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

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June 29, 2022

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 for two British cohorts we examine how the occupational outcomes of children depend on both initial occupations and occupational upgrading during their careers. We find that transitions across occupations are key for mobility and that the effect of parental income on those transitions has become stronger over time. Moreover, the impact of parental income increased the most in the regions where the share of middling employment fell the most, suggesting that greater employment polarization may be one of the factors behind the observed decline in mobility.

Keywords: Inter-generational mobility, Labour market polarization, Occupational transition.
JEL Codes: J62, J21, J24.

*We are grateful to Jo Blanden, Bertrand Garbinti, Jan-Luca Hennig, Paul Maarek, Giovanni Pica, Xavier Raurich, Marc Sangnier, Philippe Van Kerm, Thierry Verdier, and Yanos Zylberberg, as well as to audiences at the Ninth ECINEQ Meeting, the 'Genes, Social Mobility, and Inequalities across the Life-Course' Conference, the CEPR-AMSE-Banque de France Conference on Social Mobility and seminar participants at the Aix-Marseille School of Economics, Compass Lexecon, King's College London, the Université Catholique de Louvain, and University College London for useful comments and suggestions. This work was supported by the "France 2030" initiative (French National Research Agency grant ANR-17-EURE-0020), the ANR-18-CE41-0003-01 grant, and the Excellence Initiative of Aix-Marseille University - A*MIDEX.

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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 share in total employment of low- and high-paying occupations has 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 structure of employment despite the fact that both phenomena have taken place roughly simultaneously.[1] Yet the timing of the two events 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. Such question has been recently addressed in two closely related papers by Guo (2022) and Hennig (2021), who focus on the impact that the structure of employment has for education decisions in the US. Their conceptual frameworks maintains 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 and is, consequently, applicable to a broader range of economies. We maintain 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 our analysis by developing a model aimed at illustrating a simple way in which polarization may affect occupational mobility. We consider a setup with two employment periods and three occupations, low-paying, middling, and high-paying ones. Individuals differ in parental income, that 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. Individuals also differ in their innate ability, that can be either low or high, and initially is not observable by firms. During the first period, high-ability individuals increase their human capital through on-the-job learning, while low-ability workers keep their inherited human capital. Crucially, we assume that different 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.

provide different opportunities for on-the-job learning, which is highest for high-paying and lowest for low-paying occupations. In the second period, firms can observe the (potentially higher) human capital of mature workers and reallocate them across occupations.

In this context, the availability of middling jobs is the key element determining the extent of mobility. With few middling jobs, the majority of those from low-income backgrounds will start their careers in low-paying occupations. As a result, few of them have sufficient learning opportunities and thus only a few individuals with low-income parents will be promoted into high-paying jobs. Moreover, this implies that since few positions are left vacant, few of those who started in high-paying occupations will be demoted, even if they are of low ability. 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 which uses 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 address 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 the literature tends to do;[3] rather we focus on occupations and define occupational categories in line with the employment polarization literature. 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 initial job that individuals hold. The data allow us to consider occupational outcomes both at the start of the individual's career, i.e. in their twenties, as well as when workers are mature, i.e. in their forties, and hence to consider occupations at different stages of the work-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]While economists have tended to examine income mobility (e.g. Blanden et al. 2007, Blanden et al. 2013, Chetty et al. 2014a), the literature on social mobility focuses on the analysis of socio-economic class. See Erikson and Goldthorpe (1992), as well as Chan and Goldthorpe (2007) and Erikson and Goldthorpe (2010), for a discussion on social class and inter-generational mobility in the United-Kingdom.

occupation and parental income on the occupation at age 42.[4] We 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 results for the 1958 cohort and those for 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.

To further 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 allows us to correlate the decline in mobility and the change in the share of middling employment at the regional level in order to ask whether these two variables have moved together.

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% and 30%, respectively, of those initially in low-paying and middling occupations are in high-paying occupations when they are 42. In fact, for those two groups, less than half of those who were in each occupational category when young are in the same one as mature workers, with both the probabilities 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 identified in previous work also appears when we focus on occupations.[5] Moreover, the reduction in mobility is apparent at all the stages that determine an individual's occupation

[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.

[5]A few studies 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. For example, Long and Ferrie (2013) build four categories: white-collar, farmer, skilled and semi-skilled, and unskilled. Bell et al. (2022) use narrow occupational categories that they rank by median wages.

when mature. Both the effect of parental income on first-period occupation and that on the job when mature—controlling for initial occupation—have 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 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 what job they initially held. That is, we observe that the possibility of career progression has become more dependent on parental background.

Lastly, when we exploit the regional dimension of our data we find a correlation between mobility and polarization which appears both over time and in the cross-section. At the individual level, our results indicate that the effect of parental income on occupational outcomes is stronger for individuals that—when young— lived in areas with greater job polarization, indicating that a possible reason for the observed decline in mobility across the two cohorts is the disappearance of middling jobs. We then consider differences across large regions and find that regions that have experienced a greater decline in the share of middling jobs are also those in which the impact of parental income has increased the most. These correlations are indicative that the disappearance of middling jobs may be one of the reasons behind the observed decline in mobility.

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.[6] Much of the focus has been on how individual characteristics affect income dynamics across generations, notably education, non-cognitive skills and personality traits, and the quality of the neighborhood.[7] Yet little attention has been paid to the importance of early labour market experiences. This paper hence 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

[6] 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.

[7] 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.

career dynamics, and shows that understanding *intra-generational* mobility is essential to understand an individual's outcome when mature.

Our paper is particularly close to the recent literature that has identified a reduction in income mobility and an increased role of parental background, notably in the US and the UK. Part of this effect seems to operate through education. For example, for the UK, Blanden and Gregg (2004) and Gregg et al. (2010) find a rising impact of parental income on children's educational attainment. More recent work, such as Chetty et al. (2014b) has shown the importance of the location where the individual grew up for inter-generational income dynamics. Our contribution lies in showing that the increased importance of parental income also appears when we focus on occupational categories, and that this operates in part through a stronger influence of family background on the probabilities of moving from one occupation to another.

Lastly, our paper adds to our understanding of the consequences of employment polarization. Economists have mainly focused on the distribution of earnings,[8] 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.[9] Surprisingly, the question of whether employment polarization affects mobility has been largely ignored. To our knowledge, the only exceptions are Guo (2022) and Hennig (2021), both of whom examine the relationship between the structure of employment and income mobility.

Guo (2022) and Hennig (2021) 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 patterns of inter-generational income mobility across commuting zones in the US, with mobility measures being those obtained by Chetty et al. (2014a). 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 hence complement such approach by adding an analysis of job-to-job transitions and show that these transitions are essential to understand mobility. Second, relying on the

[8]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).

[9]The widespread view is that indeed the changing structure of employment has resulted in increased earnings dispersion; see the overview in Acemoglu and Autor (2011). Some authors nevertheless disagree; see Hunt and Nunn (2019).

cost of education as a driver of the mechanism they study implies that their analysis is not suitable for economies where this cost is small or null, as in often the case in Europe. We hence provide a mechanism which is more widely applicable. Lastly, measures of income mobility pull together changes in occupational outcomes and in the wages received by the different occupations, and these two have varied in different ways depending on the country. In contrast, our approach isolates the former, 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 the previous two analyses and, 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 that individuals with different parental backgrounds receive 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 paper is organised as follows. We start by presenting a simple model of the effect of employment polarization on occupational mobility. 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. We consider three types of jobs $j = \{1, 2, 3\}$, which can be interpreted, respectively, as low-paying, middling and high-paying jobs. Parents transfer human capital to their children and the latter's productivity, and hence allocation to jobs, is determined both by transmitted human capital and innate (and initially unobservable) ability. Children's entry jobs will be determined by parental background, but as their ability is revealed, they may move up or down the job ladder. In this setup, the model illustrates how mobility changes as the share of middling jobs falls.

2.1 Workers' skills and family background

We suppose that there are two types of parental background, which we denote 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 the possibility of accessing better schools or more years of education. We denote by z_i the share of parents with background $i = \{L, H\}$, with $z_H + z_L = 1$.

Individuals also differ in their innate ability, which will be high with probability π and low otherwise, and is assumed not to depend on parental type. Ability is assumed to have no effect on first-period productivity, i.e. when individuals are junior workers, but will affect that in the second period, i.e. when they are mature. Ability is perfectly observable—by the individual and by the firm—at the end of the first period. We suppose that *only* high-ability individuals can learn in their first-period occupation, which increases their human capital. Our key assumption is that the learning intensity, and hence the human capital gains, depends on the type of job that the individual performed in the first period. In particular, we suppose that a high-ability worker accumulates more human capital in a high-paying occupation than in a middling one, and in a middling occupation compared to a low-paying one. Denoting human capital gains by ϕ_j with $j \in \{1, 2, 3\}$ and normalizing the human capital gains by those in high-paying jobs to one, we have $0 < \phi_1 < \phi_2 < 1$.

Since parental type determines the initial skills of the child, 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 productivity is assumed to depend on parental background and, for those of high-ability, on first-period occupation. We denote by h_i^j the second-period human capital of an individual with parent-type i who is of high-ability and worked in occupation j in the first period. Individuals with low-ability keep their initial level of human capital, i.e. h_L or h_H, while those of high-ability increase it through on-the-job-learning. In order to rank the human capital of individuals we make the following assumption:

Assumption 1 *We suppose that the difference in human capital between individuals from high- and low-income parents, $h_H - h_L$, satisfies $\phi_1 < h_H - h_L < \phi_2$.*

The resulting productivities are ranked as follows:

$$h_L < h_L^1 < h_H < h_L^2 < h_H^2 < h_H^3,$$

implying that, conditional on parental background, high-ability individuals are always more productive than those with low-ability ones irrespective of the first-period occupation. In fact, Assumption 1 ensures that the human capital gains for high-ability individuals due to learning in middling jobs are sufficiently large to compensate differences in initial human capital that are due to parental background; whereas the human capital gains from low-paying jobs cannot compensate the initial gap.[10]

2.2 The structure of employment

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. Since the wage of high-paying (resp. middling) jobs is greater than that of middling (resp. low-paying) jobs, employers fill jobs of each type with the most skilled worker available, i.e. the one with the highest human capital. The model can present various allocations of individuals across occupations depending on parameter values. We focus in a particular case which illustrates the mechanism we have in mind. To do so we make two assumptions on parameter values:

Assumption 2 *We suppose that the share of low-income parents, z_L, satisfies* $1 - q_3 > z_L > q_1$.

Assumption 2 ensures that in the first period some individuals from both high- and low-income parental backgrounds are in occupation 2.

Assumption 3 *We suppose that the share of high-ability individuals, π, satisfies* $\pi < \min\left\{\frac{q_3}{1-q_1}, 1 - \frac{q_1}{z_L}\right\}$

Assumption 3 characterizes the second period allocations. It ensures that (i) not all low-ability individuals from low-income households work in occupation 1 and (ii) some low-ability individuals from high-income households work in occupation 3.

2.3 The allocation of labour

Table 1 summarizes, under Assumption 2, the distributions of jobs in the first period, with each column giving the probability that an individual of parental-type i is in each of the

[10]The first inequality is derived from $h_L^1 < h_H$, whereas the second one is derived from $h_H < h_L^2$.

occupations. The distribution 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.

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	$\frac{q_3}{z_H}$

In the second period, the allocation of individuals across jobs depends on three factors: parental background, ability, and the occupation in which the individual worked in the first period. Under our assumptions, and denoting by h_i the human capital of a low-ability individual of parental-type i and by h_i^j the human capital of a high-ability individual of parental-type i who has worked in occupation j in the first period, the resulting distribution of skills is

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

We can now consider the allocation of workers to occupations in the second period. We denote by $P_i(k)$ the probability that an individual of background i is in occupation k in the second period and report these probabilities in Table 2. Under Assumptions 2 and 3, 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	$(1-\pi)\left(1-\frac{q_1}{z_L}\right)$	$1-\pi-\frac{q_3-\pi(1-q_1)}{z_H}$
High-paying	$\pi\left(1-\frac{q_1}{z_L}\right)$	$\pi+\frac{q_3-\pi(1-q_1)}{z_H}$

Changes in q_1 and q_3 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 gains from each type of 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, which would tend to increase the share of L-workers in low-paying occupations and decrease that in middling occupations. 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 gains of the various jobs. A higher value of q_1 implies that in the first period fewer L-workers were in occupation 2. As a result, fewer high-ability individuals increased their human capital by ϕ_2 and more gained only ϕ_1, thus reducing the share of high-ability L-workers that manage to move into high-paying occupations. The small number of high-ability L-workers that obtain high-human capital also benefits individuals with high-income parents, notably those with low-ability that would have downgraded to occupation 2 if more L-workers had moved into 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-workers, notably low-ability ones, work in occupation 3 rather than in occupation 2. Interestingly, an increase in q_3 does not affect the likelihood that L-workers worker in high-paying occupations, as their possibility to do so is limited by their extent of learning rather than by the availability of jobs.

2.4 Transition probabilities

Table 2 captures the extent of inter-generational mobility, which in turn depends both on the effect of parental background on entry positions and on the probabilities of moving across occupations between periods 1 and 2. The latter, which we can think of as intra-generational mobility, can be computed as the probability $P_i(k|j)$ that an individual of parental background i and initial occupation j ends in occupation k when mature. Table 3 summarizes the transition probabilities. [11]

Recall that those from an L-background are randomly allocated across occupations 1

[11] To understand how these transition probabilities are obtained, consider those with low parental income. In the second period, there are $(1-\pi)z_L$ workers with skills h_L and $q1$ positions in sector 1, implying that the probability that a worker with that skill level ends up in sector 1 is $q_1/(1-\pi)z_L$. Therefore a worker of type L that was initially in sector 1 ends up in the same sector with probability $(1-\pi)(q_1/((1-\pi)z_L)) = q_1/z_L$ and in sector 2 with the complementary probability. A worker of type L employed in sector 2 during the first period ends up in sector 1 with probability q_1/z_L, in sector 3 with probability π, and in sector 2 with probability $1-\pi-q_1/z_L$. Similar calculations allow us to compute the transition probabilities for those with H-background.

