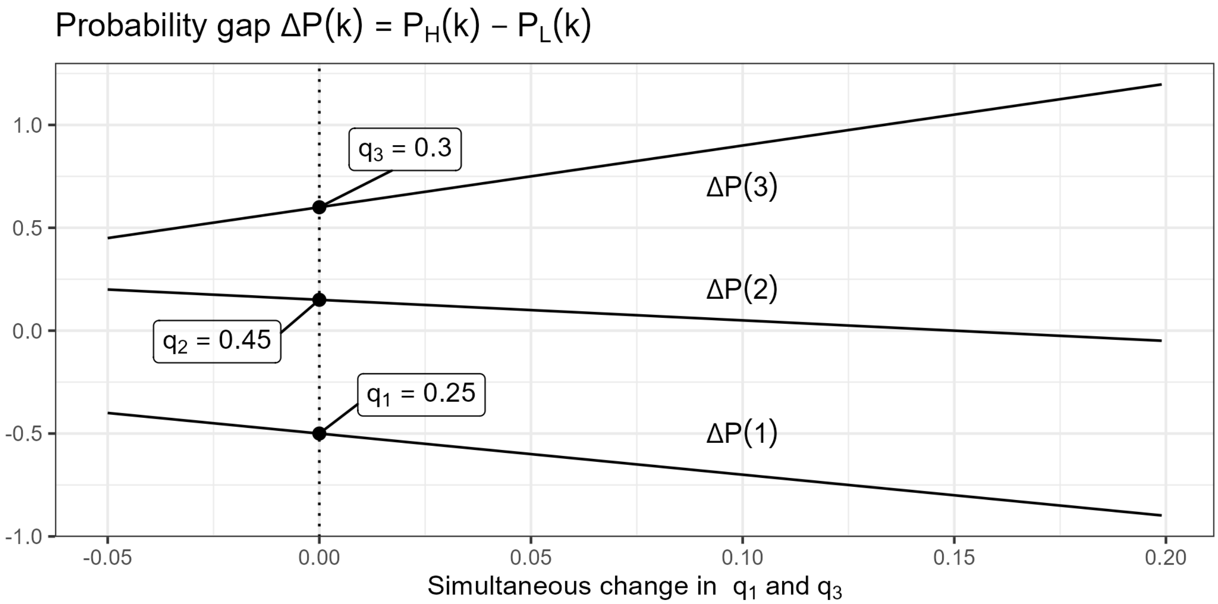
Table A.1: Transition probabilities across occupations

		End 1	End 2	End 3
L-workers	Initial 1	$\frac{q_1}{q_1+(1-\pi)(z_L-q_1)}$	$\frac{(1-\pi)(z_L-q_1)}{q_1+(1-\pi)(z_L-q_1)}$	0
	Initial 2	$\frac{(1-\pi)q_1}{q_1+(1-\pi)(z_L-q_1)}$	$\frac{(1-\pi)^2(z_L-q_1)}{q_1+(1-\pi)(z_L-q_1)}$	π
H-workers	Initial 2	0	$1-\frac{q_3-\pi(1-q_1)}{z_H}$	$\pi+\frac{q_3-\pi(1-q_1)}{z_H}$
	Initial 3	0	$1-\frac{q_3-\pi(1-q_1)}{z_H}$	$\pi+\frac{q_3-\pi(1-q_1)}{z_H}$

To understand how these transition probabilities are obtained, consider those with low parental income. In the second period, there are $q_1 + (1-\pi)(z_L - q_1)$ workers with skills h_L and q_1 positions in sector 1, therefore a worker of type L that was initially in sector 1 ends up in the same sector with probability $\frac{q_1}{q_1+(1-\pi)(z_L-q_1)}$ and in sector 2 with the complementary probability. A proportion π of worker of type L employed in sector 2 during the first period learn and end up in sector 3. A proportion $1-\pi$ of these workers do not learn and among them a proportion $\frac{q_1}{q_1+(1-\pi)(z_L-q_1)}$ end up in sector 1 and the rest in sector 2. Similar calculations allow us to compute the transition probabilities for those with H-background.

Turning now to how polarization affects inter-generational mobility, we complement the case examined in section 2 by considering that in which there is a simultaneous increase in q_1 and q_3 at the expense of q_2. The effect on the gap in the probability of being in each

Figure A.1: Probability gap in second-period occupations between H and L background according to change in q_1 and q_3



Notes: This figure presents the probability gap in second-period occupations between children from H and L parental income, i.e. $\Delta P(k)$, according to changes in the share of low- and high-paying jobs, i.e. q_1 and q_3. Changes in q_1 and q_3 are of equal magnitude and at the expense of q_2 since $q_1 + q_2 + q_3 = 1$. Parameters of the model are set such that $z_L = 0.5$, $z_H = 0.5$, and $\pi = 0.25$. The dotted line represents the baseline occupational distribution where $q_1 = 0.25$, $q_2 = 0.45$, and $q_3 = 0.30$.

occupation, $\Delta P(k)$, is depicted in Figure A.1. We increase simultaneously q_1 and q_3 by the same amount, reducing q_2 until only 25% of workers are in middling occupations (and 35% and 40% in q_1 and q_3 respectively). The horizontal axis depicts the change in q_1 and q_3 in percentage points.

As polarization increases the advantage in accessing high-paying occupations that those from high-income background have relative to those from low-income households rises. For low-paying occupations, the relative likelihood of being in such jobs (which is negative, as only L-workers are employed in occupation 1) falls with polarization. H-workers have an advantage in being in occupation 2 for low levels of polarization, but this advantage falls as q_1 and q_3 increase. For high levels of polarization there are more L- than H-workers in middling jobs; the reason is that as q_1 increases, fewer high-ability L-workers manage to move to high-paying occupations, raising their likelihood to be in middling occupations and increasing the number of high-paying jobs available for H-workers who have not learnt.

B Data and summary statistics

This appendix presents further details on the data as well as summary statistics. We provide additional tables and figures about the structure of employment and the extent of job polarization observed in the data.

B.1 Occupational structure in the cohort studies

Table B.1 describes the classification of occupations that we use, following Goos et al. (2014). Occupational groups (high-paying, middling and low-paying) correspond to those in Goos et al. (2014), except for occupations 11, 23, 34, 61 and 92 that were removed from their analysis. We add these missing occupations to the categories where the closest occupations are, relying on the 1-digit ISCO-88 classification.

Table B.2 presents the probability of being in each occupational category in each period, for both cohorts. The first-period probabilities indicate that BCS70 individuals are about 8.1 pp. less likely to start in middling occupations then NCDS58 ones, while they are about 12.1 pp. more likely to start their careers in a high-paying occupation.

We group occupations into three broad categories in line with the polarization literature, as reported in Figure 3 in the text. Figure B.1 performs a similar exercise using the original ISCO-88 categories. Occupations are depicted in light gray for those we place in the low-paying category, in dark grey for those in the middling category, and in black for high-paying ones. Although there are differences within the three broad categories, a clear pattern of polarization emerges both when we consider young and mature individuals. The change has been particularly large for young individual's occupations, for whom the reduction in the share of middling jobs has been marked.

B.2 The Labour Force Survey (1981-2012)

As a complementary dataset we use the Labor Force Survey (LFS). It is a random sampling of households living in the UK which collects data on labour market status and, since 1993, wages. The LFS was conducted every two years until 1983, then annually until 1992, and quarterly since then. It gives details on the occupation and industry in which individuals work, thus allowing us to take a snapshot of the structure of employment on a given year. The survey is intended to be representative of the whole population of the UK, and currently contains around 37,000 responding households in every quarter.

We use information from the LFS over the period 1981 to 2012, these being the years defined as the first period for the older and the second period for the younger cohorts. Initially the information is biannual, then annual from 1983 to 1992, and after that date

Table B.1: Overview of the ISCO-88 occupation codes

Code	Occupation
High-paying occupations	
11	Legislators and senior officials
12	Corporate managers
13	Managers of small enterprises
21	Physical, mathematical and engineering professionals
22	Life science and health professionals
23	Teaching professionals
24	Other professionals
31	Physical, mathematical and engineering associate professionals
32	Life science and health associate professionals
33	Teaching associate professionals
34	Other associate professionals
Middling occupations	
41	Office clerks
42	Customer service clerks
61	Skilled agricultural and fishery workers
71	Extraction and building trades workers
72	Metal, machinery and related trade work
73	Precision, handicraft, craft printing and related trade workers
74	Other craft and related trade workers
81	Stationary plant and related operators
82	Machine operators and assemblers
83	Drivers and mobile plant operators
Low-paying occupations	
51	Personal and protective service workers
52	Models, salespersons and demonstrators
91	Sales and service elementary occupations
92	Agricultural, fishery and related labourers
93	Laborers in mining, construction, manufacturing and transport

Notes: This table provides an overview of ISCO-88 occupation codes. Occupation groups (high-paying, middling and low-paying) correspond to those from Goos et al. (2014), except for occupations 11, 23, 34, 61 and 92 that were removed from their analysis. We classify these occupations according to proximity in the 1-digit ISCO-88 classification.

we use data from the second quarter, as it is the one that most closely fits with the period over which annual interviews were conducted. The structure of the data allows us to define occupations in exactly the same way as for the cohort data and provides information on the region of employment.

