Spreading the polarization disease: From the labour market to social mobility*

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Abstract

The increase in employment polarization observed in a number of high-income economies has coincided with a reduction in inter-generational mobility. This paper uses data for two British cohorts that entered the labour market at two points in time that differed considerably in terms of the structure of employment to re-examine the drivers of mobility. We differ from the existing literature in two aspects. First, we focus on employment categories rather than income, thus obtaining dynamics that can be understood in terms of changes in the structure of employment. Second, we argue that understanding inter-generational dynamics requires considering how individuals move from their entry jobs into other employment categories, i.e. understanding intra-generational mobility. The data indicate that occupational changes over the individual's career are an important source of mobility, with large shares of those in low-paying (respectively, middling) occupations moving into middling (resp. high-paying) ones. When we compare the two cohorts we find that these two sources of mobility have declined for the younger cohort and that, whatever the initial occupation, parental income has become more important in leading to occupational upgrading. Moreover, the impact of parental income increased the most in the regions where the share of middling employment fell the most, indicating that increased employment polarization is potentially behind the observed decline in mobility.

Keywords: Inter-generational mobility, Job polarization.
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1 Introduction

A recent literature has documented a decline in income and social mobility in the last decades of the 20th century that has strengthened the link between individuals' origins and their socio-economic outcomes; see, for example, Blanden et al. (2007) for the UK and Chetty et al. (2020) for the US. Existing work has proposed several explanations for the reduction in mobility, focusing, for example, on educational investments, non-cognitive skills or the impact of geographical location, yet little attention has been paid to the role of the structure of employment. This is surprising given that the decrease in mobility has taken place roughly at the same time as labour markets in high-income economies witnessed an increase in employment polarization. Since the 1980s, the share in total employment of low- and high-paying occupations has increased at the expense of that of middling occupations,[1] raising 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, a question also addressed by Hennig (2021), which we discus below. To do so, we depart from existing work in two respects. First, mobility is not defined in terms of income, as the literature tends to do;[2] rather we focus on occupations and define occupational categories in line with the employment polarization literature (see, for example, Goos et al. 2014).[3] This allows us to identify whether the increased impact of parental income is being driven by how family background affects occupational outcomes. 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. This change of emphasis allows us examine whether the impact of parental income is correlated to changes in the structure of employment, thus raising the question of whether polarization has been one of the causes of the decline in mobility.

To address these questions, we use data from two mature British cohorts, the National

[1]See, for example, Autor et al. (2003) for the US, Goos and Manning (2007) for the UK and Goos et al. (2014) for European countries.

[2]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.

[3]A few studies have considered occupational mobility, notably Long and Ferrie (2013) who take a three-generation perspective, and Bell et al. (2019) 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.

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.[4] Because we are interested in the structure of employment, we define four occupational categories, low-paying, middling and high-paying jobs, in line with the employment polarization literature, as well as a category including those out-of-work. The data also allows us to consider occupational outcomes both at the start of the individual's career[5] as well as when workers are mature, i.e. at age 42, and hence to consider occupations at different stages of the work life.

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 life-time dynamics independently of parental background.[6] Our empirical framework aims 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 occupation on the occupation at age 42, as well as whether there is any remaining direct effect of parental income. We can hence ask whether the decline in mobility observed over the period is due to a greater impact of parental background on entry jobs or if the change has occurred mainly through differences in transition probabilities over the child's lifetime.

Our focus is the comparison between the results for the 1958 cohort, who entered the labour market when middling jobs were plentiful, and those for the 1970 cohort which faced greater employment polarization. To further understand the correlation between polarization and mobility, in the last part of the paper we proceed to compute both measures at the regional level. This allows us to correlate the change in the impact of parental income on occupational outcomes (i.e. the degree of *immobility*) 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 structure of employment.

[4]See for example Blanden et al. (2007), Nicoletti and Ermisch (2007), and Blanden et al. (2013), as well as the work by sociologists such as Goldthorpe and Jackson (2007) and Erikson and Goldthorpe (2010).

[5]The ages at which interviews take place for the two cohort are not identical. Both were interviewed at 42 years of age, but differ in the ages of the earlier interviews, with those born in 1958 (resp. 1970) having an interview at age 23 (resp. 26). We use these ages to measure early-career occupations.

[6]See Jäntti and Jenkins (2015) for a review.