Table 3: Transition probabilities across occupations

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

and 2 in the first period. Those who start in 2 experience lower persistence, and will move upwards or downwards depending on their revealed ability. The outcome for those who start their careers in 1 depends on q_1, with a higher share of low-paying jobs leading to lower upwards mobility (i.e. into middling occupations) for this group.

Consider now H-workers and note that, by Assumption 3, $q_3 - \pi(1-q_1) > 0$. For those who started in middling occupation, whether or not they move into high-paying occupations depends exclusively on their ability, so that they have a probability π (resp. $1-\pi$) or being in occupation 3 (resp. 2) in the second period. For those who started in occupation 3, the likelihood of downwards mobility depends on both q_1 and q_3, with higher values of either resulting in a lower probability that (low-ability) H-workers move downwards.

2.5 The impact of polarization

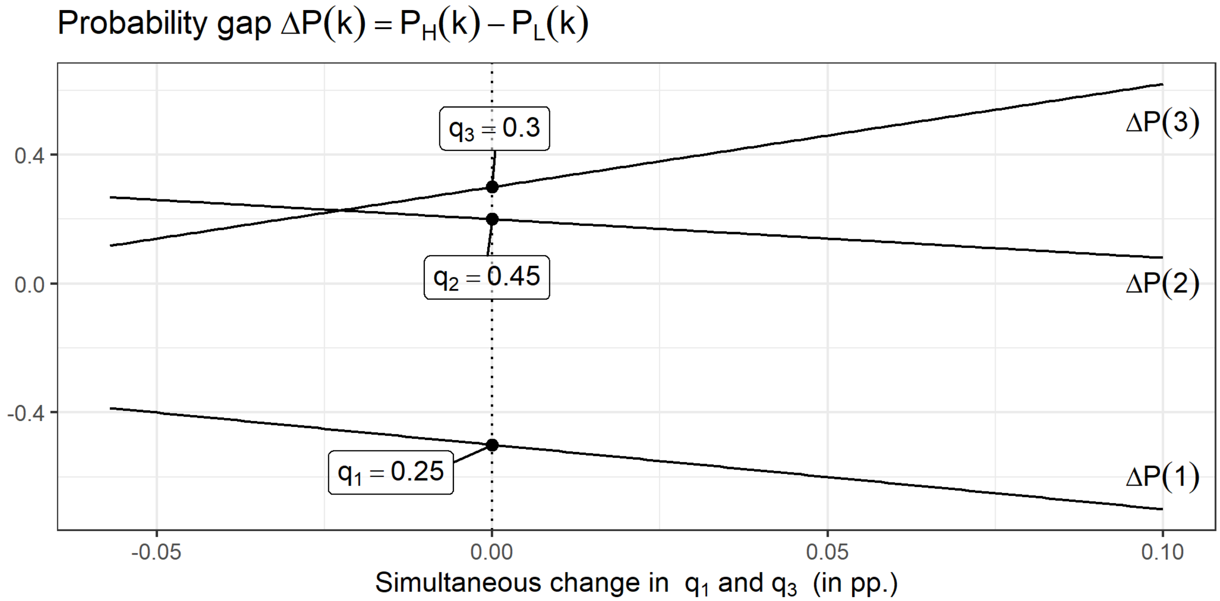
We can now consider how polarization affects inter-generational mobility. We define *polarization* as a simultaneous increase in q_1 and q_3 at the expense of q_2. For ease of exposition, we suppose that the share of the two occupations increases by the same amount and that there is no change between the two periods of an individual's active life.[12]

Polarization affects both entry jobs and the transition probabilities (intra-generational mobility), which together will shape the extent of inter-generational mobility. Greater polarization has only a direct effect on the first-period allocation of labour since, as can be seen in Table 1, it increases in a mechanical way the share of individuals with low-income (resp. high-income) parents that are in low-paying (resp. high-paying) occupations. It thus implies a stronger influence of parental income on the occupations of young agents.

The transition probabilities across occupations are affected by both the availability of jobs

[12] 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 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 $q_3 = 0.30$.

when individuals are mature and by the fact that the number of L-background individuals who were in middling occupations determines how many of them will experience upwards mobility. As can be seen from Table 3, an increase in q_1, q_3, or both reduces the likelihood to escape the initial occupation, thus causing more intra-generational persistence.

Since in our framework first-period occupations depend only on parental income, higher intra-generational persistence undermines inter-generational mobility. To see this, we turn now to the probabilities of being in the various occupations when mature. There are various ways of measuring inter-generational persistence. To capture it in a simple way, we measure it by the advantage that parental background gives in terms of accessing the various occupations when mature. We hence define *inter-generational mobility* as the gap between H-workers and L-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.

Figure 1 presents the relationship between 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 are figures similar to those found in the data, as we will see below. To capture polarization 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.

The figure indicates that as polarization increases the advantage in accessing high-paying occupation that those from high-income background have relative to those from low-income households rises. The opposite occurs with low-paying occupations, where the relative likelihood of being in such jobs (which is negative, as only L-workers are employed in occupation 1) grows in absolute value with polarization. H-workers also have an advantage in being in occupation 2 for low level of polarization, but this advantage falls as q_1 and q_3 increase, and for high levels of polarization there are more L-workers than H-workers in middling jobs. The reason for this 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 low-ability H-workers.

Our results imply a negative relationship between the extent of polarization and the degree of occupation mobility. Greater employment polarization—as measured by an increase in q_1 and q_3—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.

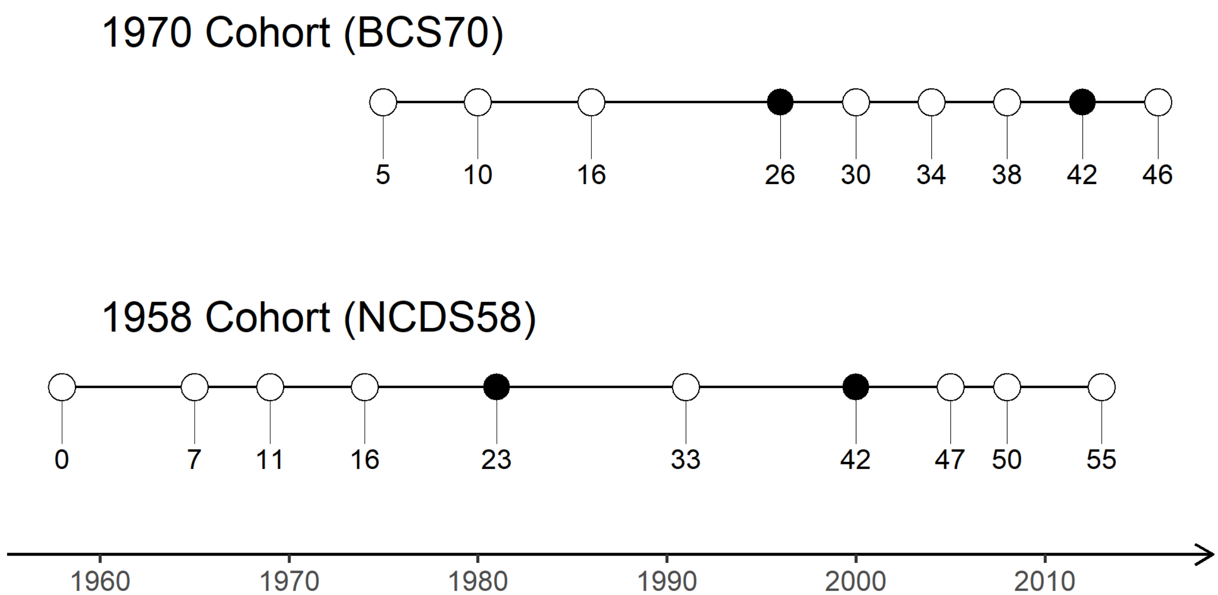
3 Data and employment polarization

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 life. 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

Figure 2: Dates of interviews



Notes: This figure presents the dates at which individuals in the BCS70 and NCDS58 cohorts may have been interviewed and the corresponding years. Black circles represent the first and second periods we consider in the analysis for both cohorts.

market. Those in the NCDS58 cohort are observed at age 23 and those in the BCS70 cohort at age 26. Both cohorts are interviewed at age 42, which we define as the second period.

Income and wages. We have information on parental income, which is 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.[13] In order to adjust both for inflation, aggregate income growth and changes in the dispersion of income, parental income is standardized, so that for both cohorts it has mean 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 cohorts studies provide the full activity histories to the nearest month from which we can derive the ISCO-88 occupations.[14] We aggregate ISCO-88 occupations into three categories: high-paying, middling and low-paying occupations.

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

[14]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 CAMSIS project which cover both SOC occupational unit codes and translations into ISCO-88.

This classification follows the job-polarization literature and is consistent with that used in Goos et al. (2014) and Mahutga et al. (2018).[15] Table A.1 in the appendix presents the classification. 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.

As has been shown in previous work, occupational categories are closely related to remuneration levels, and we document this for our cohort data in the appendix. Table A.2 reports the average weekly pay by occupation, and displays the expected correlation between occupations and pay. In contrast to the US, in the UK employment polarization does not seem to have been accompanied by greater wage polarization, as has been previously shown (see, for example, Jin 2022).

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

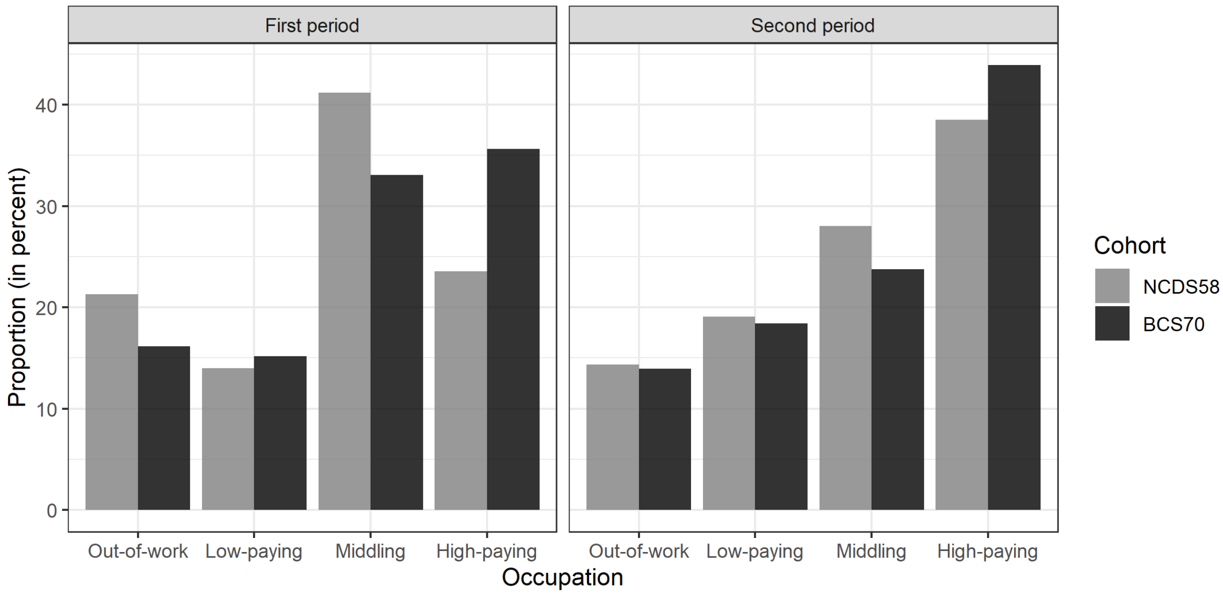
Once we restrict the data to those individuals for whom we have the key characteristics, i.e. parental income and occupations, our sample consists of 6,780 individuals in the NCDS58 and 7,983 in the BCS70, as reported in the Online Appendix.

The Labour Force Survey. As a complementary dataset we use the Labor 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 A for the details), and allows us to compare the changes in the occupational structure in the cohort data with those from a larger sample, as well as to compute measures of polarization at the regional level.

[15] A large body of literature on social mobility relies on the National Statistics Socio-Economic Classification (NS-SEC), starting with Erikson and Goldthorpe (1992) and Rose (1996). However, such classification uses a definition of routine occupations that does not match that used in the job-polarization literature. For instance, the NS-SEC considers that an employee in the 3-digit occupation *Bar staff (622)* has a routine occupation. However, it cannot be considered as a routine job following the definition of Autor et al. (2003) who define this type of job as a non-routine interactive job. We hence chose not to rely on the NS-SEC for our analysis.

[16] For England, this is the highest sub-national division, while the other countries in Britain consists of a single region. 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.

Figure 3: Occupation distribution across cohorts



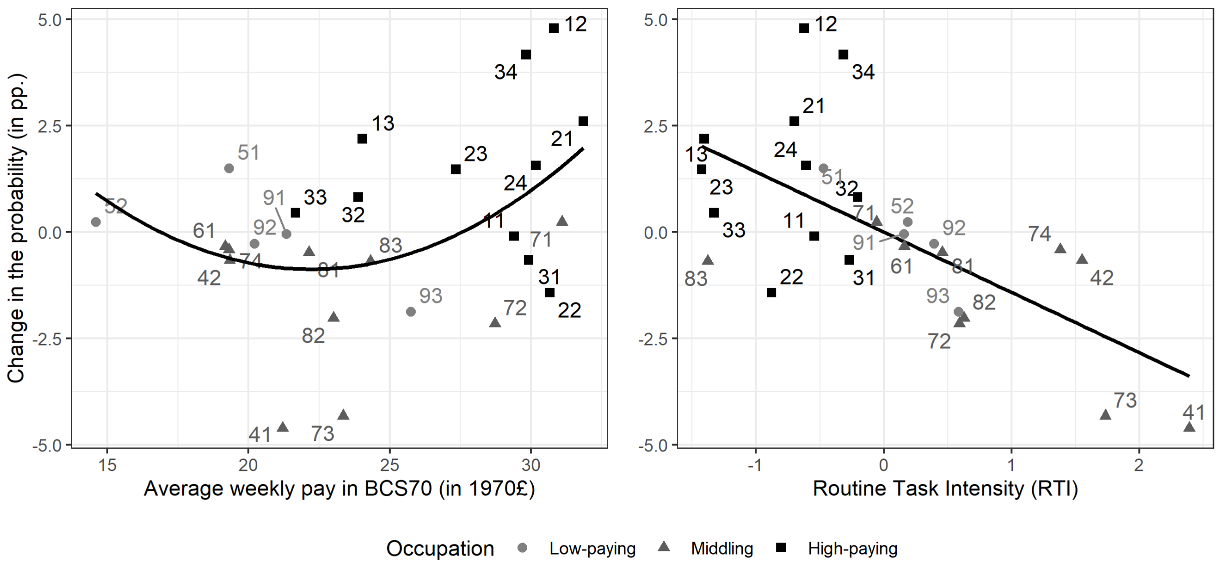
Notes: This figure reports the proportion of individuals, expressed in percent, in each type of occupation (out-of-work, low-paying, middling, high-paying) for the NCDS58 and BCS70 cohorts according to the period.