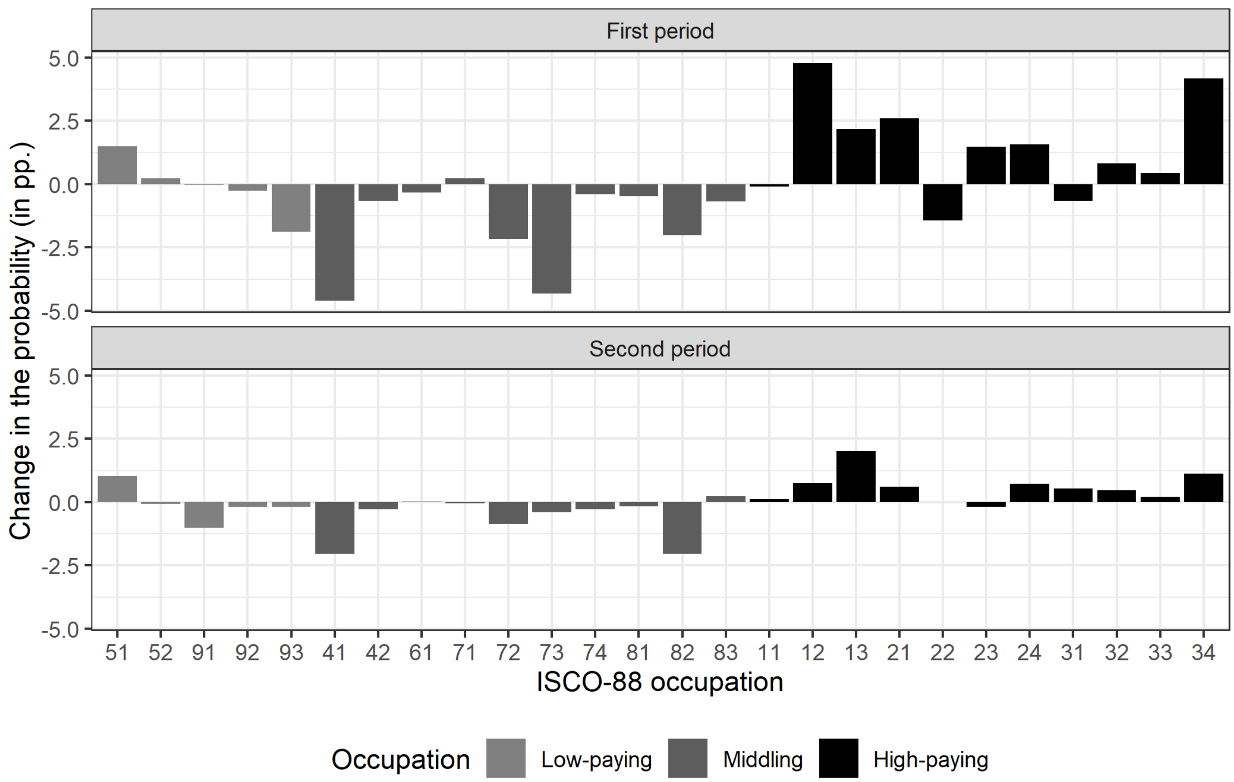
Figure B.2 shows the extent of job polarization at the national level using the LFS data

Table B.2: Probability of being in each occupation at each period, (in percent)

	First period			Second period		
Occupation	BCS70	NCDS58	Δ	BCS70	NCDS58	Δ
Out-of-work	16.2	21.3	-5.1	13.9	14.4	-0.4
Low-paying	15.2	14.0	1.2	18.4	19.1	-0.7
Middling	33.1	41.2	-8.1	23.8	28.0	-4.2
High-paying	35.6	23.6	12.1	43.9	38.5	5.4

Notes: This table shows the probability, expressed in percent, of being in each first- and second-period occupation for the BCS70 and NCDS58 cohorts. Differences between both cohorts, expressed in percentage points, are reported in the last column for each period.

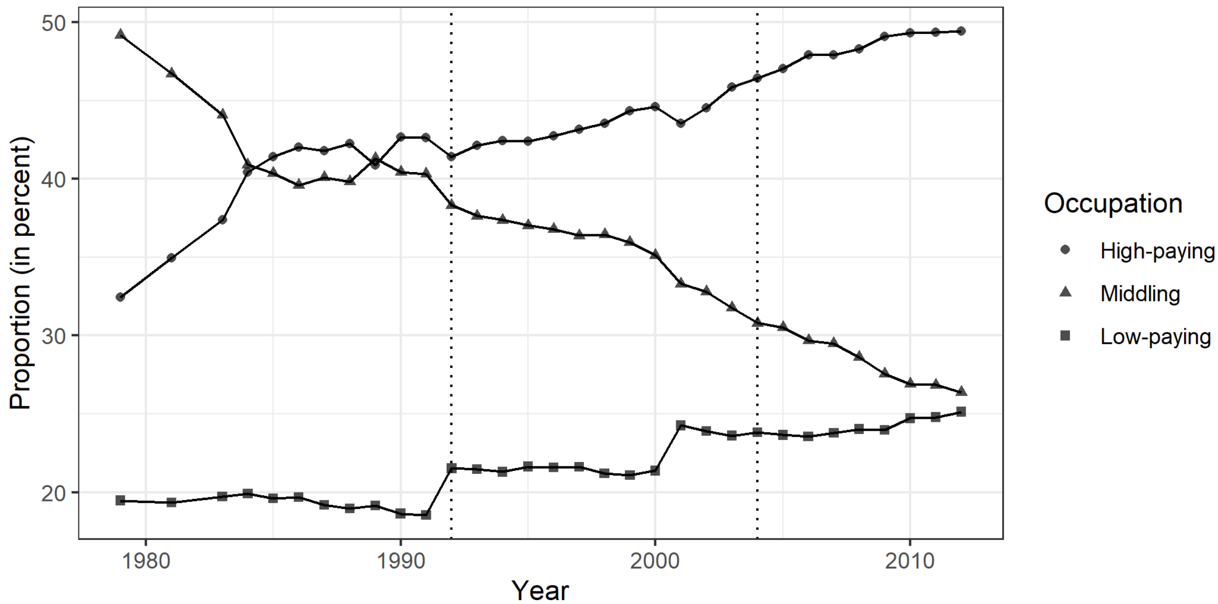
Figure B.1: Change in the probability of being in each ISCO-88 occupation in each period



Notes: This figure presents the difference, expressed in percentage points, between the BCS70 and NCDS58 cohorts in terms of the probability of being in each ISCO-88 occupation in each period.

for both relevant-age cohorts. The share of middling jobs has declined by over 20 percentage points from 1981 to 2012. This reduction has been offset by an increase in the share of high-paying occupations by 14 percentage points over the same period, whereas the share of low-paying jobs has increased by 6 percentage points. Figure B.3 shows the extent of job

Figure B.2: Job polarization at the national level (Labour Force Survey)

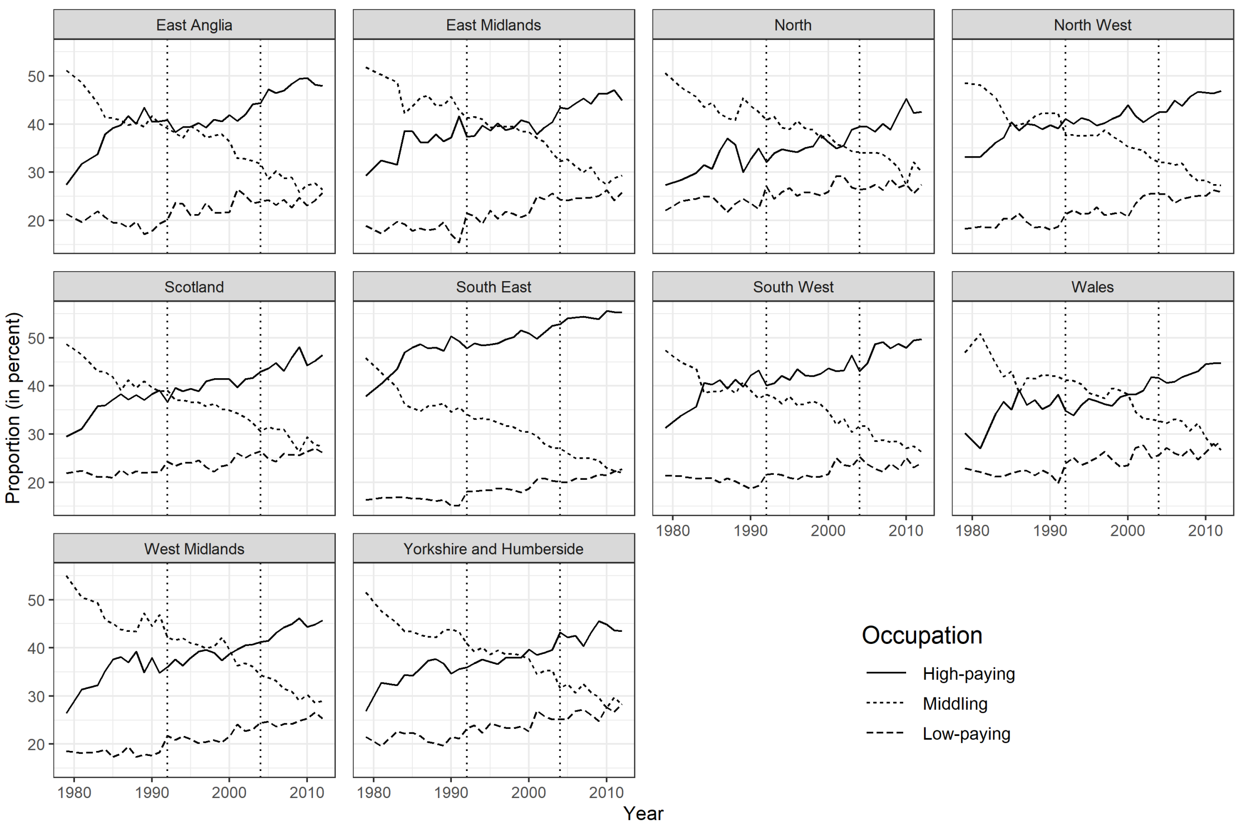


Notes: This figure presents employment shares at the national level using Labour Force Survey (LFS) data from 1981 to 2012. The curves represent the share of individuals aged 25 to 49 in low-paying, middling, and high-paying occupations.

polarization at the regional level using the LFS data for both relevant age cohorts.