The data indicate that the polarization that has been observed at the aggregate level also appears when we consider the employment structure for each cohort. Individuals born in 1970 have faced a more polarized labour market than those born in 1958, and the change in the structure of employment has been particularly marked regarding first-period occupations. Moreover, we find that occupational change over the individual's lifetime is an important source of upwards mobility. In particular, for those born in 1958, 20% of those initially in low-paying occupations move into middling ones and 31% of those in middling occupations move into high-paying ones. Two significant changes appear in the data: the probability for those in low-paying occupations to move into middling ones has declined across cohorts, and the fraction of individuals who start their careers in middling occupations—and hence have a high probability to move into high-paying jobs—has fallen markedly. Consequently, for the younger cohort these two sources of upwards mobility have weakened.

Second, we find an increased impact of family background at all the stages that determine an agent's occupation when mature, as both the effect of parental income on first-period occupation and 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 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, we consider differences in *immobility* across large regions. For each region we construct a measure of employment polarization for each cohort using data from the Labour Force Survey, and compute the change in the extent of polarization faced by the two cohorts. We find that regions which 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. This correlation is 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 inter-generational dynamics in income and social class.[7] Much of the focus has been on how individual characteristics affect income dynamics across generations, and three key aspects have been considered: education (Blanden and Macmillan 2014, Blanden and Macmillan 2016, Crawford et al. 2016, Neidhöfer et al. 2018, Björklund and Jäntti 2012), individual characteristics such as gender or race (Chadwick and Solon 2002, Chetty et al. 2020), and childhood outcomes—including non-cognitive skills and personality traits—that can be linked to family background and the quality of the neighborhood (Blanden and Gregg 2004, Heckman et al. 2006, Blanden et al. 2007, Björklund and Jäntti 2012, Heckman et al. 2013, Chetty et al. 2014a). All these aspects are either immutable or determined in the early stages of the lifecycle, and are used to explain observed outcomes decades latter, yet little attention has been paid to the importance of early labour market experiences. We provide a bridge between the literatures on *inter-generational* and *intra-generational* mobility by focusing on access to jobs at the beginning of the career and the subsequent career dynamics, and show that understanding *intra-generational* mobility is essential to understand an individual's outcome when mature and how it relates to family background.

Much of the recent literature cited above has identified an increased role of parental background on children outcomes, 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, while Bukodi and Goldthorpe (2013) obtain similar results looking at various parental characteristics (class, status and education). Our contribution lies in examining the relevance of parental income at the various stages of the individual's career. Our results indicate that parental income matters at all stages, even when conditioning on previous outcomes, and that that intra-generational mobility has become increasingly dependent on parental background. Notably, we find that those from better-off backgrounds have become more likely to climb up the job ladder, while those from worse-off backgrounds have become more likely to get stuck at the bottom. Even individuals who managed to start their careers in high-paying jobs have become more likely to experience downwards mobility if they come from a lower-income family than was the case for the older cohort. That is, part of the decrease in mobility can be accounted for the fact that moving up the job ladder has become more dependent on family background than it used to be.

Lastly, our paper adds to our understanding of the consequences of employment polar-

[7] See, for example, Nicoletti and Ermisch (2007), Kopczuk et al. (2010), Blanden et al. (2013), Long and Ferrie (2013), and Chetty et al. (2014b), Chetty et al. (2017) 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.

ization,[8] which have been addressed by a large literature, not only in economics.[9] Although there is some work on the impact on educational attainment or the labour supply (Spitz-Oener 2006; Verdugo and Allègre 2020), economists have mainly focused on the distributional implications. 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 the distribution of wages, and much work has been devoted to trying to understand to what extent polarization has driven observed increases in inequality.[10] Surprisingly, the question of whether employment polarization affects mobility has been largely ignored. To our knowledge, the only exception is Hennig (2021), who examines the relationship between the structure of employment and income mobility. He builds a model in which the disappearance of routine jobs results in a polarization of education and lower inter-generational mobility, predictions that are shown to be consistent with patterns of inter-generational income mobility in the US. In his framework, the occupation of mature workers is determined exclusively by their educational choice; we hence complement it by adding an analysis of job-to-job transitions. We show that these transitions are essential when understanding mobility and, when we turn to regional data, that they are correlated with the increase in polarization across cohorts.

The paper is organised as follows. Section 2 presents the cohort data, while section 3 describes the structure of employment along with occupational dynamics. Section 4 focuses on the patterns of mobility, examining the effect of parental income on the occupations of mature workers, which is then decomposed into the various stages. Section 5 provides evidence on the correlation between job polarization and changes in mobility across regions. Section 6 concludes.