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 the change in the distribution of occupations at ages 23/26 and 42 for both cohorts, reported in Figure 3.[17] In the first period there is an increase across cohorts in the probability of working in a high- and low-paying occupation and a decline in that of working in a middling-paying occupation. When we consider the occupations 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 that 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 A.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). The differences between the first and second period distributions are interesting for our purposes, as they raise the question of whether polarization in the first period matters even when the changes in the distribution of employment are small for mature individuals. To better understand these dynamics, Figure A.1 in the Appendix performs a similar exercise using the

[17] We report the proportion of individuals in each occupation for the two cohorts in Table A.3; see also the Online Appendix for more details.

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



Notes: The left-hand side panel of the figure presents the positive relationship between the change, expressed in percentage points, between the BCS70 and NCDS58 cohorts in terms of probability of being in each ISCO-88 occupation in the first period and the average weekly pay, expressed in 1970£, in this occupation for the BCS70 cohort. The right-hand side panel shows the same probability change and the Routine Task Intensity (RTI) index from Mahutga et al. (2018).

ISCO-88 categories, and shows a clear pattern of polarization, which has been particularly large for young individual.

As an alternative way of thinking about polarization we examine how occupations with either different average pay or "routine task intensity" (RTI) have changed across the two cohorts, reported in Figure 4. 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, were the latter indicate whether they are in our category of low-paying (circle), middling (triangle) or high-paying (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. The right panel plots the change in the share of each occupation for young individuals against the RTI index provided by Mahutga et al. (2018). The downward slopping line in Figure 4 corresponds to the fitted curve implied by the data, and indicates that the change is negatively correlated with the degree of routinization.

The various pieces of evidence in this section thus indicate that the strong polarization

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 shows 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.

identified in cross-sectional data by previous work is also present when we focus on two specific cohorts. Routine intensity seems to be highly correlated with changes in the share of occupations, with low RTI ones having gained share and those with high RTI having lost it. Moreover, polarization appears whether we use the RTI index to categorize occupations or when we look at average weekly pay.

3.3 Occupational dynamics

While the literature on inter-generational mobility has traditionally focused on the outcomes of children when they are 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.[18]

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 careers in low-paying and middling occupations have probabilities of staying there of around 40% 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 for 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

[18] To understand why the probability of moving from 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 separate category, hence not included in out-of-work, are reported in the Online Appendix, and display the expected (large) difference between those in education and the rest of those out-of-work.

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 the transitions across occupations, and raise the question of whether a reduction in the share of middling jobs can be a break to mobility. If mobility occurs partly through individuals progressing up the income ladder during their careers, the disappearance of middling jobs can have important consequences. On the one hand, a large proportion of those who are in high-paying occupations at age 42 start their careers in middling occupations. If fewer individuals are in such occupations when young, as indicated by Figure 3, then there will be fewer individuals that can move into high-paying jobs. On the other, those who start in low-paying occupations have access to fewer middling jobs and hence are more likely to stay in their initial occupations. The importance of such changes for 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 in order to assess to what extent 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 to start her career in each occupation, where the possible occupations are out-of-work (O), low-paying (L), middling (M) and high-paying (H). We define the out-of-work occupation as the baseline occupation category. Let p_j be the probability to start 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-standardized. 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 occupational outcome of the mature child.[19] This expression is consistent with the approach usually found in the literature on inter-generational mobility in which 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 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 when the individual was in occupation $j \in \{O, L, M, H\}$ when young.

The expression in equation (3) shares with the literature on intra-generational mobility the idea that individuals may change position in the income ladder and that it is important to understand how those 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 can 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 direct impact of parental income. The alternative approach would be to consider a three-step setup in which parental income determines education, which then determines first-period occupation, which in turn determines

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

the second-period job.[20] The advantage of the latter approach is that it would allow us to infer how much of the parental-income advantage operates through education and how much is a direct effect; the drawback is that educational attainment is correlated with unobservable characteristics, notably ability but also the type of school attended, hence the effect that we may be attributing to years of education could be capturing other aspects, whether innate or related to parental background.[21] We hence focus exclusively on the two occupational outcomes, although our findings hold when we perform the three-step analysis.[22]

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 includes outcomes that are better and outcomes that are worse than middling, 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 to be in each of the three employment categories to that of the reference group, out-of-work. The multinomial regressions have the advantage of considering simultaneously all the possible outcomes, yet they are harder to interpret as the coefficients represent odds relative to the omitted group.

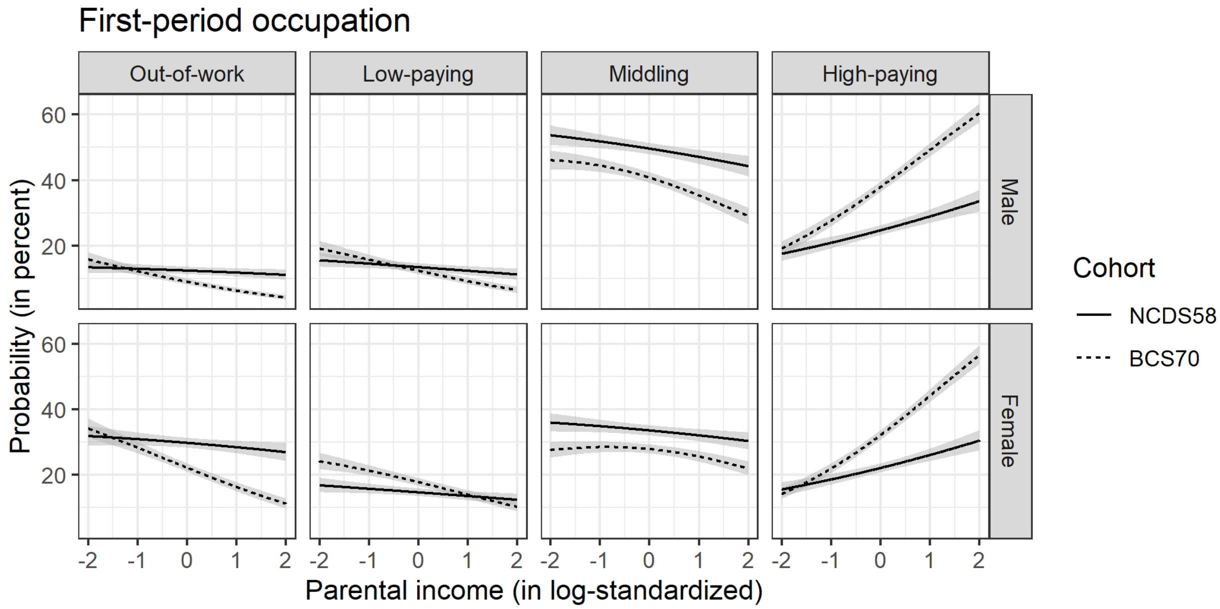
Our reference outcome in the multinomial regressions is being out-of-work. It is important to note that the transition from this category into the three employment occupations occurs with roughly equal probabilities. For the NCDS58 (BSC70) the probability of transiting from out of work to low- and high-paying occupations was, respectively, 24.7 pp. (25.3 pp.) and 27.3 pp. (26.4 pp.), i.e. of very similar magnitude. The likelihood to move 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).

[20] A large literature has considered the role of education for social mobility, and in particular examined to what extent the influence of parental background takes place through educational achievement. Examples of this literature are Blanden and Gregg (2004), Gregg et al. (2010), Blanden and Macmillan (2014), Blanden and Macmillan (2016), and Major and Machin (2018).

[21] See Harmon et al. (2003) for a discussion of the difficulty of differentiating between the returns to education and those to (innate or socially-acquired) ability.

[22] See the Online Appendix, Appendix E.

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 first period according to parental income, in log-standardized. Probabilities are computed for males and females in both cohorts according to the multinomial logistic regression reported in Table B.1 in the appendix.

4.2 Initial occupations

We start by estimating the impact of parental income on the child's first-period occupations, before considering the occupation of mature individuals in the next section. We estimate equation (1) and report the results in the appendix, Table B.1. Logit coefficients are hard to interpret, hence to visualize the results Figure 5 displays the estimated probability to be 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. The probabilities are reported separately for the two cohorts and for the two genders; 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 occupation, with high income increasing the probability to be 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 men and women, 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 are depicted by the dashed lines. The regressions on which these results are based, reported in Table B.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.[23] 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 that we observe 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 E for a discussion). Other explanations are that non-cognitive skills have become more important and that they are positively associated with the household's income, or that parental income could be a proxy for the child's social network, either its size or 'quality', which in turn has become more important in determining access to jobs.[24]

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, those 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 has pivoted 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.

Consider now the schedules for women. Starting from the right, 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 non-monotonic. At the bottom of the parental income distribution, an increase in income raises the probability of being in middle occupations, with the effect then turning negative. This

[23]The regressions coefficients also indicates that for the three outcomes the coefficient on parental income is significantly different across the two cohorts.

[24]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 between both 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.

seems to indicate that in the lower segment of the parental income distribution, an increase in income confers women a occupational advantage, allowing them to access middling rather than low-paying jobs. 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 to be 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 job at the start of their career. We hence consider both an expression that does not include the effect of initial occupations, as given by equation (2), and one in which they are included, as in equation (3). The former specification is equivalent to those usually found in the literature.

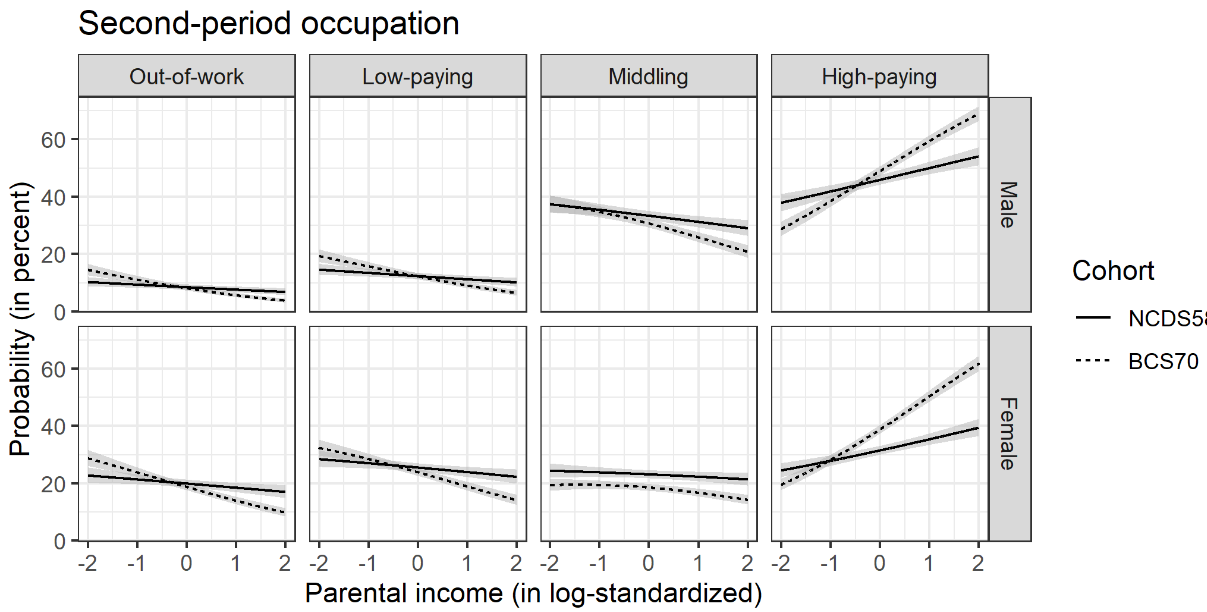
The relationship between parental income and occupational dynamics is depicted in Figure 6 which reports the probabilities of being in each occupational category at age 42 as a function of parental income, for both genders. The probabilities are obtained from the baseline multinomial regression in which we do not consider the effect of initial occupations. The regression, reported in Table B.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.

As for initial occupations, 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 to be in a high-paying occupation by 21% for the older cohort, this same increase raises the odds by 73% for the younger one.[25]

The main difference with 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 the two cohorts. Figure 5 indicates that, as far as initial occupations

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

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 second period according to parental income, in log-standardized. Probabilities are computed for males and females in both cohorts according to the multinomial logistic regression reported in Table B.2 in the appendix.

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 for the younger than for 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 of being in a high-paying occupation in both cohorts; those with lower parental income, experienced 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 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 results indicate, not surprisingly, that the occupational structure is behind the observed changes in income mobility and closely mimic their findings when we consider 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 generations can be due to changes in either 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 her initial occupation, an individual progresses over her career.

Table B.2 in the appendix reports the multinomial results when we introduce initial occupations in the regressions for occupation at 42 and we provide a graphical analysis in Figure 7. The figure displays the difference, 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 between the BCS70 and the NCDS58 cohorts. Each panel represents the gap across cohorts in a particular transition probability for various levels of (standardized) 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 those for men, with the equivalent figure for women provided in appendix C—see Figure C.1.