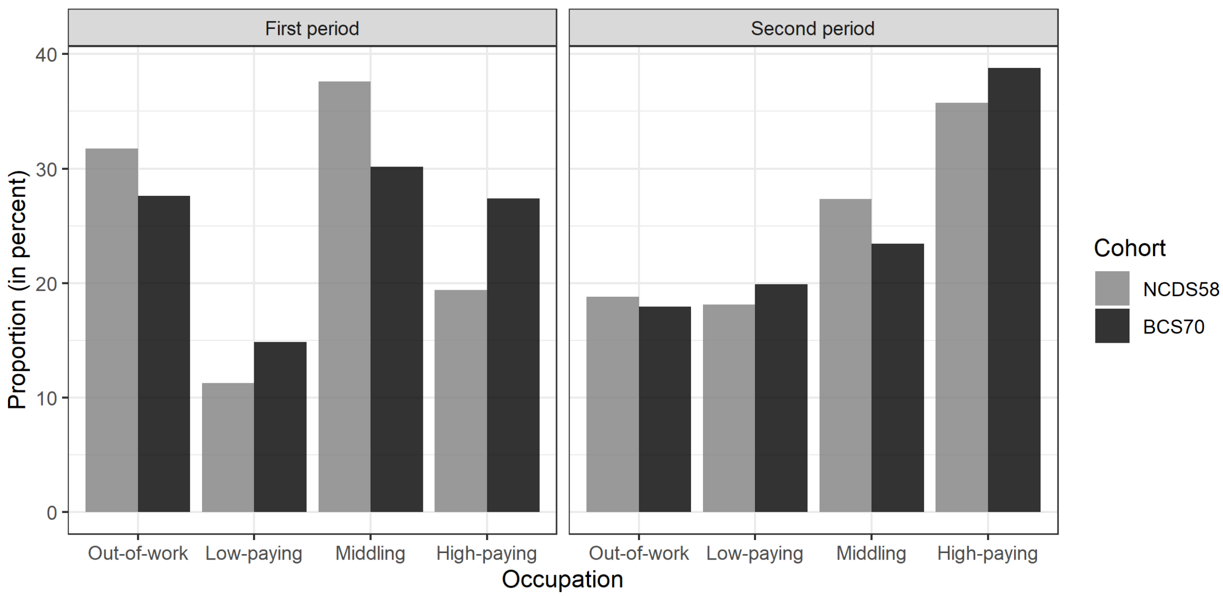
Figure B.4 reports the distribution of occupations using the LFS data for individuals aged 23/26 and 42 in the same years as those in the NCDS58 and BCS70 and of the same age and at the same period as the cohort data. The main difference between the two datasets it that the LFS data reports more out-of-work individuals than the cohort data, notably for young individuals. The dynamics are otherwise similar to those reported in Figure B.4. The increase in polarization is particularly strong for young workers, driven by large increase in the share of high-paying occupations and a moderate one in that of low-paying occupations.

Figure B.3: Job polarization at the regional level (Labour Force Survey)



Notes: This figure presents employment shares at the regional level using Labour Force Survey (LFS) data from 1981 to 2012. The curves represent the share of individuals aged 25 to 49 in low-paying, middling, and high-paying occupations.

Figure B.4: Occupation distribution across cohorts (Labour Force Survey)



Notes: This figure reports the proportion of individuals, expressed in percent, in each type of occupation (out-of-work, low-paying, middling, high-paying) from the Labour Force Survey with the same age and the same periods as the NCDS58 and BCS70 cohorts.

C Multinomial logistic regressions

This appendix provides the regression tables for occupations under the multinomial specifications of the logistic regressions. We also discuss the complementarity of both specifications and how they help interpret coefficients.

C.1 First-period occupation

Table C.1 reports the coefficients of the multinomial logistic regression in equation (1) for the first-period occupation. The results indicate that the likelihood to be in a high-paying occupation is strongly affected by parental income, with the coefficient doubling across cohorts (from 0.21 to 0.42). The insignificant coefficients on "Par. Inc." indicate that, for the NCDS58 cohort, parental income does not give an advantage to get low-paying or middling jobs relative to being out of work. However, it does confer such an advantage for the younger cohort.

C.2 Second-period occupation

Table C.2 reports the coefficients of the multinomial logistic regression for second-period occupation from equations (2) and (3).

The first three columns report the coefficients for the baseline regression, while the next also include initial occupations. For the interpretation of the impact of the first-period occupations, we have to keep in mind that the omitted group are those out of work. Thus absolute coefficients are the difference in log-odds with respect to out-of-work young individuals (middle panel) and the coefficients for BCS70 indicate the change in the log-odds between both cohorts (bottom panel). The positive coefficients in the second panel indicate that being in either of these occupations when young increases the probability of being in employment at age 42. The figures display a considerable degree of persistence, with the coefficients on the diagonal being large and highly significant. Note that being in a middling occupation when young implies not only a high probability of being in that occupation when mature (coefficient of 1.47) but also a high probability of moving into a high-paying occupation (coefficient of 0.82).

Parental income has a large impact on occupational outcomes at age 42, with the coefficient for high-paying jobs almost doubling across cohorts. A one-standard-deviation increase in parental income raises the odds to be in a high-paying occupation by 21% for the older cohort and by 73% for the younger one. These coefficients are obtained by taking the exponential of the change in log odds, i.e. $\exp(0.19) = 1.209$ and $\exp(0.19 + 0.36) = 1.733$.

When we compare the impact of initial occupation across the cohorts (bottom panel)

Table C.1: Probability of being in each occupation in the first period (multinomial)

	Multinomial logit - Dep. var.: First-period occupation		
	Low-paying	Middling	High-paying
Intercept	0.08	1.39^{***}	0.69^{***}
	(0.07)	(0.06)	(0.06)
BCS cohort	0.24^{**}	0.12	0.75^{***}
	(0.10)	(0.08)	(0.09)
Female	-0.79^{***}	-1.27^{***}	-0.99^{***}
	(0.09)	(0.07)	(0.08)
Female × BCS	0.25^{**}	-0.02	-0.08
	(0.12)	(0.10)	(0.11)
Par. inc.	-0.03	-0.00	0.21^{***}
	(0.04)	(0.03)	(0.04)
Par. inc. × BCS	0.10^{*}	0.22^{***}	0.41^{***}
	(0.06)	(0.05)	(0.05)
Num. obs.	14763	14763	14763

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Out-of-work occupation in the first period is the base outcome of the multinomial logistic regression. Males in the NCDS58 cohort are the reference group. Parental income is log-standardised.

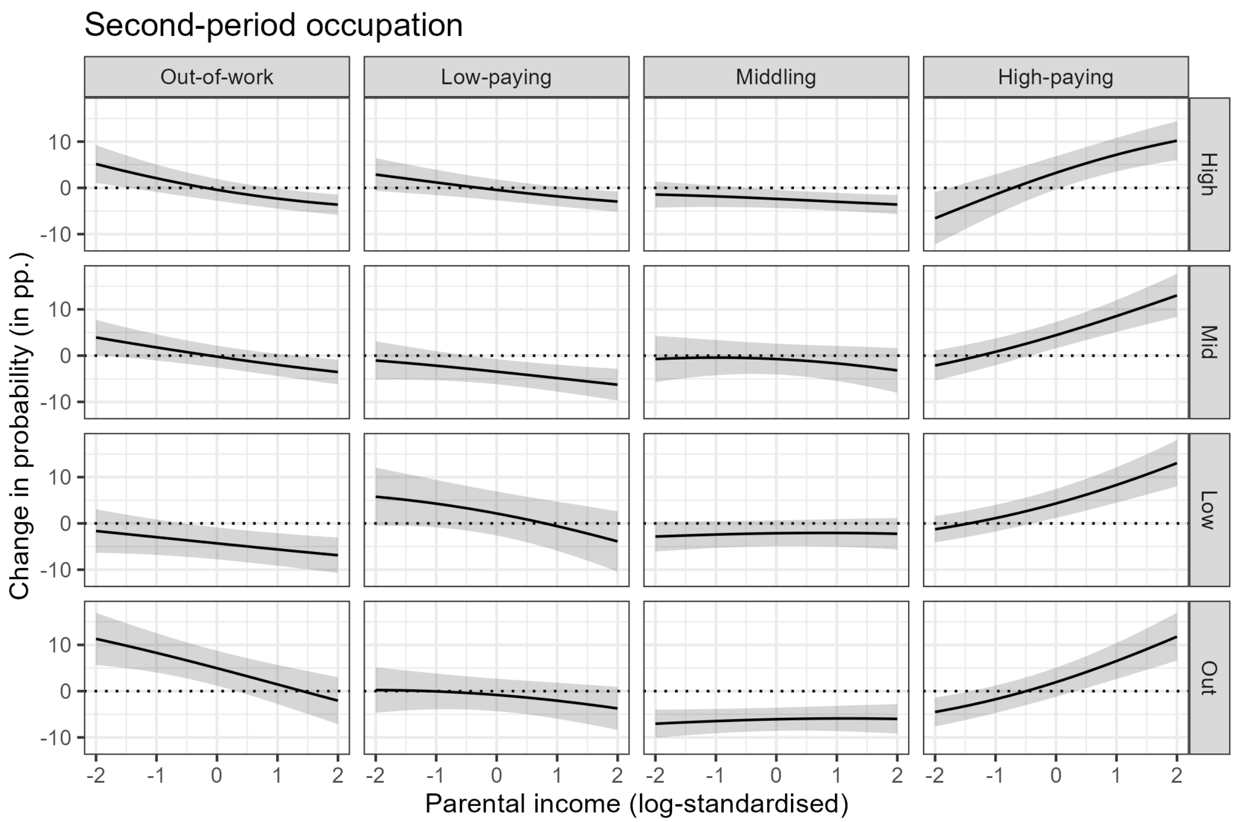
there are only two significant changes. First, we see a considerable improvement in the outcomes for those who started in a low-paying occupation, for whom the odds of being out-of-work fell for the younger cohort. Second, for those who started in middling occupations, persistence increased considerably. Persistence did not increase for those in high-paying occupations.