Consider first 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. for those who started in such occupation but declined for those starting in low-paying occupations or out of work. This indicates a reduction in upwards mobility for those starting 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 although the probability of being in a high-paying occupation at 42 has slightly increased (by 0.71 pp.), 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—for those with mean parental income—the probability of being in such an occupation has fallen irrespective of the 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 at the top and the bottom of the parental income distribution the changes are large and of opposite sign. Notably, for those who came from a household with parental income 2-standard-deviations below the mean there is a reduction in the probability of attaining the

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 the NCDS58 cohorts in terms of probability of being in each type of second-period occupation (out-of-work, low-paying, middling, high-paying), conditional on the first-period occupation, according to parental income, in log-standardized. Probabilities are computed for males in both cohorts according to the multinomial logistic regression reported in columns (2) of Table B.2

top occupations, irrespective of the initial occupation, which is of considerable magnitude, between 7.2 and 11 pp.. 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, there is an increase in the likelihood of remaining in or moving to the top, with those who started in a low-paying occupation experiencing a particularly large increase in the probability, by 8 pp.

The second important 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 progression in which individuals would move from low-paying into middling occupations as their careers evolved seems to have weakened, and has been replaced by higher probabilities of either staying in the occupation of origin or jumping up to a high-paying one, with the transition probabilities being strongly dependent on the individual's background. An equivalent pattern is found when considering those who started in middling occupations, with those 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

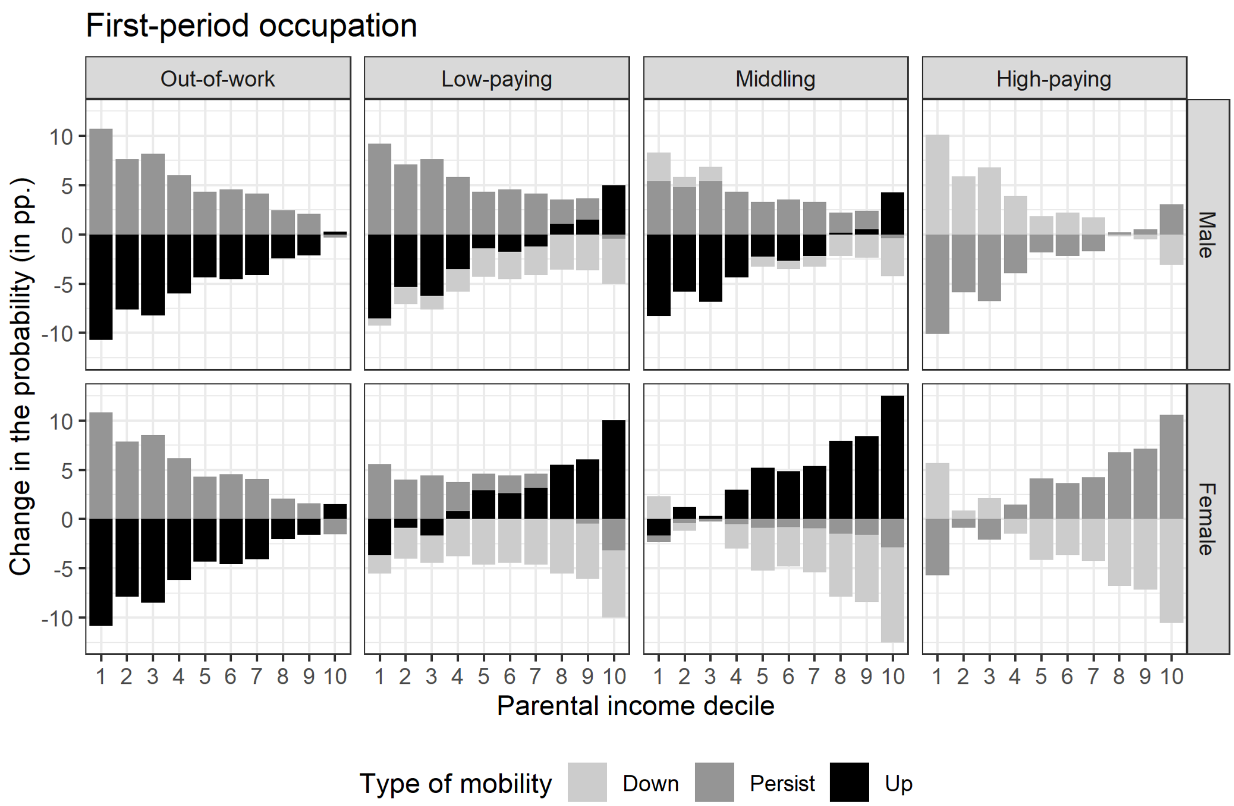
In order to provide a compact measure of mobility, we define three possible outcomes for the second period. Downward mobility is defined as ending up in a category with lower average pay than the individual's initial category; persistence consists of remaining in the same category, and upwards mobility occurs when the individual moves to a category with higher average pay. Hence for those starting in a low-paying occupation, downward 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, remaining in, 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 those born in 1958. The reverse effect appears for those at the bottom of the parental income distribution, with those in the bottom decile being 10 pp. more (less) likely to experience downwards mobility (remain in the occupation). The reduction in persistence falls 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*, whereby for those in the middle of the distribution there have been only moderate changes in mobility, while at the extreme the changes have been large and of opposite sign for those at the bottom and at the top.

An equivalent pattern is observed for those that start their careers in middling occupa-

Figure 8: Change in intra-generational mobility across cohorts



Notes: This figure presents the difference, expressed in percentage points, between the BCS70 and the NCDS58 cohorts in terms of type of mobility (down, persist, up) conditional on the first period occupation (out-of-work, low-paying, middling, high-paying) according to the 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 B.2 in the appendix.

tions. Those at the bottom of the parental distribution witnessed sharp declines in upwards mobility and higher persistence and likelihood of moving down, with the size of the changes declining 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 those in the top decile of the parental income distribution witness an increase in the 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 individuals had parents at the top or at the bottom of the income distribution.

Not surprisingly, the dynamics for women differ considerably from those for men, as women of the older cohort where much less likely to occupy middling and especially high-paying occupations. The bottom panels of Figure 8 capture, however, the advantage that parental income gives in providing the means for upwards mobility. Irrespective of parental income, women starting in a high-paying occupation (resp. middling) have a greater probability of remaining there (moving upwards) for the younger cohort. This is not surprising in view of the occupational upgrading experienced by women of the younger cohort. In contrast, for those who started in low-paying occupations, a polarization appears, although the turning point occurs for lower parental incomes than in the case of men (4th decile), indicating the tension between the general occupational upgrading of women and the 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 increased 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,[26] and in this section we turn to exploring 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 when they were young. 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 get 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 local level.

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

5.1 Regional polarization

Our data provide information on the 10 regions that constitute the UK.[27] For both analyses we need to construct a measure of polarization at the regional level, and to do so we define an individual's region as that in which she lived at age 16 and measure polarization in that region as the share of middling employment in the year in which she was 23/26 years-old. [28] Our cohort data have the drawback that sample sizes at the regional level are small and thus measures of regional polarization based on it 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.

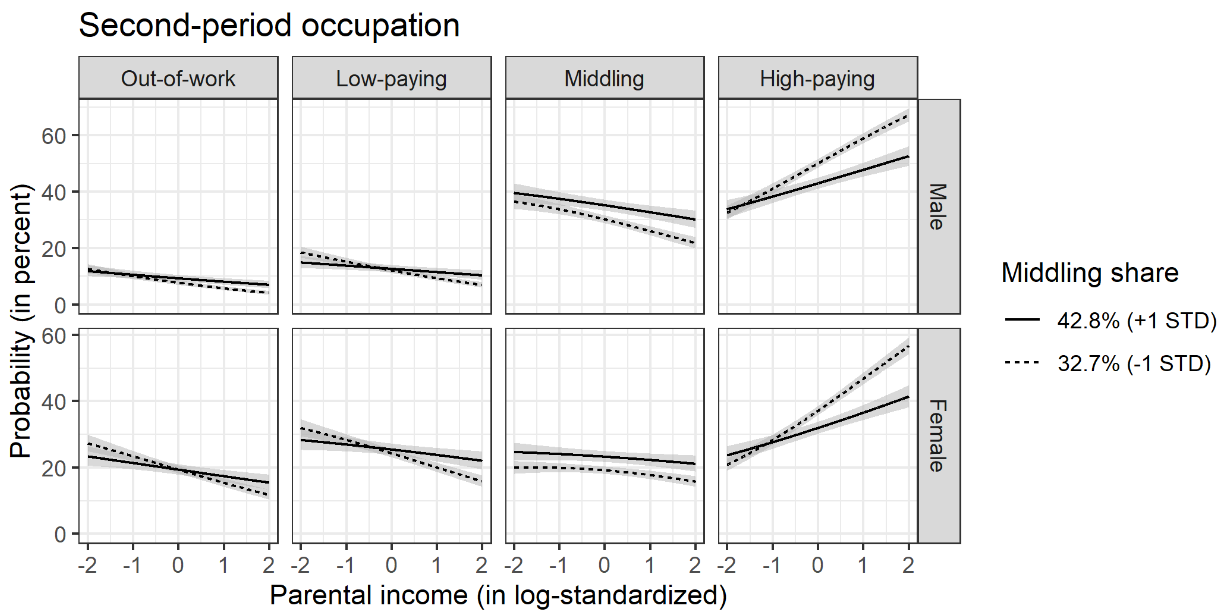
When computing the extent of polarization we face two concerns. First, as shown in the appendix, the share of middling employment has fallen in all regions, but whether this has occurred at the expense of low-paying or high-paying occupations varies. For this reason, rather than focusing exclusively on the share of middling jobs we consider changes in the share of jobs in all three occupations.

Second, we need to define the labour market that individuals in our dataset were facing and measure the extent of polarization in that particular market. To do so we consider the distribution of employment for the relevant age cohorts in the LFS. We hence suppose that members of a cohort are in competition for jobs with individuals that were born in the 5 years before and 5 years after them. That is, for the NCDS58 cohort we consider individuals born between 1953 and 1963, and for the BCS70 those born between 1965 and 1975. We measure the share of employment in each year between the initial and final period that we use for each cohort, and compute the average over the whole period in which each cohort has been exposed to employment changes. That is, for the NCD58 we consider the structure of employment between 1981 and 2000, for the BCS70 between 1996 and 2012. We then measure the extent of polarization as changes in the occupational shares obtained for the 1953-63 cohorts and those for the 1965-75 ones. Appendix A.3 gives details on the LFS data and our measures of polarization, and shows the increase in polarization for both relevant age cohort at the national and regional levels (see Figures A.2 and A.3).

[27]Unfortunately, these regions are relatively large and hence do not allow us to identity 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.

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

Figure 9: Second-period occupation probability according to parental income and middling share 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 second period according to parental income, expressed in log-standardized, and the share of middling jobs in first period (age 23/26) in the region of residence at the age of 16. Probabilities are computed for males and females from East Anglia (referent group) according to the multinomial logistic regression reported in Table C.1 in the appendix.

5.2 Individual outcomes and regional employment patterns

Several factors may be behind the increased importance of parental income for occupational outcomes across cohorts. Here we explore the possibility that employment polarization is one of these factors. To do so, we substitute all the interacted cohort dummies BCS in equation (2) with our measure of polarization at the regional level. Thus, our specification becomes:

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

where Pol^r is the share of middling jobs when individuals are young (age 23/26) in the region r where they resided at age 16, X are control variables, and ψ_r are region fixed effects.

Figure 9 reports the probabilities of being in each occupational category at age 42 as a function of parental income, for both genders, for two values of the middling share. We present the probabilities according to parental income at plus and minus one standard-deviation of the middling share distribution across regions, which are, respectively, shares of 42.8% and 32.7%. The figures indicate steeper slopes—i.e. a stronger impact of parental income—when the share of middling jobs is lower.

These results are close to those obtained in 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, obtaining that for the NCDS58 (resp. BCS70) it is 0.845 standard deviations below (above) the mean. Using these figures, the coefficients we obtain (see Table C.1, column (6) in the appendix) imply that a one standard deviation increase in parental income raised the probability of being in a high-paying occupation by 0.14 pp. for the older cohort and by 0.44 for the younger one. These values are close to those obtained in our core specification (Table B.2, column (3)) of 0.19 and 0.55, indicating that using the differences in polarization across cohorts yield effects that are close to those obtained with the cohort dummy.

5.3 Regional mobility

Our final step consists in considering the correlation between regional mobility and polarization. We 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 local 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:[29]

$$\log\left(\frac{p_k^r}{p_O^r}\right) = \alpha_{5k}^r + \beta_{5k}^r Y^p + \gamma_{5k}^r X. \tag{5}$$

We hence use individual data to estimate 10 coefficients β_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. As before, we need to recall that these are the coefficients relative to the probability of being out-of-work (see Figures C.2 and C.3 in the Appendix that report the overall effect).

These regressions allow us to make two inferences. First, we can ask whether 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. When we split the data we find that for the vast majority of regions (7/10) parental income parental income has a large impact for the older cohort's likelihood

[29] 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.

to be in a high-paying occupation, with the magnitude being often close to the 0.19 point estimate we obtained at the national level. The coefficients are not always significant, which is potentially due to a lack of statistical power given the limited number of observations (per region and also in certain region-occupation cells). The other three regions—North, Wales and Yorkshire—display coefficients that are close to zero, unsurprisingly given the very small number of high-paying observations we have in those regions (see Figure A.3 in the Appendix that reports the share of high-paying jobs in the LFS). For those born in 1970, the likelihood to be in a high-paying occupation exhibits systematically large and significant coefficients on parental income. Out of the 10 regions only two (South West and West Midlands) do not display a significant coefficient. 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. These results indicate that the increase in the importance of parental income across cohorts holds at the regional level.

Second, the estimates 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 than in the least mobile locations (see Table 5). This raises the question of whether the magnitude of the changes in mobility is correlated to the degree of employment polarization observed at the regional level.