Table C.2: Probability of being in each occupation in the second period (multinomial)

	Multinomial logit - Dep. var.: Second-period occupation					
	(1)			(2)		
	Low	Mid	High	Low	Mid	High
Intercept	0.38^{***}	1.37^{***}	1.69^{***}	-0.10	0.44^{***}	0.81^{***}
	(0.08)	(0.07)	(0.07)	(0.11)	(0.10)	(0.10)
BCS cohort	0.04	-0.04	0.11	-0.07	-0.46^{***}	-0.32^{**}
	(0.11)	(0.09)	(0.09)	(0.15)	(0.15)	(0.14)
Female	-0.13	-1.23^{***}	-1.23^{***}	-0.01	-0.98^{***}	-1.13^{***}
	(0.09)	(0.08)	(0.08)	(0.10)	(0.09)	(0.09)
Female $\times$ BCS	-0.04	-0.12	0.16	-0.11	-0.09	0.25^{**}
	(0.13)	(0.12)	(0.11)	(0.13)	(0.12)	(0.12)
Par. inc.	0.01	0.04	0.19^{***}	0.02	0.05	0.14^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Par. inc. $\times$ BCS	0.05	0.15^{***}	0.36^{***}	0.05	0.11^{**}	0.25^{***}
	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)
Change with respect to the referent group as first period occupation (Out-of-work)						
Low-paying				1.00^{***}	0.31^{**}	0.14
				(0.12)	(0.13)	(0.13)
Middling				0.50^{***}	1.47^{***}	0.82^{***}
				(0.11)	(0.10)	(0.10)
High-paying				0.06	0.52^{***}	1.96^{***}
				(0.14)	(0.14)	(0.12)
Change between cohorts						
Low. $\times$ BCS				0.47^{***}	0.66^{***}	0.55^{***}
				(0.17)	(0.19)	(0.18)
Mid. $\times$ BCS				0.02	0.55^{***}	0.25^{*}
				(0.15)	(0.15)	(0.15)
High. $\times$ BCS				0.17	0.37^{**}	0.15
				(0.19)	(0.19)	(0.16)
Num. obs.	14763	14763	14763	14763	14763	14763

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Out-of-work occupation in second period is the base outcome of the multinomial logistic regression. Males out-of-work in the first period from the NCDS58 cohort are the reference group. Parental income is log-standardised. Coefficients in the middle panel capture the change in the marginal effect of the first-period occupation with respect to the reference one, i.e. out-of-work. Coefficients in the bottom panel indicate the change across cohorts in the marginal effect of the first-period occupation.

Figure D.1: Change in probability to be in each occupation in the second period according to first-period occupation and parental income (female only)



Notes: This figure presents the difference between the BCS70 and the NCDS58 cohorts in the probability of being in each type of second-period occupation (out-of-work, low-paying, middling, high-paying), conditional on the first-period occupation. We compute it at various points of the (log-standardized) parental income distribution. Probabilities are computed for females in both cohorts according to the multinomial logistic regression reported in columns (2) of Table C.2.

D Additional tables and figures

This appendix provides various additional figures and tables that complete our analysis.

Figure D.1 provides the change in the probability of being in each occupation in the second period conditional on first-period occupation for women, at several points of the parental income distribution.

Table D.1 displays the results obtained from the multinomial regressions, with the first three columns reporting again the estimates when we use the cohort dummies, and the last three columns those from the specification that includes the share of middling jobs. We also used alternative measures of polarization, for example employing data on only the initial year to measure of polarization for each cohort (1981 and 1996), and found equivalent results to those reported here (results not reported).

Table D.1: Probability of being in each occupation in the second-period as a function of the share of non-middling occupations in the region

	Multinomial logit - Dep. var.: Second-period occupation					
	(1)			(2)		
	Low	Mid	High	Low	Mid	High
BCS cohort	0.05	−0.03	0.11			
	(0.11)	(0.09)	(0.09)			
Middling share				−0.08	−0.03	-0.17^{***}
				(0.06)	(0.05)	(0.05)
Parental income	0.01	0.04	0.19^{***}	0.04	0.11^{***}	0.35^{***}
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Par. inc. × BCS	0.05	0.16^{***}	0.36^{***}			
	(0.06)	(0.05)	(0.05)			
Par. inc. × Mid. share				−0.00	-0.05^{*}	-0.12^{***}
				(0.03)	(0.03)	(0.02)
Num. obs.	14763	14763	14763	14763	14763	14763

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Being out-of-work in the second period is the base outcome of the multinomial logistic regression. Males in the NCDS58 cohort are the reference group in (1), while being male is the reference group in (2). Parental income is log-standardized at the cohort level. Middling share is the share of workers in middling occupations in total employment in the region where the individual lived at age 16. These shares have been standardized for ease of interpretation of the coefficients when interacted with parental income. Control variables in (1) include Intercept, Female and Female × BCS, while control variables in (2) include Intercept, Female and Female × Mid. share. Both sets of regressions also include region fixed effects.

The coefficients of interest have the expected sign. A higher share of middling employment is associated with a lower average probability of being in a high-paying occupation, as we would expect. There is no significant effect on the other employment categories, implying that higher polarization does not affect the allocation of workers between out-of-work, low-paying jobs and middling jobs. Parental income has, as expected, a positive impact on the likelihood to be in middling and high-paying jobs, and the interaction terms indicate that as polarization increases the effect of background becomes stronger.

Figures D.2 and D.3 depict the probabilities of being in each second period occupation for various levels of parental income at the regional level, for men and women respectively. They indicate that the pattern found at the national level also holds at the regional level. The underlying regressions are available upon request.

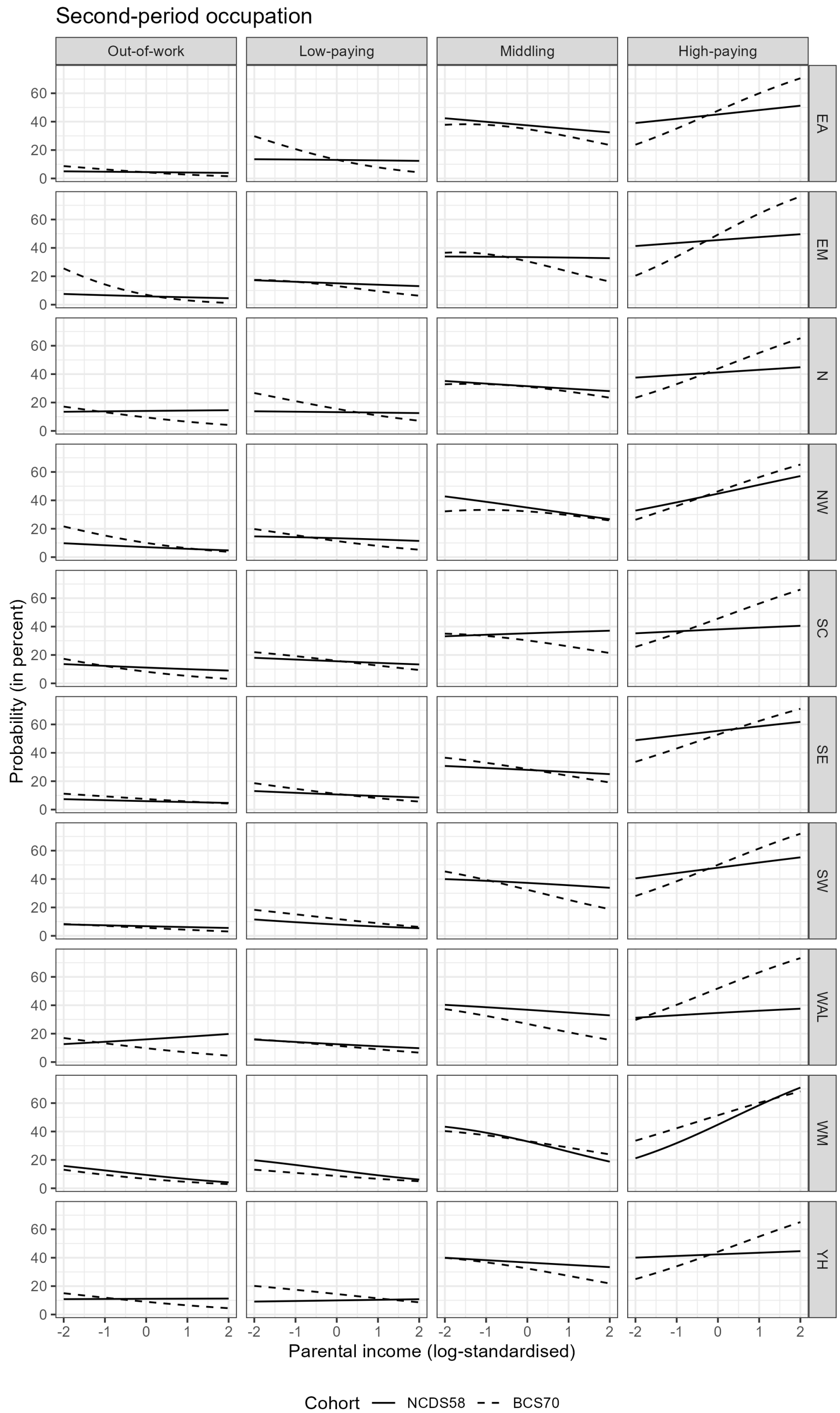
Figure D.4 presents the first-stage IV regression. Figure D.5 presents the second-stage IV regression without control variables. The solid regression line includes all regions, while the dashed regression line excludes West Midlands (WM). Table D.2 presents the second-stage IV regressions.