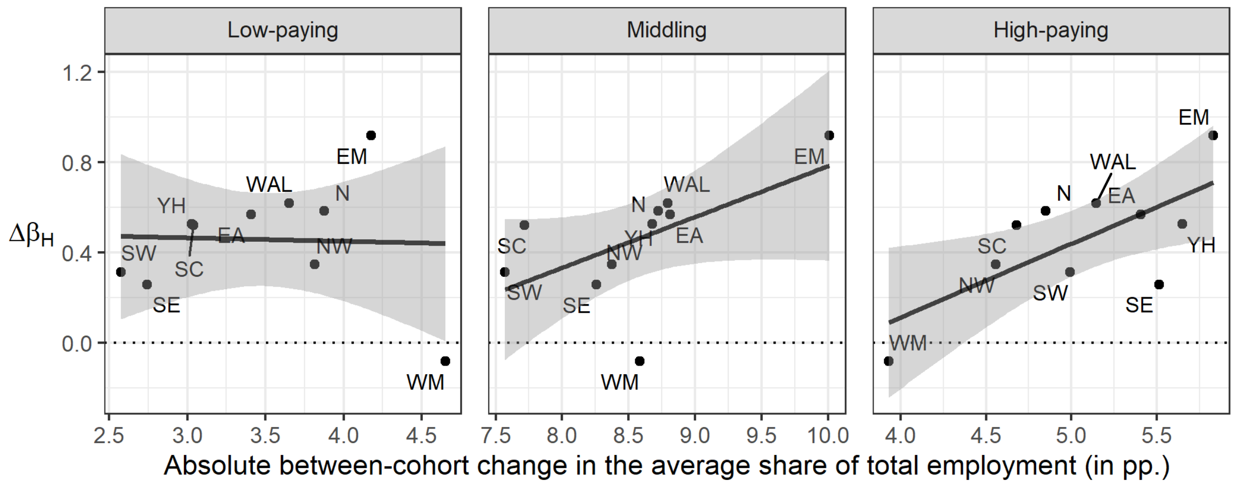
To capture changes in mobility in region r, we focus on the between-cohort change in the role of parental income for being in high-paying occupation, namely, $\Delta\beta_H^r$ which correspond to the "Par. Inc. $\times$ BCS" coefficients in the last column of Table 5. We hence compute the correlation between mobility and polarization with the following regression:

$$\Delta\beta_H^r = \delta_H + \eta_H \Delta Pol^r, \tag{6}$$

where ΔPol^r is the change in our measure of polarization at the regional level. The change in the extent of regional polarization is measured by the change across cohorts in regional polarization as measured from the LFS. Figure 10 displays the correlation between the two variables, with both measured in percentage points. The three panels report, in the horizontal axis, the changes in absolute value of the share of employment in each of the three categories. The actual changes are positive for high- and low-paying occupations and negative for middling ones, hence reporting the absolute value implies that for all three occupational categories moving from the left to the right of each graph implies an increase in polarization. The vertical axis displays the regional $\Delta\beta_H$ described above.

Each dot represents one of the 10 regions, while the line corresponds to the linear regression line. Consider the right-most graph. The upward slope indicates that regions where the

Figure 10: Change in parental income coefficient for high-paying second-period occupation according to job polarization at the regional level



Notes: This figure presents the correlation across regions between the change in the parental income coefficient for the high-paying occupation in second period $\Delta\beta_H$ and the between-cohort change in absolute value in the average share of total employment of low-paying, middling, and high-paying occupations, in percentage points. Note that, by taking the absolute value of the change, we reversed the x-axis for the middling panels (middle column). Thus, regions on the left-hand (resp. right-hand) side of each panel are those where the polarization of employment has been lower (resp. larger).

share of high-paying occupations (in the relevant age group) increased the most are also the regions where the impact of parental income in accessing high-paying occupations rose the most. Similarly, the middle graph also displays an upwards-slopping schedule when we plot the magnitude of the change in the share of middling occupations against $\Delta\beta_H$, indicating that regions where the share of middling income jobs declined the most are also those where parental impact became strongest. The left-hand graph depicts the correlation between the change in the coefficient and the change in the share of low-paying occupations, and displays a flat schedule, which is driven by an outlier, the West-Midlands. Removing this observation, yields a positive correlation between the change in polarization and the change in the effect of parental income. We obtain similar results when we consider the change in the coefficients on parental income for the probability of being in middling and low-paying occupations, namely, $\Delta\beta_M$ and $\Delta\beta_L$, the main difference being that we also find a positive correlation in the case of low-paying occupations.[30]

This section provides suggestive evidence that the increase in employment polarization may be a cause of the reduction in occupational mobility observed across the two cohorts. When we exploit the time dimension, 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

[30] See Figure C.4 in the appendix.

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 that we observe 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. In contrast, the question of whether the change in the employment structure has also had an impact on social mobility has only recently been addressed. This paper raises 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. Individuals differ in parental background and innate (and initially unobservable) ability. Parental background affects the child's human capital and determines her entry job. We suppose that in the first period there is on-the-job learning, the extent of which depends on both ability and the type of job performed, with better paying jobs generating more learning. As the workers accumulated human capital is revealed to firms, they may 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 greater job persistence across generations.

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 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 work-life.

The data indicate that intra-generational occupational changes are an important source of mobility, with large shares of those starting in low-paying and middling occupations moving, respectively, to middling and high-paying jobs over their work lives. When we compare 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, the probability for those who start in low-paying jobs to move upwards has remained stable on average, but this average hides the fact that it has considerably increased for those with high-income parents and declined by 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. Moreover, our analysis of local mobility patterns finds that regions where employment polarization rose the most across the two cohorts are also those where *immobility* increased the most.

Although our data do not allow to establish causality, the patterns we identify are suggestive that as middling jobs have been eroded, 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 a country characterized by a regionally-homogeneous social protection system, and argue 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 emphasized the importance of *multi-generational mobility* and our results point towards the possibility that there is a transmission of polarization across generations, as 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 referent 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 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.

A.1 Occupational classification

Table A.1 describes the classification of occupations that we use, providing an overview of ISCO-88 occupation codes along with the routine task intensities from Goos et al. (2014) and Mahutga et al. (2018).

A.2 Occupational structure in the cohort studies

Table A.2 reports the average weekly pay by occupation in the cohort data. 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 table indicates that the average pay has increased for every type of occupation between both cohorts. The change across cohort of pay at age 42 is roughly the same for the three categories, lying between 14 and 15%. In contrast, for young individuals, the change has been 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).

Table A.3 presents the probability to be in each occupational category at both periods, for both cohorts. The first-period probabilities indicate that BCS70-cohort individuals are about 8.1 pp. less likely to start in middling occupations, while they are about 12.1 pp. more likely to start their careers in a high-paying occupation.

In our data, occupations are reported according to ISCO-88 categories and we grouped them into three broad categories in line with the polarization literature, as reported in Figure 3 in the text. Figure A.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.

Table A.1: Overview of ISCO-88 occupation codes and routine task intensity

Code	Occupation	RTI GMS	RTI LIS
High-paying occupations			
11	Legislators and senior officials		-0.54
12	Corporate managers	-0.75	-0.62
13	Managers of small enterprises	-1.52	-1.41
21	Physical, mathematical and engineering professionals	-0.82	-0.70
22	Life science and health professionals	-1.00	-0.88
23	Teaching professionals		-1.43
24	Other professionals	-0.73	-0.61
31	Physical, mathematical and engineering associate professionals	-0.40	-0.27
32	Life science and health associate professionals	-0.33	-0.20
33	Teaching associate professionals		-1.33
34	Other associate professionals	-0.44	-0.32
Middling occupations			
41	Office clerks	2.24	2.39
42	Customer service clerks	1.41	1.55
61	Skilled agricultural and fishery workers		0.16
71	Extraction and building trades workers	-0.19	-0.06
72	Metal, machinery and related trade work	0.46	0.59
73	Precision, handicraft, craft printing and related trade workers	1.59	1.73
74	Other craft and related trade workers	1.24	1.38
81	Stationary plant and related operators	0.32	0.46
82	Machine operators and assemblers	0.49	0.63
83	Drivers and mobile plant operators	-1.50	-1.38
Low-paying occupations			
51	Personal and protective service workers	-0.60	-0.47
52	Models, salespersons and demonstrators	0.05	0.18
91	Sales and service elementary occupations	0.03	0.16
92	Agricultural, fishery and related labourers		0.39
93	Laborers in mining, construction, manufacturing and transport	0.45	0.58

Notes: This table provides an overview of ISCO-88 occupation codes and their corresponding Routine Task Intensity (RTI) from Goos et al. (2014) (GMS) and Mahutga et al. (2018) (LIS). 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 add these missing occupations to categories according to closest occupations, hence, relying on the 1-digit ISCO-88 classification.

A.3 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,

Table A.2: Average weekly pay by occupation (in 1970£)

Occupation	First period		Second period	
	NCDS58	BCS70	NCDS58	BCS70
Low-paying	17.05	19.35	17.75	20.25
	(0.30)	(0.61)	(0.39)	(0.37)
Middling	19.60	23.42	25.26	29.07
	(0.16)	(0.34)	(0.45)	(0.39)
High-paying	19.51	29.23	40.82	46.64
	(0.17)	(0.40)	(0.64)	(0.55)

Notes: This table presents the average weekly pay, expressed in 1970£, in each first- and second-period occupations for the NCDS58 and BCS70 cohorts. Standard errors between parentheses. We exclude the very bottom and top of the pay distribution for each cohort, i.e. pay which are below £1 and above £300.

Table A.3: Probability of being in each occupation at both periods, for both cohorts (in percent)

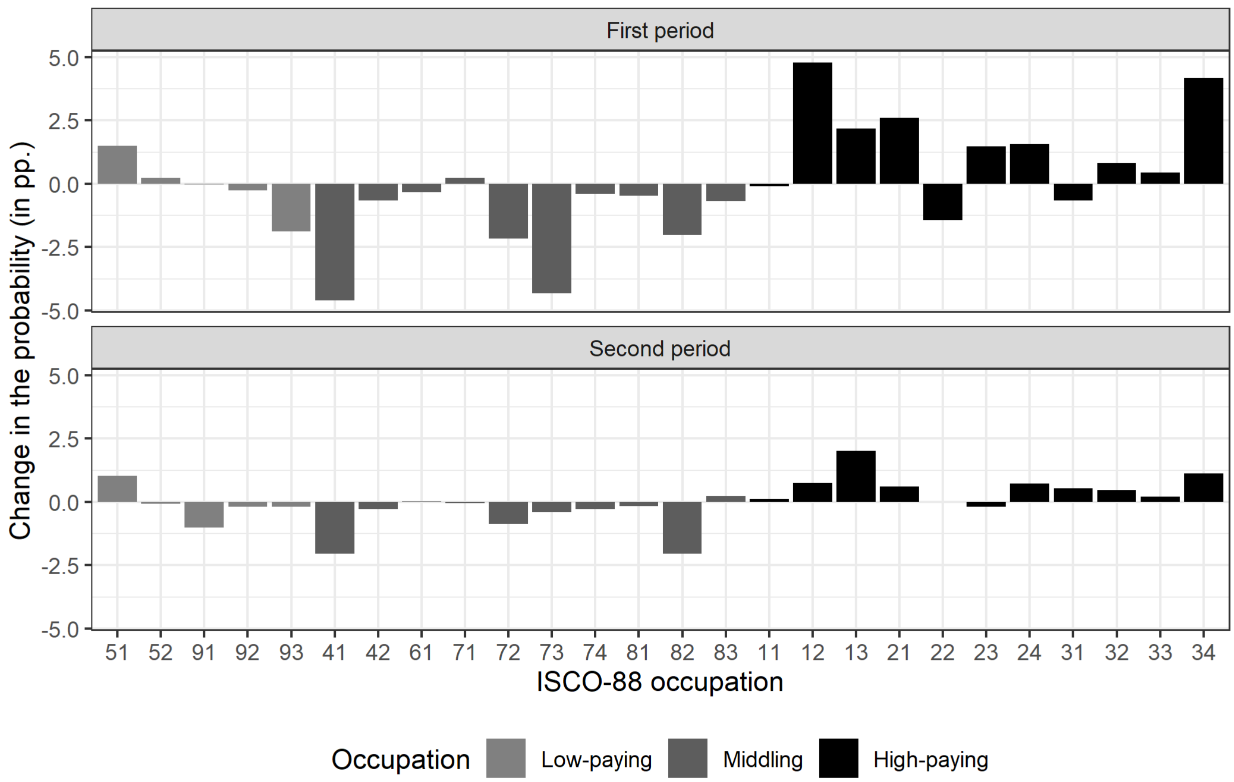
Occupation	First period			Second period		
	BCS70	NCDS58	Δ	BCS70	NCDS58	Δ
Out-of-work	16.2	21.3	-5.1	13.9	14.4	-0.4
Low-paying	15.2	14.0	1.2	18.4	19.1	-0.7
Middling	33.1	41.2	-8.1	23.8	28.0	-4.2
High-paying	35.6	23.6	12.1	43.9	38.5	5.4

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 of both periods.

wages. The LFS was conducted every two years until 1983, then annually until 1992, and quarterly since then. It has the advantage of giving 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 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.

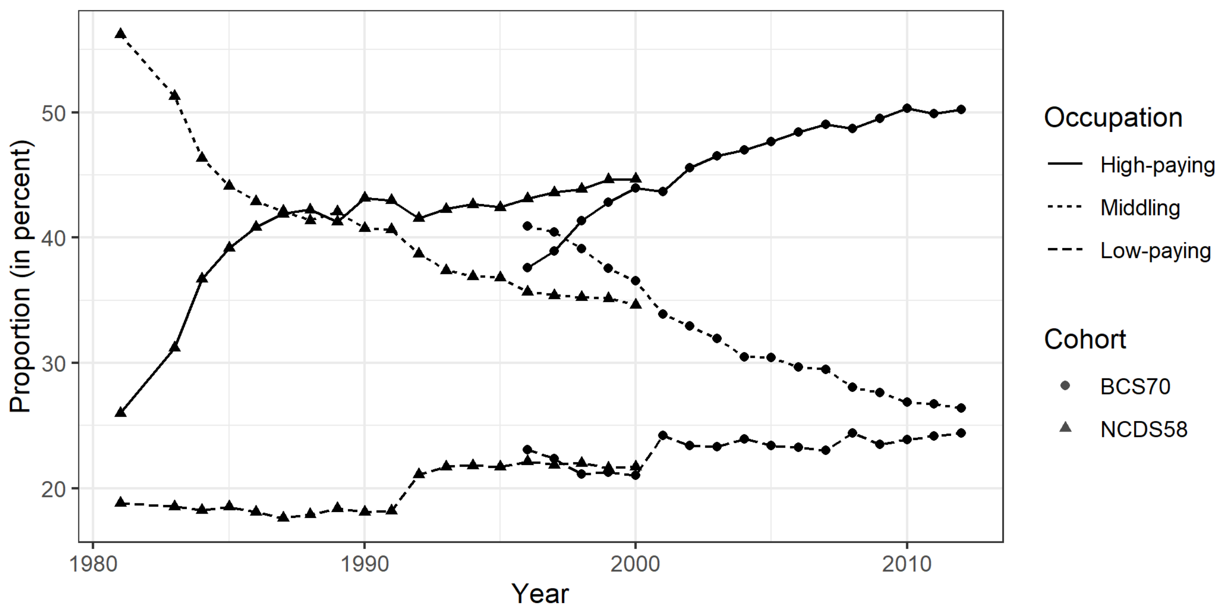
Figure A.1: Change in the probability of being in each ISCO-88 occupation in both periods



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

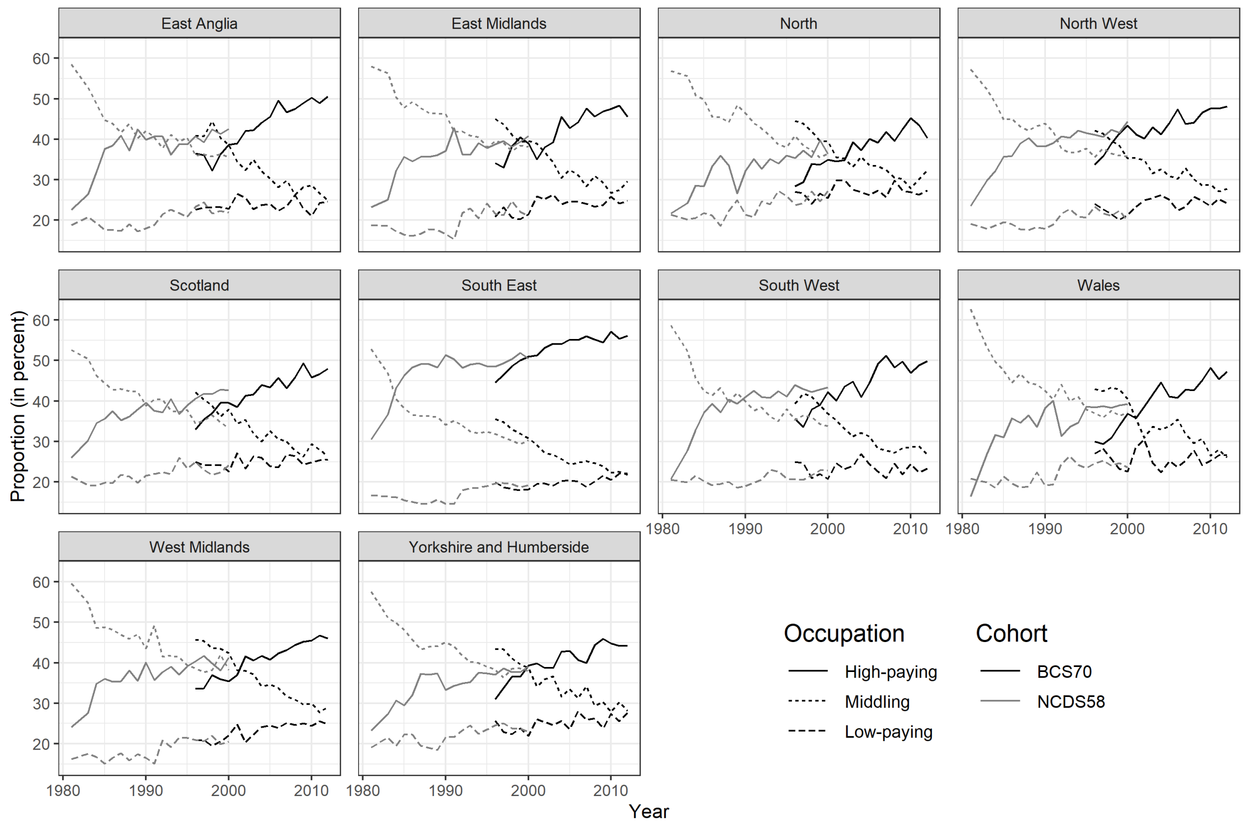
Figure A.2 shows the extent of job polarization at the national level using the LFS data for both relevant-age cohorts. The share of middling jobs has declined by over 20 percentage points from 1981 to 2012. This reduction has been offset by an increase in the share of high-paying occupations by 16 percentage points over the same period, whereas the share of low-paying jobs has increased by 7 percentage points. Figure A.3 shows the extent of job polarization at the regional level using the LFS data for both relevant age cohorts.

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



Notes: This figure presents the job polarization at the national level using the Labour Force Survey (LFS) data from 1981 to 2012. Curves represent the share of individuals in low-paying, middling, and high-paying occupations for the relevant age cohort in the LFS, i.e. from those born five years before to those born five years latter.

Figure A.3: Job polarization at the regional level over the lifecycle of both cohorts



Notes: This figure presents the job polarization at the regional level using the Labour Force Survey (LFS) data from 1981 to 2012. Curves represent the share of individuals in out-of-work, low-paying, middling, and high-paying occupations for the relevant age cohort in the LFS, i.e. from those born five years before to those born five years latter.

B 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 to interpret coefficients as the the multinomial coefficients are relative to the baseline occupation category, namely, out-of-work.

B.1 First-period occupation

Table B.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.

B.2 Second-period occupation

Table B.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 three consider the role played by 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 to 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. This result is in line with the extensive work that has found an increased correlation in parent-child incomes, as discussed in the introduction. While a one-standard-deviation increase in parental income used to raise the odds to be in a high-paying occupation by 21% for the older cohort, this same increase

Table B.1: Probability of being in each occupation at 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 first period is the base outcome of the multinomial logistic regression. Male in the NCDS58 cohort is the referent group. Parental income in logarithm and then standardized at the cohort level.

raises the odds by 73% for the younger one.[31]

When we compare the impact of initial occupation across the cohorts (bottom panel) 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. This contrasts with the finding that persistence did not increase for those in high-paying occupations.

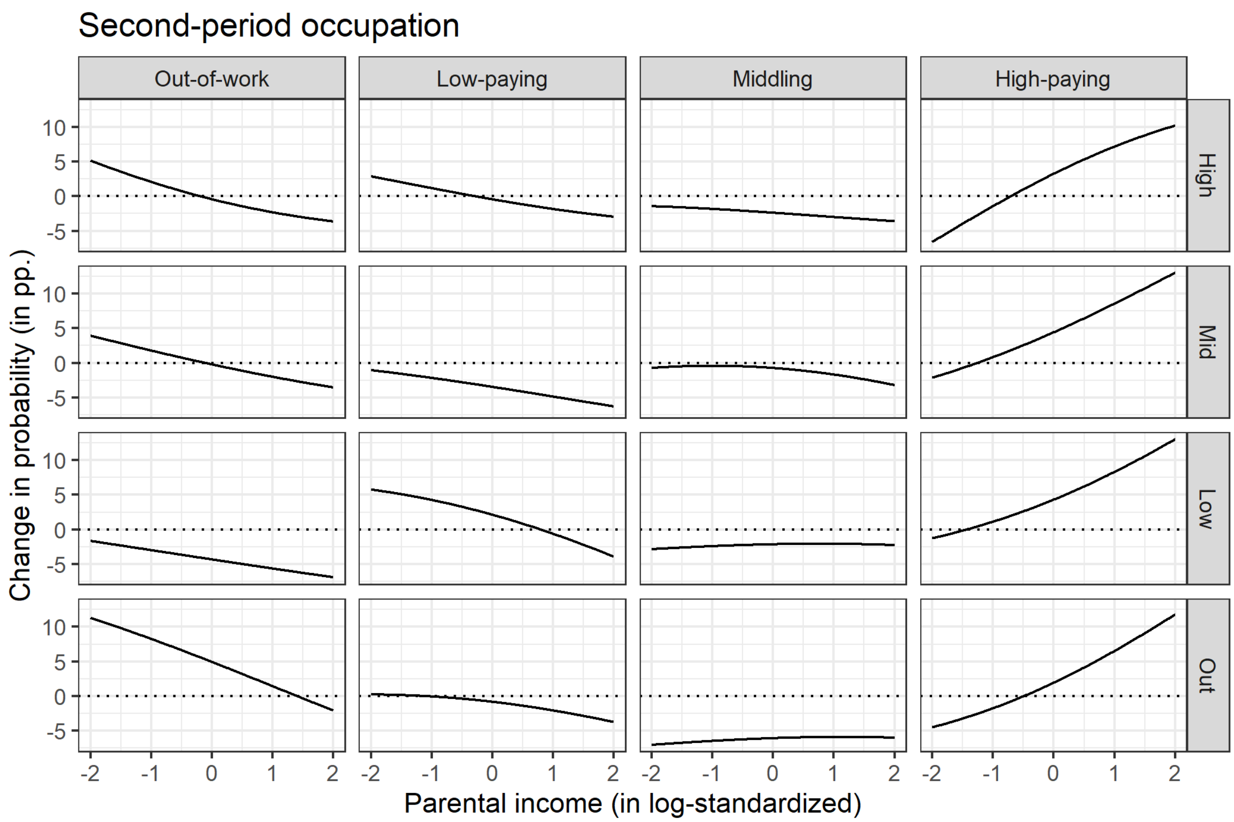
[31] These coefficients are obtained by taking the exponential of the change in log odds, i.e. $\exp(0.19) = 1.209$ and $\exp(0.19 + 0.36) = 1.733$.

Table B.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 × 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. × 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. × BCS				0.47^{***}	0.66^{***}	0.55^{***}
				(0.17)	(0.19)	(0.18)
Mid. × BCS				0.02	0.55^{***}	0.25^{*}
				(0.15)	(0.15)	(0.15)
High. × 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. Male in the NCDS58 cohort in out-of-work occupation in first period is the referent group. Parental income in logarithm and then 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 referent 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.

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



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

C Additional tables and figures

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

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

Table C.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.[32] Both regressions also include region fixed effects, hence we added region fixed effects to our

[32] We also used alternative measures of polarization using data on only the initial year measure of polarization for each cohort (1981 and 1996) rather than the average over the working-life and found equivalent results to those reported here (results not reported).

Table C.1: Second-period occupation probability according to share of non-middling occupations in the region at the age 16

	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				-0.07	-0.02	-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	-0.04^{*}	-0.11^{***}
				(0.03)	(0.02)	(0.02)
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. Male in the NCDS58 cohort is the referent group in (1), while male is the referent group in (2). Parental income in logarithm and then standardized at the cohort level. Middling share corresponds to the share of occupations that are middling in total employment in the region at age 16. The shares has 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.

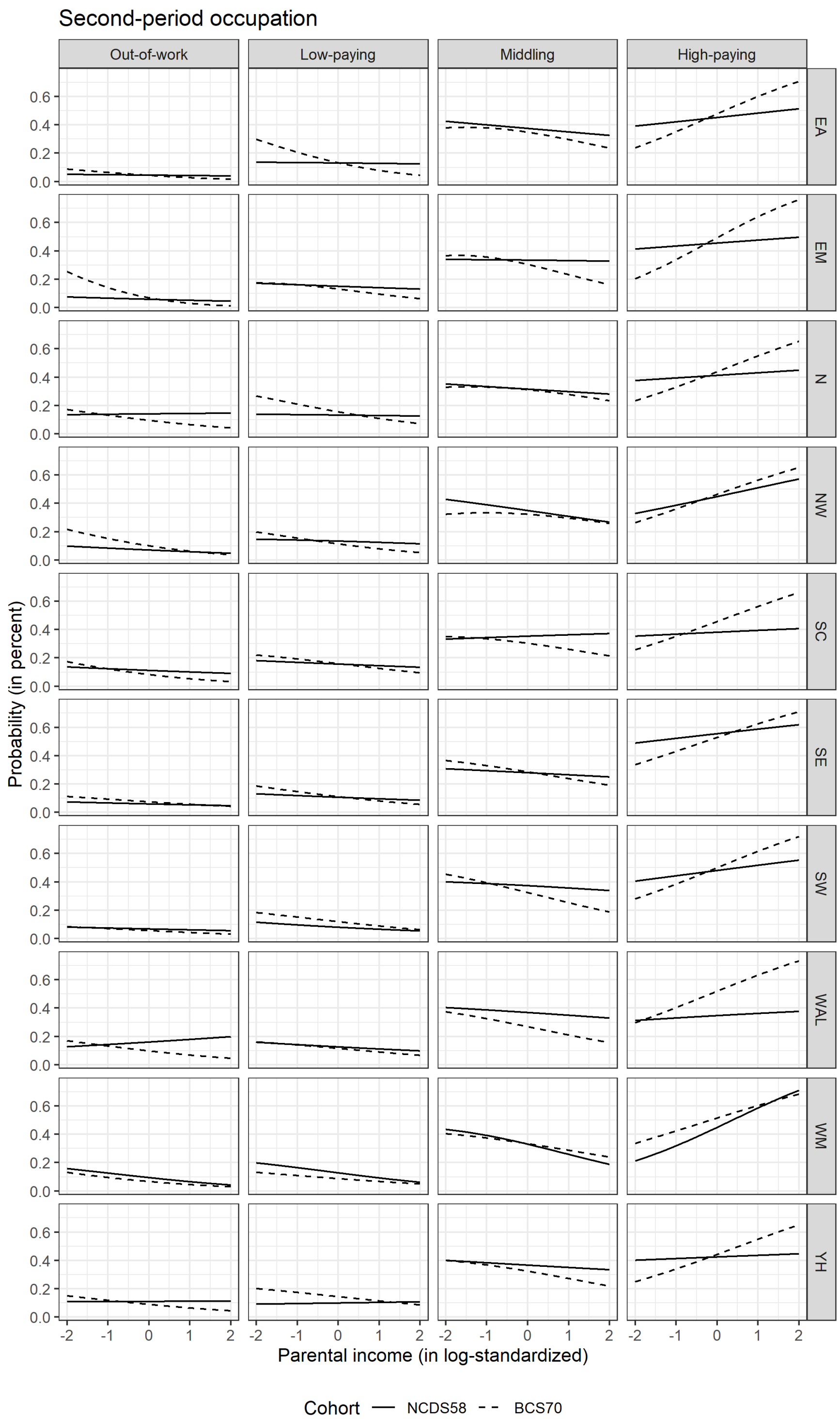
specification (2) for comparison.