Table D.2: Second stage IV regression

	Linear regression - Dep. var.: $\Delta\beta_k$		
	Low-paying	Middling	High-paying
Intercept	-0.18	-0.15	0.40
	(0.43)	(0.43)	(0.53)
ΔPol^r	0.72	0.66	0.81
	(0.38)	(0.38)	(0.42)
Par. Inc.	-0.79	-0.53	-0.89^{**}
	(0.52)	(0.52)	(0.34)
Unemployment change	0.11	0.08	0.15
	(0.06)	(0.07)	(0.08)
R^2	0.52	0.39	0.78
Adj. R^2	0.29	0.09	0.68
Num. obs.	10	10	10

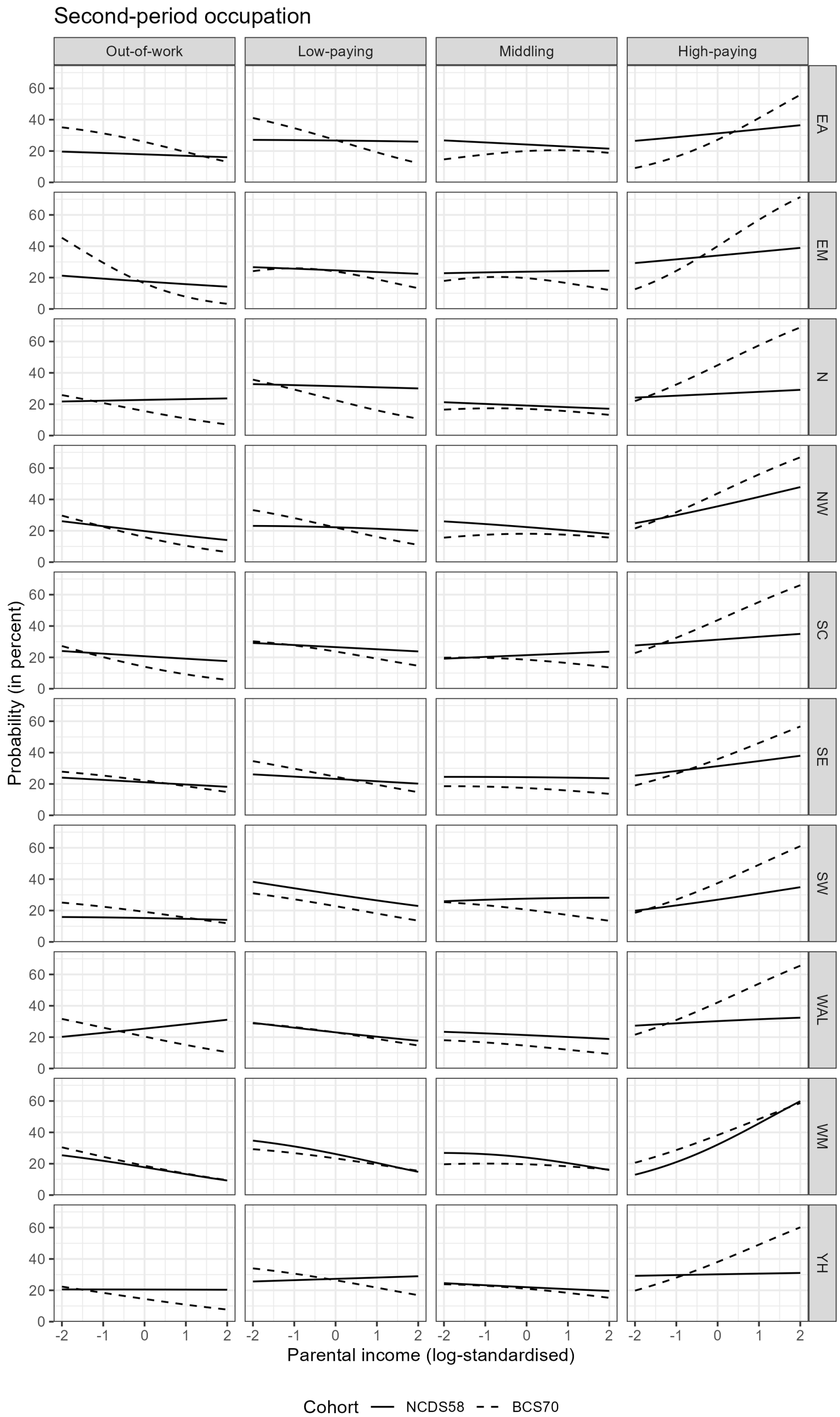
Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table presents the second stage of the IV shift-share regression which estimates the relationship between the change in the role of parental income in determining child's occupation at age 42 and the change in employment polarization at the regional level. Control variables include the parental income coefficient for the NCDS58 cohort and the change in the unemployment rate.

Figure D.2: Probability of being in each occupation in the second-period as a function of parental income at the regional level (male only)



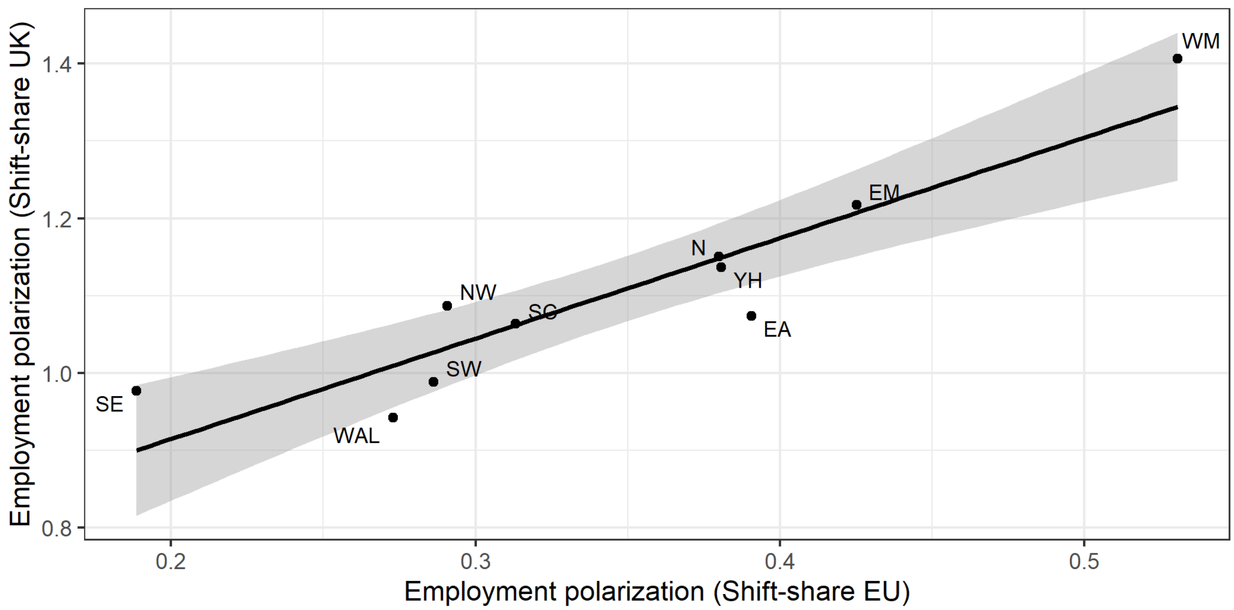
Notes: This figure presents the probability, expressed in percent, of being in each type of occupation (out-of-work, low-paying, middling, high-paying) in the second period as a function of (log-standardised) parental income, for each region. Probabilities are computed for males in both cohorts from the multinomial logistic regressions in Table 5.

Figure D.3: Probability of being in each occupation in the second-period as a function of parental income at the regional level (female only)



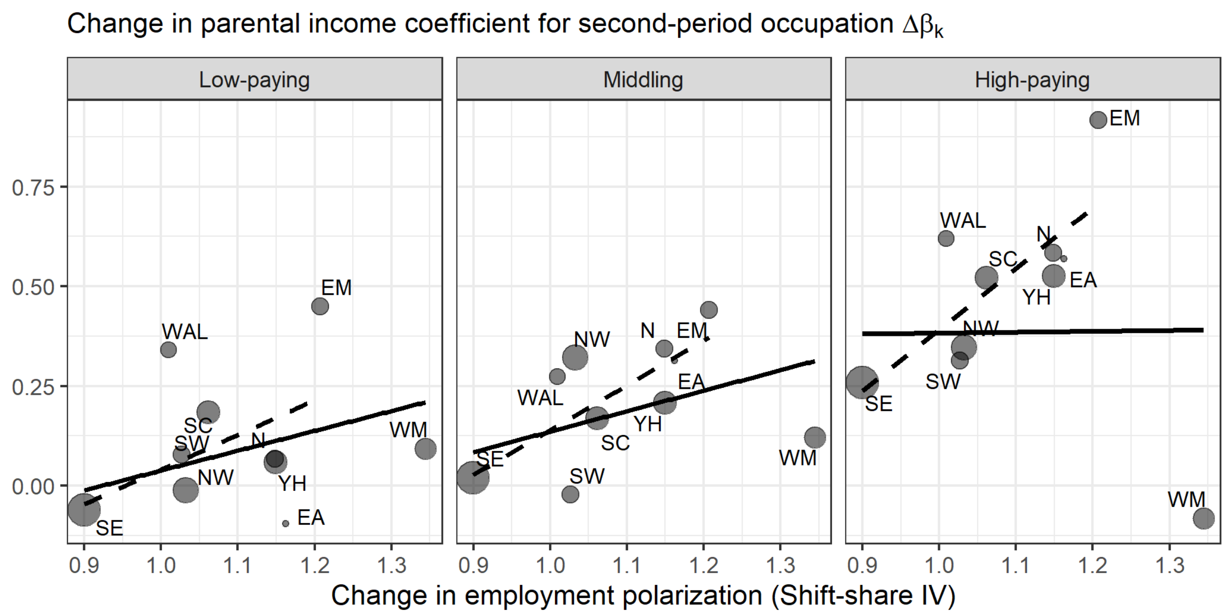
Notes: This figure presents the probability, expressed in percent, of being in each type of occupation (out-of-work, low-paying, middling, high-paying) in the second period as a function of (log-standardised) parental income, for each region. Probabilities are computed for females in both cohorts from the multinomial logistic regressions in Table 5.

Figure D.4: First-stage IV regression



Notes: This figure presents the first-stage of the IV shift-share regression which predicts the change in employment polarization in UK regions with the change in employment polarization in a set of European countries (Denmark, France, Germany, Italy, the Netherlands, and Spain). The x-axis is the change in employment polarization measured with a shift-share based on changes in 1-digit ISCO-08 occupations and instrumented with the average occupational changes in other European countries. The y-axis is the change in employment polarization measured by a shift-share based on changes in 1-digit ISCO-08 occupations in the UK. The 95% confidence interval is indicated by grey shading. The coefficient of the slope is 1.299 with standard error 0.202. The R^2 and F-stat of the first-stage regression are, respectively, 0.838 and 41.51.

Figure D.5: Second-stage IV regression (without controls)



Notes: This figure presents the second-stage of the IV shift-share regression which estimates the relationship between the change in the role of parental income in determining the child's occupation at age 42 and the change in employment polarization at the regional level. The x-axis represents the change in employment polarization measured with a shift-share based on changes in 1-digit ISCO-08 occupations and instrumented with the average occupational changes in a set of European countries (Denmark, France, Germany, Italy, the Netherlands, and Spain). The y-axis measures the between-cohort change in the parental income coefficient for the second-period occupation of the child and is estimated with a multinomial logistic regression at the regional level. Each panel refers to a second-period occupation. Region are weighted by the inverse of the standard errors from the estimated parental income coefficient. The dashed (solid) line represents the regression line excluding (including) the West-Midlands (WM).

Online Appendix

Can workers still climb the social ladder as middling jobs become scarce? Evidence from two British Cohorts

Cecilia García-Peñalosa, Fabien Petit and Tanguy van Ypersele

E Data: The structure of employment

This appendix provides additional tables on the structure of employment. Table OA.1 reports the probabilities of being in each first- and second-period occupation defining those in education as a separate category, i.e. not included in out-of-work. Table OA.2 provides the probability of being in each second-period occupation conditional on the first-period occupation, isolating those in-education from the out-of-work. Figure OA.1 presents the change across cohorts in the probability of being in each ISCO-88 second-period occupation as a function of the occupation's average weekly pay.

Table OA.1: Probability to be in each occupation at both periods, isolating those in-education (in percent)

	First period			Second period		
Occupation	BCS70	NCDS58	Δ	BCS70	NCDS58	Δ
Out-of-work	13.5	19.1	-5.6	13.6	13.7	-0.1
In-Education	2.7	2.2	0.5	0.3	0.6	-0.3
Low-paying	15.2	14.0	1.2	18.4	19.1	-0.7
Middling	33.1	41.2	-8.1	23.8	28.0	-4.2
High-paying	35.6	23.6	12.1	43.9	38.5	5.4

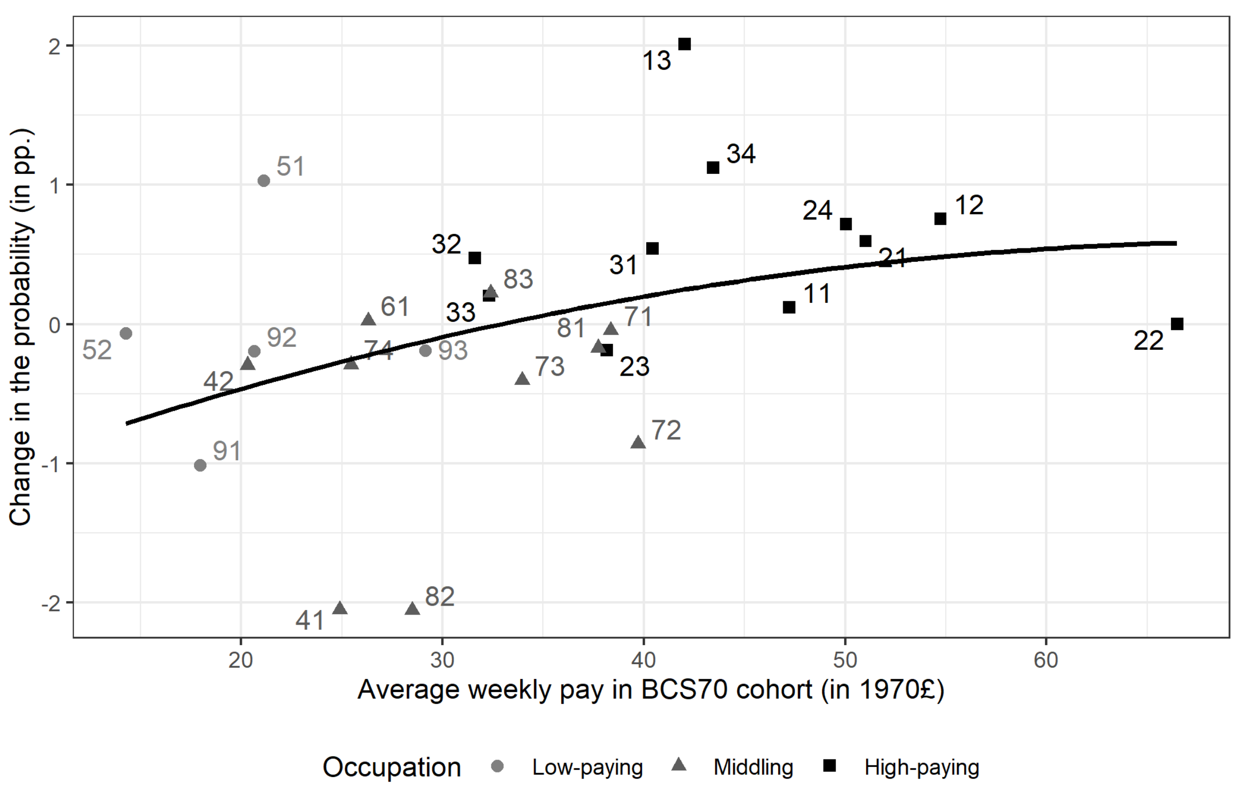
Notes: This table reports the probability, expressed in percentage points, of being in each first- and second-period occupation for the BCS70 and NCDS58 cohorts. For each period, differences between both cohorts, expressed in percentage points, are reported in the last column.

Table OA.2: Conditional probabilities of changing occupations during the career, isolating those in-education (in percent)

	BCS70					NCDS58				
Occupation	Out	Educ	Low	Mid	High	Out	Educ	Low	Mid	High
Out-of-work	37.0	0.7	28.3	15.2	18.9	28.5	0.9	26.9	22.1	21.6
In-Education	14.0	0.5	10.7	11.2	63.7	10.7	0.0	5.3	8.0	76.0
Low-paying	13.3	0.3	45.1	17.5	23.8	15.8	0.5	40.0	20.3	23.4
Middling	10.2	0.3	13.8	44.9	30.8	9.9	0.5	15.4	43.4	30.8
High-paying	8.0	0.2	8.2	11.0	72.6	7.6	0.8	8.1	12.3	71.2

Notes: This table reports the probability, expressed in percentage points, of changing occupations between the first and second period for the BCS70 and NCDS58 cohorts.

Figure OA.1: Change across cohorts in the probability of being in each ISCO-88 occupation in the second period



Notes: The figure presents the positive relationship between the change across cohorts in the probability of being in each ISCO-88 occupation in the second period, expressed in percentage points, and the average weekly pay, expressed in 1970£, in the occupation for the BCS70 cohort.

F Accounting for education

This section replicates our core analysis but considers a three-step process in which we also account for education.

F.1 Data

We start by describing additional variables that will be used in this analysis. We observe both child and parental education as time-invariant variables. A number of family characteristics are also available in our dataset.

All education variables are ranked at the cohort level in peer-inclusive downward-looking ranking.[38] This approach is particularly suited to our data given the massive expansion of secondary and higher education that occurred between the two cohorts.

Child education. We define the child's education as the highest academic qualification ever obtained.[39] Figure OA.2 presents the distribution of the child's education for both cohorts. We have regrouped child education into four categories for ease of exposition.

Parental education. Data about the highest academic qualification ever obtained are not available, hence we use the age at which each parent left full-time education as a proxy. Figure OA.3 presents the distributions of education for fathers and mothers.

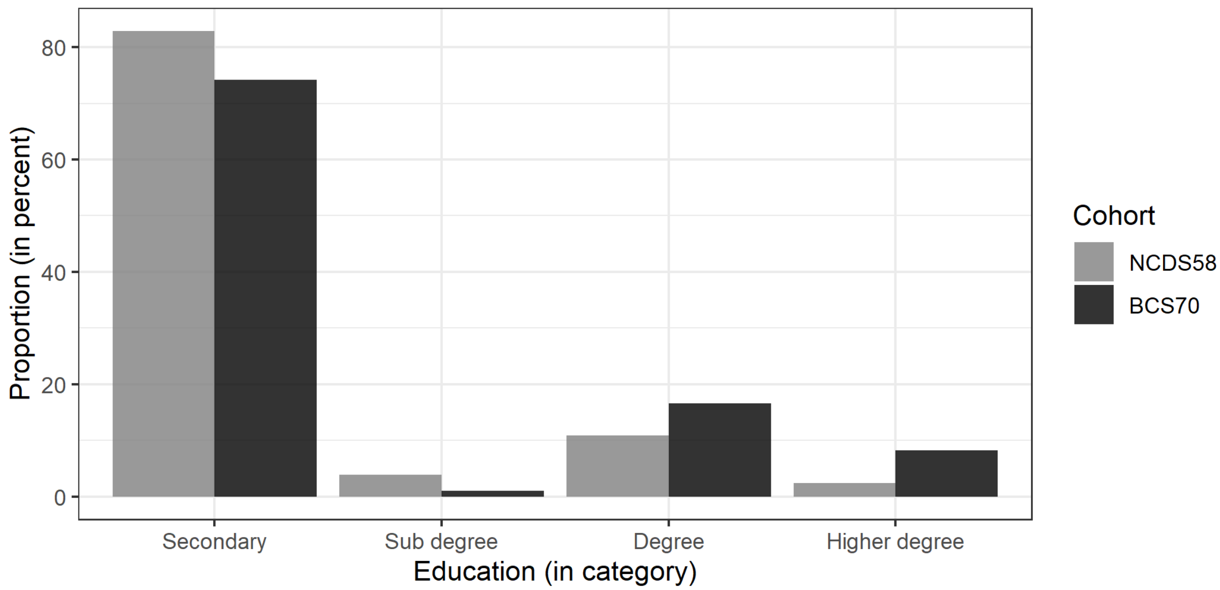
Family characteristics. Father's social class is provided at age 11 for the NCDS58 cohort and 10 for the BCS70 cohort. We refer to the Registrar General's Social Classes (RGSC) that are defined with five categories: professional occupations (I); managerial and technical occupations (II); non-manual skilled occupations (III-N); manual skilled occupations (III-M); partly skilled occupations (IV); and unskilled occupations (V). We then rank father's social class at the cohort level in peer-inclusive downward-looking ranking according to the aforementioned list.

We also consider the number of siblings at age 16, and create a dummy variable that equals one if the cohort member is the eldest child. An additional variable available is parents' interest in education. During interviews at age 11 (NCDS58) and 10 (BCS70), parents answered a question on their interest in their own child's education, with the following possible replies: very interested; moderate interest; little interest; and cannot say.

[38] We follow Cowell and Flachaire (2017) and define the peer-inclusive downward-looking ranking. It corresponds to the rank within the sample of an individual divided by the number of individuals in the sample. Peer-inclusive means that when two individuals have the same value for the variable they have the same rank. An observation with a value of 0.3 means that 30% of the sample has a lower or equal level of the variable. See, for example, Jenkins (2021) for an application.