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 C.2 and C.3 depict the probabilities of being in each second period occupation according to parental income at the regional level, for men and women respectively. They indicates that the pattern found at the national level also holds at the regional level. The underlying regression results are available upon request.

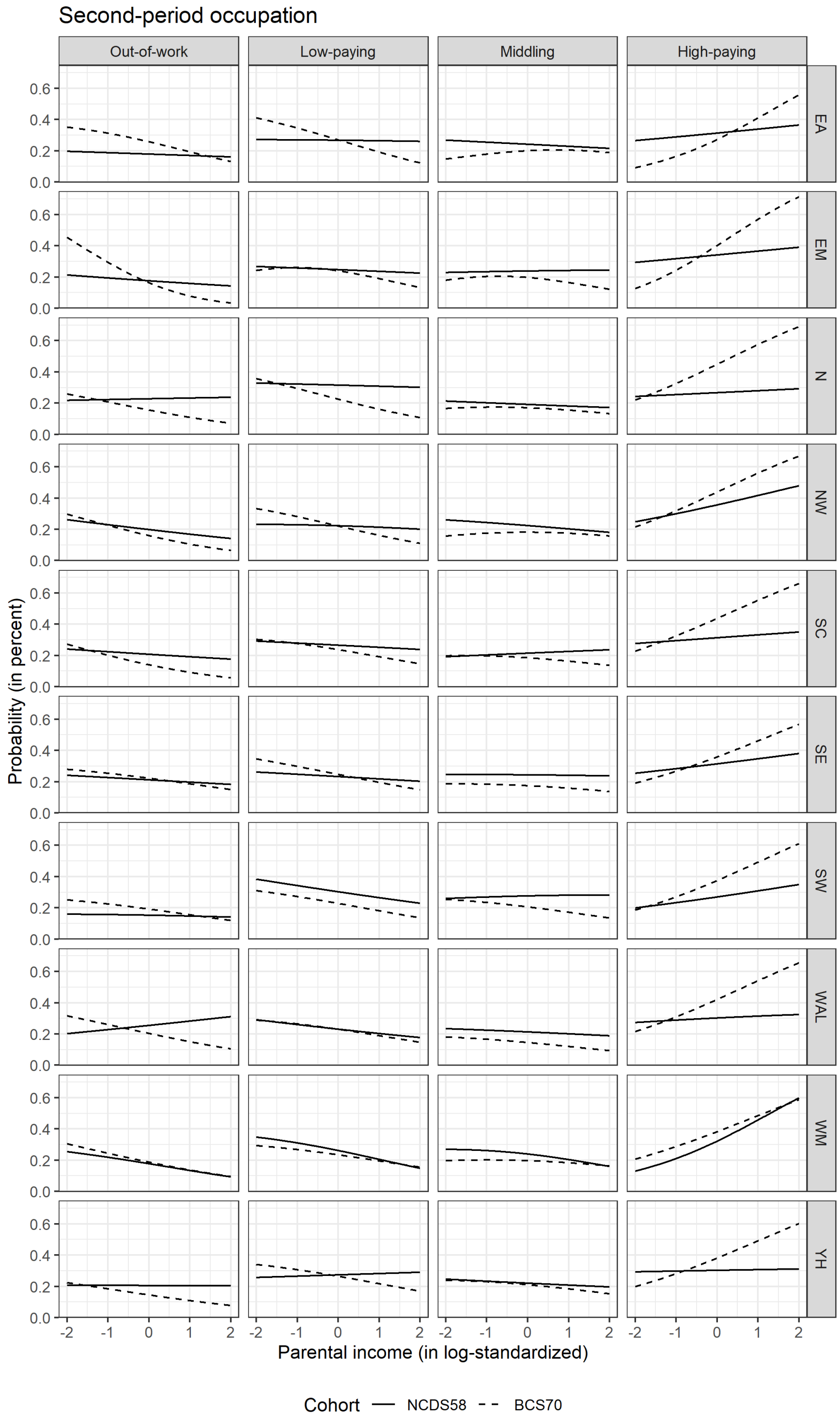
Figure C.4 depicts the correlation between the change in the parental income coefficient for second-period occupations and the change in job polarization at the regional level. The top panel is the same as that reported in Figure 10, depicting the correlation between the change in polarization and that in the impact of parental income on the probability to be in an high-paying occupation. The next two panels depict, respectively, the correlation between the change in polarization and those in the impact of parental income on the probabilities to be in a middling and in a low-paying occupation.

Figure C.2: Second-period occupation probability according to parental income at the regional level (male only)



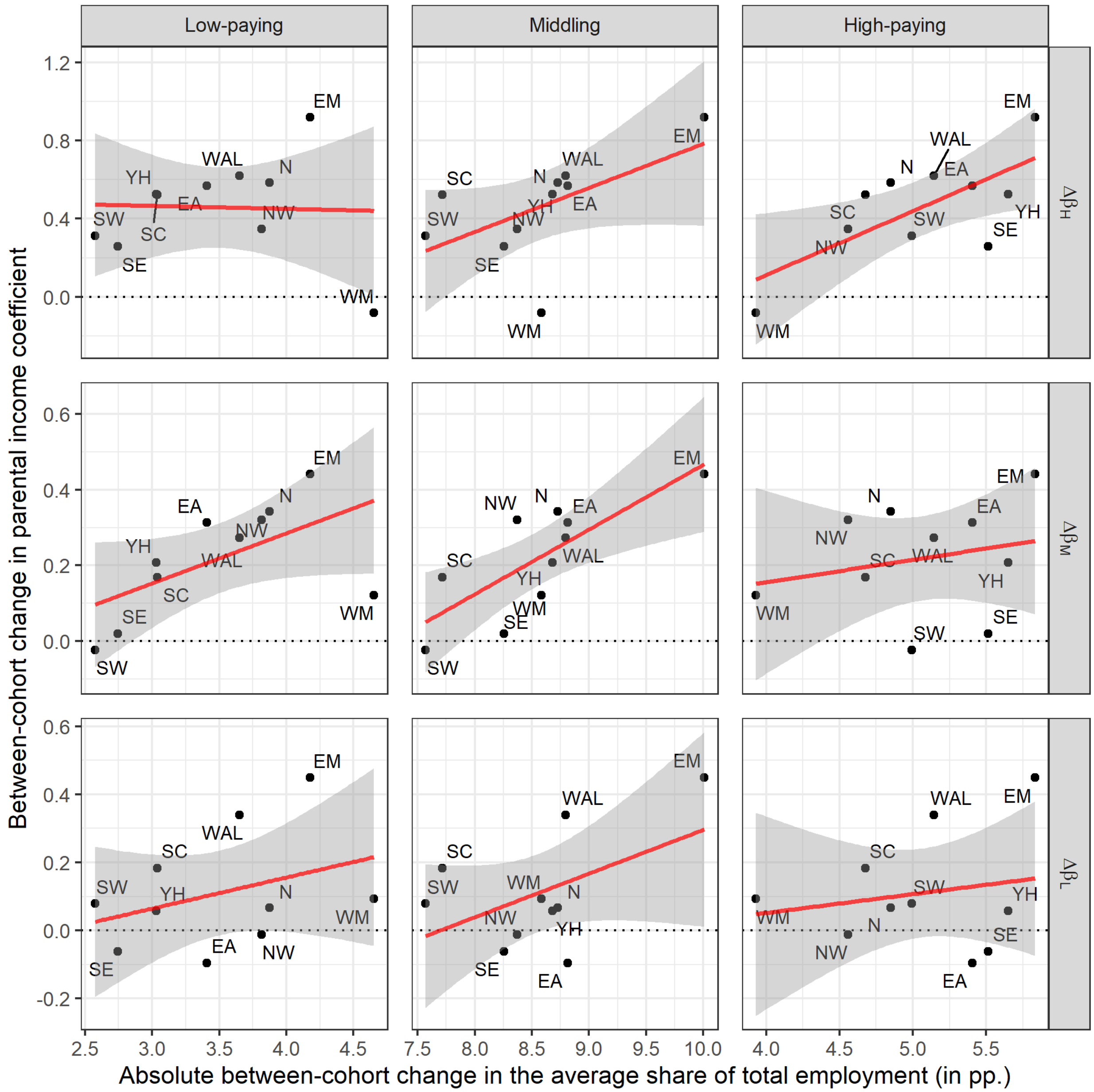
Notes: This figure presents the probability, expressed in percent, of being in each type of occupation (out-of-work, low-paying, middling, high-paying) in second period according to parental income, in log-standardized, for each region. Probabilities are computed for males in both cohorts from the multinomial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

Figure C.3: Second-period occupation probability according to 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 second period according to parental income, in log-standardized, for each region. Probabilities are computed for females in both cohorts from the multinomial logistic regressions in Table 5.

Figure C.4: Change in parental income coefficient for second-period occupation according to job polarization at the regional level



Notes: This figure presents the correlation across regions between the change in the parental income coefficient for each occupation (low-paying, middling, and high-paying) in second period $\Delta\beta_k$ and the between-cohort change in absolute value in the average share of total employment of low-paying, middling, and high-paying occupations, in percentage points. Note that, by taking the absolute value of the change, we reversed the x-axis for the middling panels (middle column). Thus, regions on the left-hand (resp. right-hand) side of each panel are those where the polarization of employment has been lower (resp. larger).

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

D 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 with those in education in a separate category, hence 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 in the probability of being in each ISCO-88 second period occupation between the two cohorts according to its average weekly pay (left-panel) and its routine task intensity (right-panel).

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

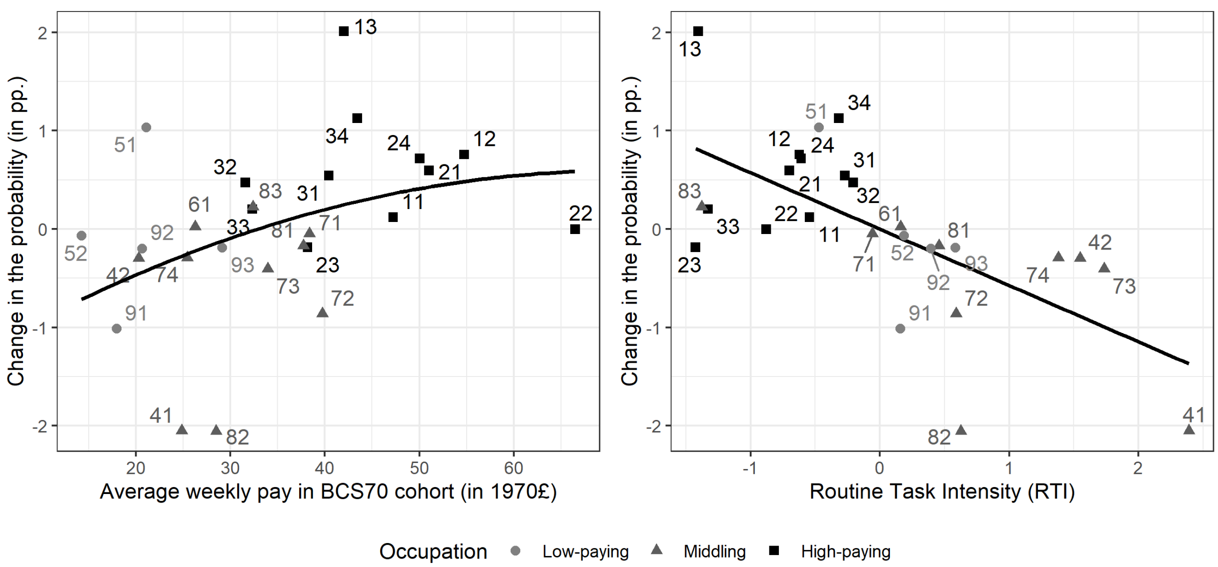
Notes: This table shows the probability, expressed in percent, of being in each first- and second-period occupation for the BCS70 and NCDS58 cohorts. Differences between both cohorts, expressed in percentage points, are reported in the last column of both periods.

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: Conditional probabilities with people in education included in out-of-work are reported in the paper, see table 4.

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



Notes: The left-hand side panel of the figure presents the positive relationship between the change, expressed in percentage points, between the BCS70 and NCDS58 cohorts in terms of probability of being in each ISCO-88 occupation in the second period and the average weekly pay, expressed in 1970£, in this occupation for the BCS70 cohort. The right-hand side panel shows the same probability change and the Routine Task Intensity (RTI) index from Mahutga et al. (2018).

E Accounting for education

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

E.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 data.

All education variables are ranked at the cohort level in peer-inclusive downward-looking ranking.[33] This approach is particularly suited to the period, given the massive expansion of secondary and higher education that occurred between the two cohorts.

Child education. To define the child education variable, we take the highest academic qualification ever obtained from the educational qualifications history.[34] 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. For 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.

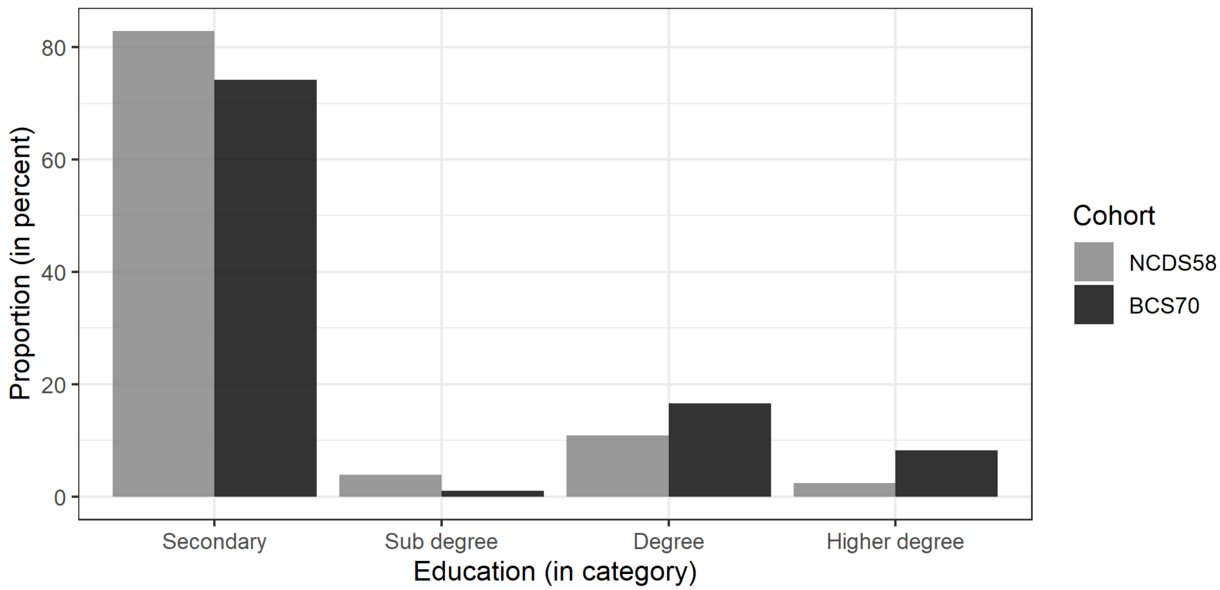
Family characteristics. Father's social class is provided at the age of 11 for the NCDS58 cohort and 10 for the BCS70 cohort. We refer to the Registrar General's Social Classes (RGSC) that are defined with five categories: professional occupations (I); managerial and technical occupations (II); non-manual 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 the age of 16, and create a dummy variable

[33] We follow Cowell and Flachaire (2017) to define the peer-inclusive downward-looking ranking. It corresponds to the rank within the sample of an individual on the variable's dimension 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, while downward-looking means that we attribute the value of 1 (respectively, 0) to the individual with the highest (respectively, lowest) value in the sample. 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.

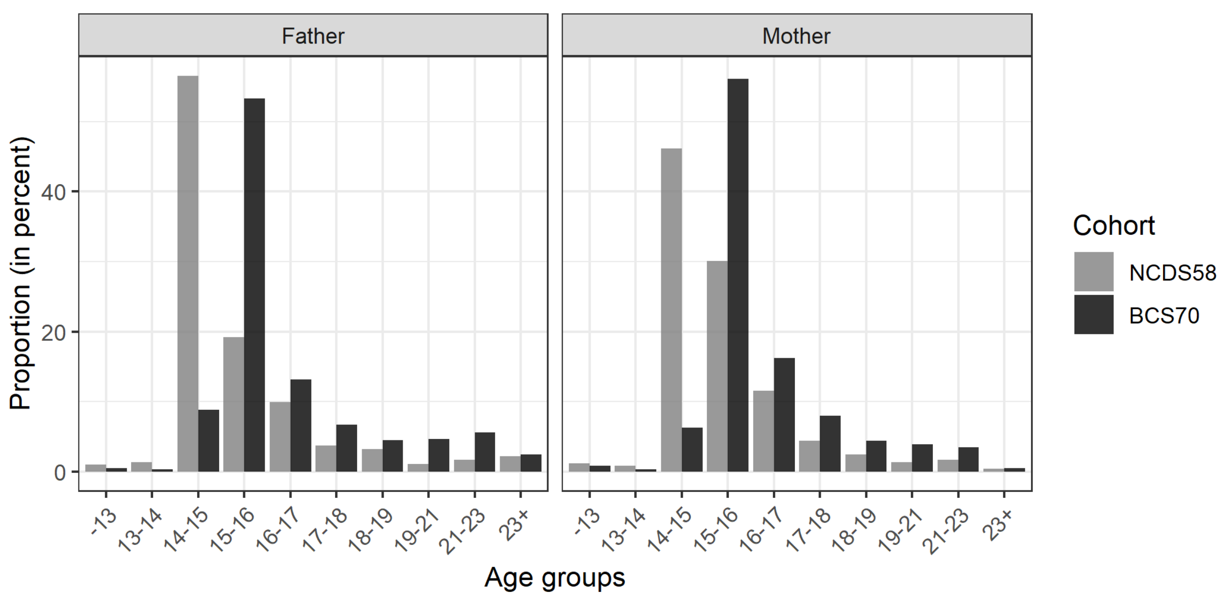
[34] There are 11 categories which are (from the lowest to the highest): no qualifications; less than O-level; less than 5 O-levels; 5+ O-levels; 1 A-level and less than 5 O-levels; 1 A-level and 5+ O-levels; 2+ A-levels and less than 5 O-levels; 2+ A-levels and 5+ O-levels; Sub degrees; Degree - lower 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. Parental education refers to the age at which parents left school that is used as a proxy. Education levels at the bottom and top are grouped for readability.

that equals one if the cohort member is the eldest child. An additional available variable is parents' interest in education. During interviews at the age of 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.

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

E.2 Determinants of child's education

We start by estimating the impact of parental income on child education, and 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. Education variables are measured in peer-inclusive downward-looking ranking. 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.

E.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 of the occupations j. Comparing these results with those in Table B.1 we see that, as far as high-

Table OA.3: Summary statistics - Additional data

Variable	N = 14763 Mean	SD	Min	Q1	Median	Q3	Max	NA
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.

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

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 $\times$ 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. $\times$ BCS	0.11^{***}	0.11^{***}	0.08^{***}	0.05^{**}	0.06^{***}
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Father's educ. $\times$ BCS		-0.10^{***}	-0.07^{***}	-0.04^{*}	-0.03
		(0.02)	(0.02)	(0.02)	(0.02)
Mother's educ. $\times$ BCS		-0.03	-0.02	-0.03^{*}	-0.05^{**}
		(0.02)	(0.02)	(0.02)	(0.02)
Father's soc. class $\times$ BCS			-0.06^{***}	-0.04^{**}	-0.05^{**}
			(0.02)	(0.02)	(0.02)
Number of siblings $\times$ BCS					0.08^{***}
					(0.02)
Eldest child $\times$ 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 referent group. Parental income in logarithm and child education in peer-inclusive ranking, both are standardized at the cohort level.

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, Table OA.6 reports regressions in which it depends on education as well as on parental income and the initial job. The coefficients on

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 first period is the base outcome of the multinomial logistic regression. Male in the NCDS58 cohort is the referent 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.

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 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 coefficients across the two cohorts.

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 second period is the base outcome of the multinomial logistic regression. Male in the NCDS58 cohort in out-of-work occupation in first period is the referent 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 referent 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.

Reviewer 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

This appendix presents several tables and figures that support statements made in the text of the paper. The appendix is not intended for publication and the text makes no direct reference particular tables or figures. Its use is to provide the reviewers with the necessary evidence to support those statements.

F Binomial logistic regressions

This appendix presents results for binomial logit estimations in which each regression compares the probability of being in occupation j relative to the other three outcomes. The results obtained are consistent with those presented in the paper for the multinomial logistic regressions.

Table RA.1 reports the coefficients regressions for the equivalent binomial specification for first-period occupations, while Table RA.2 reports the coefficients for the second-period binomial specification.

Table RA.1: Probability of being in each occupation at first period (binomial)

	Binomial logit - Dep. var.: First-period occupation			
	Out-of-work	Low-paying	Middling	High-paying
Intercept	-1.96^{***}	-1.87^{***}	-0.02	-1.12^{***}
	(0.05)	(0.05)	(0.03)	(0.04)
BCS cohort	-0.37^{***}	-0.11	-0.39^{***}	0.62^{***}
	(0.08)	(0.07)	(0.05)	(0.05)
Female	1.10^{***}	0.10	-0.67^{***}	-0.14^{**}
	(0.06)	(0.07)	(0.05)	(0.06)
Female × BCS	-0.04	0.31^{***}	0.08	-0.10
	(0.09)	(0.10)	(0.07)	(0.07)
Par. inc.	-0.05	-0.08^{**}	-0.07^{***}	0.22^{***}
	(0.03)	(0.03)	(0.02)	(0.03)
Par. inc. × BCS	-0.29^{***}	-0.17^{***}	-0.04	0.27^{***}
	(0.04)	(0.04)	(0.03)	(0.04)
Pseudo R^2	0.05	0.01	0.02	0.04
Log Likelihood	-6687.29	-6085.09	-9482.35	-8664.53
Num. obs.	14763	14763	14763	14763

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Male in the NCDS58 cohort is the referent group. Parental income in logarithm and then standardized at the cohort level.

Table RA.2: Probability of being in each occupation in the second period (binomial)

	Binomial logit - Dep. var.: Second-period occupation							
	Out-of-work		Low-paying		Middling		High-paying	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	-2.39^{***}	-1.59^{***}	-1.97^{***}	-1.76^{***}	-0.69^{***}	-1.07^{***}	-0.16^{***}	-0.52^{***}
	(0.06)	(0.09)	(0.05)	(0.08)	(0.04)	(0.08)	(0.04)	(0.07)
BCS cohort	-0.06	0.27^{**}	-0.02	0.13	-0.15^{***}	-0.33^{***}	0.12^{**}	-0.18^{*}
	(0.09)	(0.12)	(0.07)	(0.12)	(0.05)	(0.12)	(0.05)	(0.10)
Female	0.99^{***}	0.80^{***}	0.89^{***}	0.85^{***}	-0.51^{***}	-0.39^{***}	-0.61^{***}	-0.66^{***}
	(0.08)	(0.08)	(0.07)	(0.07)	(0.05)	(0.06)	(0.05)	(0.06)
Female × BCS	-0.04	-0.06	-0.09	-0.19^{**}	-0.17^{**}	-0.17^{**}	0.20^{***}	0.30^{***}
	(0.10)	(0.11)	(0.09)	(0.10)	(0.08)	(0.08)	(0.07)	(0.08)
Par. inc.	-0.09^{***}	-0.07^{**}	-0.08^{***}	-0.05	-0.06^{**}	-0.03	0.17^{***}	0.12^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Par. inc. × BCS	-0.23^{***}	-0.16^{***}	-0.18^{***}	-0.10^{**}	-0.07^{**}	-0.04	0.28^{***}	0.19^{***}
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Change with respect to the referent group as first period occupation (Out-of-work)								
Low-paying		-0.54^{***}		0.88^{***}		-0.10		-0.33^{***}
		(0.11)		(0.09)		(0.10)		(0.10)
Middling		-0.98^{***}		-0.36^{***}		0.97^{***}		-0.03
		(0.09)		(0.08)		(0.08)		(0.07)
High-paying		-1.25^{***}		-1.15^{***}		-0.71^{***}		1.76^{***}
		(0.11)		(0.11)		(0.10)		(0.08)
Change between cohorts								
Low. × BCS		-0.57^{***}		0.11		0.26^{*}		0.13
		(0.15)		(0.13)		(0.15)		(0.14)
Mid. × BCS		-0.26^{**}		-0.18		0.47^{***}		0.08
		(0.13)		(0.12)		(0.12)		(0.11)
High. × BCS		-0.22		0.03		0.29^{**}		0.03
		(0.14)		(0.15)		(0.14)		(0.11)
Pseudo R^2	0.04	0.08	0.03	0.10	0.02	0.10	0.03	0.14
Log Likelihood	-5771.10	-5530.48	-6886.99	-6378.03	-8257.73	-7541.67	-9679.83	-8582.94
Num. obs.	14763	14763	14763	14763	14763	14763	14763	14763

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Male in the NCDS58 cohort in out-of-work occupation in first period is the referent group. Parental income in logarithm and then 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 referent 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.

G Regions

This appendix reports, in Table RA.3, the share of cohort members in each region, expressed in percent, for the NCDS58 and BCS70 cohorts when young and old. Table RA.4 reports the regression coefficients obtained when estimating a multinomial logit model for the probability of being in each occupation in the second period as a function of the shares of middling and high-paying occupations in the region where the individual lived at age 16.

Table RA.3: Share of cohort members in each location

	NCDS58		BCS70	
Region	Age 23	Age 42	Age 26	Age 42
East Anglia	3.8	4.7	4.7	4.6
East Midlands	7.3	7.6	7.8	8.2
North	7.4	7.4	6.4	6.2
North West	12.5	11.9	12.2	12.2
Scotland	11.9	11.7	9.5	9.6
South East	32.2	30.4	34.0	32.0
South West	8.9	10.5	9.6	10.3
Wales	5.9	5.9	5.4	6.2
West Midlands	10.1	9.8	10.3	10.6

Notes: This table presents the share of cohort members in each region, expressed in percent, for the NCDS58 and BCS70 cohorts when young and old.

Table RA.4: Probability of being in each occupation in the second period according to the shares of middling and high-paying occupations in the region at the age 16 (multinomial)

	Multinomial logit - Dep. var.: Second-period occupation								
	(1)			(2)			(3)		
	Low	Mid	High	Low	Mid	High	Low	Mid	High
Middling share	-0.07	-0.02	-0.17^{***}				0.22	-0.22	-0.21
	(0.06)	(0.05)	(0.05)				(0.34)	(0.32)	(0.30)
High-paying share				0.10	-0.01	0.28^{***}	0.37	-0.41	-0.25
				(0.07)	(0.06)	(0.06)	(0.51)	(0.48)	(0.46)
Parental income	0.04	0.11^{***}	0.35^{***}	0.04	0.11^{***}	0.36^{***}	0.05	0.12^{***}	0.38^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Par. inc. $\times$ Mid. share	0.00	-0.04^{*}	-0.11^{***}				-0.06	-0.13^{**}	-0.29^{***}
	(0.03)	(0.02)	(0.02)				(0.06)	(0.05)	(0.05)
Par. inc. $\times$ High. share				-0.01	0.02	0.05^{**}	-0.06	-0.09^{*}	-0.17^{***}
				(0.02)	(0.02)	(0.02)	(0.05)	(0.05)	(0.05)
Num. obs.	14763	14763	14763	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. Male is the referent group in all regressions. Parental income in logarithm and then standardized at the cohort level. Middling and High-paying shares correspond to, respectively, the shares of middling and high-paying in total employment in the region at age 16. Both shares have been standardized for the interpretability of coefficients when interacted with parental income. Control variables in (1) include Intercept, Female and Female $\times$ BCS, while control variables in (2) include Intercept, Female and Female $\times$ Non-Mid. share.