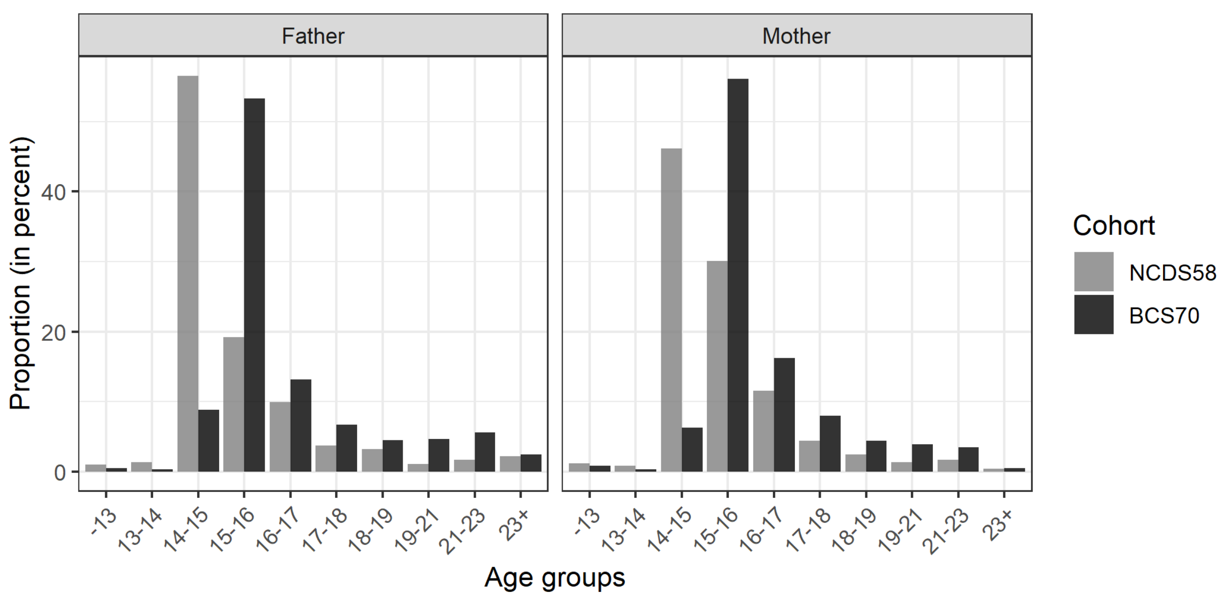
[39] There are 11 categories which are (from the lowest to the highest): no qualifications; less than O-level; less than 5 O-levels; 5+ O-levels; 1 A-level and less than 5 O-levels; 1 A-level and 5+ O-levels; 2+ A-levels and less than 5 O-levels; 2+ A-levels and 5+ O-levels; Sub degrees; Degree - lower grade; Degree - first and upper second grade; and Higher degree.

Figure OA.2: Child education distribution



Notes: This figure presents the distribution of child education for the NCDS58 and BCS70 cohorts. Education corresponds to the highest academic qualification obtained by the child. Education levels are grouped into four categories for readability.

Figure OA.3: Parental education distribution



Notes: This figure presents the distribution of parents' education for the NCDS58 and BCS70 cohorts, defined as the age at which parents left education. Education levels at the bottom and top are grouped for readability.

Table OA.3: Summary statistics - Additional data

Variable	Mean	SD	Min	Q1	Median	Q3	Max	NA
	N = 14763							
Child								
BCS Cohort	0.54	0.50	0.00	0.00	1.00	1.00	1.00	0
Female	0.52	0.50	0.00	0.00	1.00	1.00	1.00	0
Education - Secondary	0.75	0.43	0.00	1.00	1.00	1.00	1.00	216
Education - Sub degree	0.03	0.16	0.00	0.00	0.00	0.00	1.00	216
Education - Degree	0.16	0.36	0.00	0.00	0.00	0.00	1.00	216
Education - Higher degree	0.06	0.24	0.00	0.00	0.00	0.00	1.00	216
Household								
Parental income	30.31	14.59	1.47	19.27	27.87	37.55	115.35	0
Sibling size	2.65	1.37	1.00	2.00	2.00	3.00	12.00	1771
Eldest child	0.56	0.50	0.00	0.00	1.00	1.00	1.00	1771
Mother								
Age	24.18	6.30	8.00	20.00	24.00	28.00	58.00	1566
Age left school	16.34	1.49	13.00	15.00	16.00	17.00	22.00	1600
Int. in educ. - Very interested	0.48	0.50	0.00	0.00	0.00	1.00	1.00	2289
Int. in educ. - Moderate interest	0.32	0.47	0.00	0.00	0.00	1.00	1.00	2289
Int. in educ. - Cannot say	0.11	0.32	0.00	0.00	0.00	0.00	1.00	2289
Int. in educ. - Little interest	0.09	0.28	0.00	0.00	0.00	0.00	1.00	2289
Father								
Age	27.16	7.08	11.00	22.00	26.00	31.00	67.00	2052
Age left school	16.42	1.78	13.00	15.00	16.00	17.00	22.00	2170
Int. in educ. - Very interested	0.37	0.48	0.00	0.00	0.00	1.00	1.00	2965
Int. in educ. - Moderate interest	0.24	0.43	0.00	0.00	0.00	0.00	1.00	2965
Int. in educ. - Cannot say	0.29	0.45	0.00	0.00	0.00	1.00	1.00	2965
Int. in educ. - Little interest	0.11	0.31	0.00	0.00	0.00	0.00	1.00	2965
Social class	3.02	0.93	1.00	2.00	3.20	3.20	5.00	3052
Occupation - High-paying	0.27	0.44	0.00	0.00	0.00	1.00	1.00	2726
Occupation - Middling	0.52	0.50	0.00	0.00	1.00	1.00	1.00	2726
Occupation - Low-paying	0.17	0.37	0.00	0.00	0.00	0.00	1.00	2726
Occupation - Out-of-work	0.04	0.20	0.00	0.00	0.00	0.00	1.00	2726

Notes: This table provides summary statistics for individual time-invariant data from the BCS70 and NCDS58 cohorts used in the specification accounting for education.

Table OA.3 reports the summary statistics for the data that we use when accounting for education.

F.2 Determinants of child's education

We consider the following linear specification:

$$E^c = \alpha_4 + \beta_4 Y^p + \phi_f E^f + \phi_m E^m + \gamma_4 X, \tag{7}$$

where E^c is the child's education, and E^f (resp. E^m) is the father's (resp. mother's) education. All terms are interacted with a dummy that equals one for those in the 1970 cohort (BCS70).

Table OA.4 reports the coefficients obtained when we run various specifications for the determinants of education. The baseline column simply regresses educational attainment on parental income and gender. The next four columns sequentially introduce other possible determinants of education such as parental education, father's social class, and the number of siblings. The most significant result is that the effect of parental income has roughly doubled across cohorts. The education of the mother and the father as well as the social class of the latter are all important factors in the child's educational outcome. Interestingly, for the BCS70 cohort the impact of such variables has fallen relative to that found for the NCDS58 (although the coefficients are not always significant). This seems to indicate that across the two cohorts parental income has gained importance and other parental characteristics have lost it in determining a child's education.

F.3 Patterns of mobility (with education)

We next estimate the multinomial logistic regressions for both first- and second-period occupations—equivalent to equations (1), (2), and (3) but introducing the child's education as an additional explanatory variable. The regressions are reported in tables OA.5 and OA.6 and reproduce the results previously obtained.

Consider the determinants of an individual's probability to start her career in each occupation j. Comparing these results with those in Table C.1 we see that, as far as high-paying occupations go, much of the effect of parental income occurs through education (or unobserved characteristics correlated with education). When we compare the two cohorts, the most important result is that while the direct effect of parental income has increased across cohorts (by the same magnitude as when we did not control for education), that of education has not.

Concerning the occupation of mature workers, reported in Table OA.6, the coefficients on initial occupations and on parental income are similar to those obtained in the specification without education. Interestingly, the relative impacts of education and parental income on the likelihood to be in a high-paying occupation have changed across cohorts, with parental

Table OA.4: Determinants of child's education

	Linear regression - Dep. var.: Education (in PIR-STD)				
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.01	0.01	0.03^{*}	-0.16^{***}	-0.21^{***}
	(0.01)	(0.01)	(0.02)	(0.04)	(0.05)
BCS cohort	-0.03	-0.05^{**}	-0.05^{**}	-0.11^{***}	-0.05
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Female	0.07^{***}	0.06^{***}	0.07^{***}	0.05^{**}	0.05^{**}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Female × BCS	0.02	0.03	0.02	0.00	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Par. inc.	0.13^{***}	0.08^{***}	0.08^{***}	0.07^{***}	0.07^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Father's education		0.19^{***}	0.14^{***}	0.09^{***}	0.09^{***}
		(0.01)	(0.01)	(0.01)	(0.01)
Mother's education		0.13^{***}	0.12^{***}	0.10^{***}	0.10^{***}
		(0.01)	(0.01)	(0.01)	(0.01)
Father's soc. class			0.19^{***}	0.13^{***}	0.13^{***}
			(0.01)	(0.01)	(0.01)
Number of siblings					-0.06^{***}
					(0.01)
Eldest child					0.07^{***}
					(0.03)
Par. inc. × BCS	0.11^{***}	0.11^{***}	0.08^{***}	0.05^{**}	0.06^{***}
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Father's educ. × BCS		-0.10^{***}	-0.07^{***}	-0.04^{*}	-0.03
		(0.02)	(0.02)	(0.02)	(0.02)
Mother's educ. × BCS		-0.03	-0.02	-0.03^{*}	-0.05^{**}
		(0.02)	(0.02)	(0.02)	(0.02)
Father's soc. class × BCS			-0.06^{***}	-0.04^{**}	-0.05^{**}
			(0.02)	(0.02)	(0.02)
Number of siblings × BCS					0.08^{***}
					(0.02)
Eldest child × BCS					-0.01
					(0.04)
Parents' interest in education				Yes	Yes
Region FE				Yes	Yes
R^2	0.04	0.09	0.11	0.18	0.18
Adj. R^2	0.04	0.09	0.11	0.17	0.18
Num. obs.	20722	17354	13901	11814	10509

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Male in the NCDS58 cohort is the reference group. Parental income in logarithm and child education in peer-inclusive ranking, both are standardized at the cohort level.

income becoming more important and (our measure of) education less so for the BCS70 than for the NCDS58 cohort. Overall, these three tables indicate that including education in the analysis has little impact on our estimates of the differences in the parental income

Table OA.5: Probability of being in each occupation at first period (multinomial)

	Multinomial logit - Dep. var.: First-period occupation		
	Low-paying	Middling	High-paying
Intercept	-0.00	1.38^{***}	0.53^{***}
	(0.07)	(0.06)	(0.06)
BCS cohort	0.22^{**}	0.11	0.88^{***}
	(0.10)	(0.08)	(0.09)
Female	-0.76^{***}	-1.26^{***}	-1.02^{***}
	(0.09)	(0.07)	(0.08)
Female × BCS	0.27^{**}	0.01	-0.12
	(0.12)	(0.10)	(0.11)
Par. inc.	-0.01	0.00	0.10^{***}
	(0.04)	(0.03)	(0.04)
Par. inc. × BCS	0.10	0.22^{***}	0.36^{***}
	(0.06)	(0.05)	(0.05)
Education	-0.28^{***}	-0.02	0.77^{***}
	(0.05)	(0.04)	(0.04)
Education × BCS	0.04	-0.04	-0.05
	(0.07)	(0.05)	(0.06)
Num. obs.	14547	14547	14547

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Out-of-work occupation in the first period is the base outcome of the multinomial logistic regression. Male in the NCDS58 cohort is the reference group. Parental income in logarithm and then standardized at the cohort level. Education variables and the father's social class are defined in peer-inclusive ranking. All variables, except dummies, are standardized at the cohort level to take into account changes in the variance of the variables' distributions between both cohorts.

coefficients across the two cohorts.

G First-period age

This appendix provides a robustness check concerning the difference across cohort in age in the first period. Tables OA.7 and OA.8 report the coefficients of the multinomial logistic regressions for the probability of being in each occupation in first and second periods, when both cohorts are either 23 or 26 years old and compare them to their respective baseline estimates from Tables C.1 and C.2.

Table OA.6: Probability of being in each occupation in the second period (multinomial)

	Multinomial logit - Dep. var.: Second-period occupation					
	(1)			(2)		
	Low	Mid	High	Low	Mid	High
Intercept	0.28***	1.38***	1.69***	−0.19*	0.45***	0.81***
	(0.08)	(0.07)	(0.07)	(0.11)	(0.11)	(0.10)
BCS cohort	0.06	−0.03	0.18*	−0.00	−0.39**	−0.17
	(0.11)	(0.10)	(0.10)	(0.16)	(0.16)	(0.14)
Female	−0.08	−1.22***	−1.43***	0.03	−0.95***	−1.25***
	(0.09)	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)
Female × BCS	−0.07	−0.11	0.22*	−0.14	−0.12	0.27**
	(0.13)	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)
Par. inc.	0.03	0.04	0.08**	0.04	0.05	0.07*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Par. inc. × BCS	0.05	0.14**	0.31***	0.04	0.09	0.22***
	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)
Education	−0.20***	0.02	0.97***	−0.17***	−0.01	0.81***
	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)
Education × BCS	−0.01	−0.02	−0.21***	0.02	0.05	−0.21***
	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)
Change with respect to the referent group as first period occupation (Out-of-work)						
Low-paying				0.98***	0.29**	0.33**
				(0.12)	(0.14)	(0.14)
Middling				0.52***	1.44***	0.90***
				(0.11)	(0.10)	(0.11)
High-paying				0.13	0.48***	1.62***
				(0.15)	(0.14)	(0.12)
Change between cohorts						
Low. × BCS				0.41**	0.61***	0.41**
				(0.17)	(0.19)	(0.19)
Mid. × BCS				−0.02	0.52***	0.19
				(0.16)	(0.15)	(0.15)
High. × BCS				0.13	0.33*	0.18
				(0.19)	(0.19)	(0.16)
Num. obs.	14547	14547	14547	14547	14547	14547

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Out-of-work occupation in the second period is the base outcome of the multinomial logistic regression. Male in the NCDS58 cohort in out-of-work occupation in the first period is the reference group. Parental income in logarithm and child education in peer-inclusive ranking, both are standardized at the cohort level. Coefficients in the first bottom panel captures the change in the marginal effect of the first-period occupation with respect to the reference one, i.e. out-of-work. Coefficients in the second bottom panel indicates the change across cohorts in the marginal effect of the first-period occupation.

Table OA.7: Probability of being in each occupation in the first period (First-period age robustness check)

	Multinomial logit - Dep. var.: First-period occupation								
	(Base)			(Age 23)			(Age 26)		
	Low	Mid	High	Low	Mid	High	Low	Mid	High
Intercept	0.08	1.39***	0.69***	0.08	1.39***	0.69***	0.31***	1.62***	1.13***
	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.08)	(0.06)	(0.07)
BCS cohort	0.24**	0.12	0.75***	−0.27***	−0.37***	−0.11	0.01	−0.11	0.31***
	(0.10)	(0.08)	(0.09)	(0.09)	(0.07)	(0.08)	(0.10)	(0.09)	(0.09)
Female	−0.79***	−1.27***	−0.99***	−0.79***	−1.27***	−0.99***	−1.17***	−1.88***	−1.59***
	(0.09)	(0.07)	(0.08)	(0.09)	(0.07)	(0.08)	(0.09)	(0.08)	(0.08)
Female × BCS	0.25**	−0.02	−0.08	0.65***	0.49***	0.48***	0.63***	0.60***	0.52***
	(0.12)	(0.10)	(0.11)	(0.12)	(0.10)	(0.10)	(0.13)	(0.11)	(0.11)
Par. inc.	−0.03	−0.00	0.21***	−0.03	−0.00	0.21***	−0.02	0.03	0.25***
	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)
Par. inc. × BCS	0.10*	0.22***	0.41***	−0.07	0.04	0.16***	0.09	0.19***	0.37***
	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
Num. obs.	14763	14763	14763	14522	14522	14522	14710	14710	14710

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Out-of-work in the second period is the base outcome of the multinomial logistic regression. Males in the NCDS58 cohort that were out-of-work in the first period are the reference group. Parental income in logarithm and then standardized at the cohort level. Coefficients in the middle panel capture the change in the marginal effect of the first-period occupation with respect to the reference one, i.e. out-of-work. Coefficients in the bottom panel indicate the change across cohorts in the marginal effect of the first-period occupation. Columns (Base) correspond to the baseline estimate from table C.1. Columns (Age 23) estimate the same regression with first-period occupation at age 23 for both cohorts. Columns (Age 26) estimate the same regression with first-period occupation at age 26 for both cohorts.

Table OA.8: Probability of being in each occupation in the second period (First-period age robustness check)

	Multinomial logit - Dep. var.: Second-period occupation								
	(Base)			(Age 23)			(Age 26)		
	Low	Mid	High	Low	Mid	High	Low	Mid	High
Intercept	−0.10	0.44***	0.81***	−0.10	0.44***	0.81***	−0.02	0.50***	0.52***
	(0.11)	(0.10)	(0.10)	(0.11)	(0.10)	(0.10)	(0.11)	(0.10)	(0.10)
BCS cohort	−0.07	−0.46***	−0.32**	−0.10	−0.30**	0.36***	−0.15	−0.52***	−0.03
	(0.15)	(0.15)	(0.14)	(0.15)	(0.15)	(0.13)	(0.15)	(0.15)	(0.14)
Female	−0.01	−0.98***	−1.13***	−0.01	−0.98***	−1.13***	−0.01	−0.88***	−0.94***
	(0.10)	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)
Female × BCS	−0.11	−0.09	0.25**	−0.14	−0.20	0.10	−0.11	−0.19	0.07
	(0.13)	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)
Par. inc.	0.02	0.05	0.14***	0.02	0.05	0.14***	0.03	0.05	0.13***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Par. inc. × BCS	0.05	0.11**	0.25***	0.06	0.13**	0.34***	0.04	0.11*	0.26***
	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.05)
Change with respect to the referent group as first period occupation (Out-of-work)									
Low-paying	1.00***	0.31**	0.14	1.00***	0.31**	0.14	1.03***	0.30**	0.40***
	(0.12)	(0.13)	(0.13)	(0.12)	(0.13)	(0.13)	(0.12)	(0.13)	(0.13)
Middling	0.50***	1.47***	0.82***	0.50***	1.47***	0.82***	0.36***	1.44***	1.00***
	(0.11)	(0.10)	(0.10)	(0.11)	(0.10)	(0.10)	(0.11)	(0.11)	(0.11)
High-paying	0.06	0.52***	1.96***	0.06	0.52***	1.96***	−0.06	0.23*	2.17***
	(0.14)	(0.14)	(0.12)	(0.14)	(0.14)	(0.12)	(0.14)	(0.14)	(0.12)
Change between cohorts									
Low. × BCS	0.47***	0.66***	0.55***	0.39**	0.55***	0.11	0.44***	0.67***	0.29
	(0.17)	(0.19)	(0.18)	(0.17)	(0.19)	(0.17)	(0.17)	(0.19)	(0.18)
Mid. × BCS	0.02	0.55***	0.25*	0.13	0.39***	−0.31**	0.16	0.59***	0.06
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.14)	(0.16)	(0.15)	(0.15)
High. × BCS	0.17	0.37**	0.15	0.48**	0.43**	−0.38**	0.29	0.66***	−0.06
	(0.19)	(0.19)	(0.16)	(0.19)	(0.19)	(0.16)	(0.18)	(0.19)	(0.16)
Num. obs.	14763	14763	14763	14522	14522	14522	14710	14710	14710

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Out-of-work in the second period is the base outcome of the multinomial logistic regression. Males in the NCDS58 cohort that were out-of-work in the first period are the reference group. Parental income in logarithm and then standardized at the cohort level. Columns (Base) correspond to the baseline estimate from columns (2) in table C.2. Columns (Age 23) estimate the same regression with first-period occupation at age 23 for both cohorts. Columns (Age 26) estimate the same regression with first-period occupation at age 26 for both cohorts.