2 Data

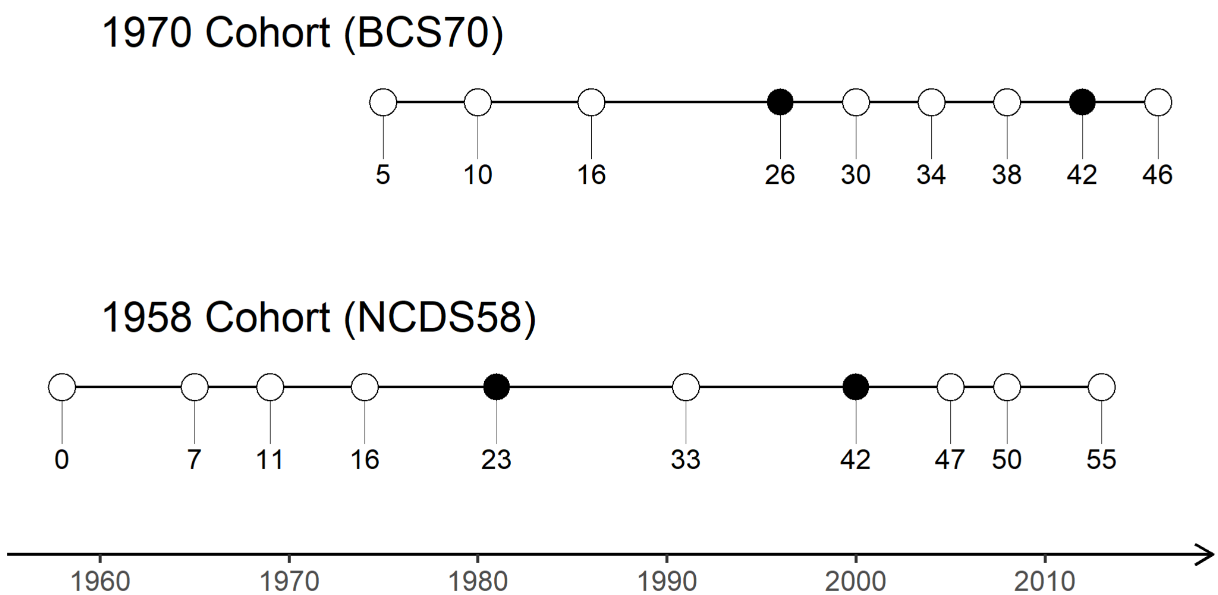
We use two mature British cohort studies that have been widely used by economists and sociologists to examine the extent of mobility in the UK. The National Child Development Study (NCDS58) is a cohort of individuals born during a given week in March 1958. The British Cohort Study (BCS70) is composed of individuals born during a given week in April

[8]See Autor et al. (2006), Goos and Manning (2007), Dustmann et al. (2009), Goos et al. (2009), and Cortes (2016) on the extent of polarization. The role of routine-biased technological change is discussed in Autor et al. (2003), Goos et al. (2014), Caines et al. (2017), Lordan and Neumark (2018), and Acemoglu and Restrepo (2020), while the resulting transformations in the labour market are the focus of Autor and Dorn (2013), Beaudry et al. (2016), Caines et al. (2017), Ross (2017), and Bárány and Siegel (2018).

[9]For example, political scientists such as Kurer and Palier (2019) have argued that changes in the structure of employment lie behind contemporary political disruptions.

[10]The widespread view is that indeed the changing structure of employment has resulted in increased earnings dispersion; see, for example, Autor and Dorn (2013), Acemoglu and Autor (2011), Acemoglu and Restrepo (2018), and Longmuir et al. (2020). Some authors nevertheless disagree; see Hunt and Nunn (2019).

Figure 1: 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.

1970. Cohort members were born in England, Scotland, Wales and Northern Ireland and participated in several interviews at different point in times over their life. Figure 1 presents all the interviews at which cohort members were interviewed and the corresponding year.

Periods. We define the first period as the year of interview closest to that in which the individual was 25 years-old, the age usually considered as that of entry into the labour market. Those in the NCDS58 cohort are observed at age 23 and those in the BCS70 cohort at age 26. Both cohorts 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.[11] 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 (see Table A.1 for the summary statistics).

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

[11] 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.

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.[12] We aggregate ISCO-88 occupations into three categories: high-paying, middling and low-paying occupations. This classification follows the job-polarization literature and is consistent with that used in Goos et al. (2014) and Mahutga et al. (2018).[13] Table A.2 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. Table A.3 displays the shares of the various activity status and occupational categories in the cohort data.

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.4 reports the average weekly pay by occupation, and displays the expected correlation between occupations and pay.

Location. Since individuals give their address at each interview, we also have their location history. We focus on the region 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).[14]

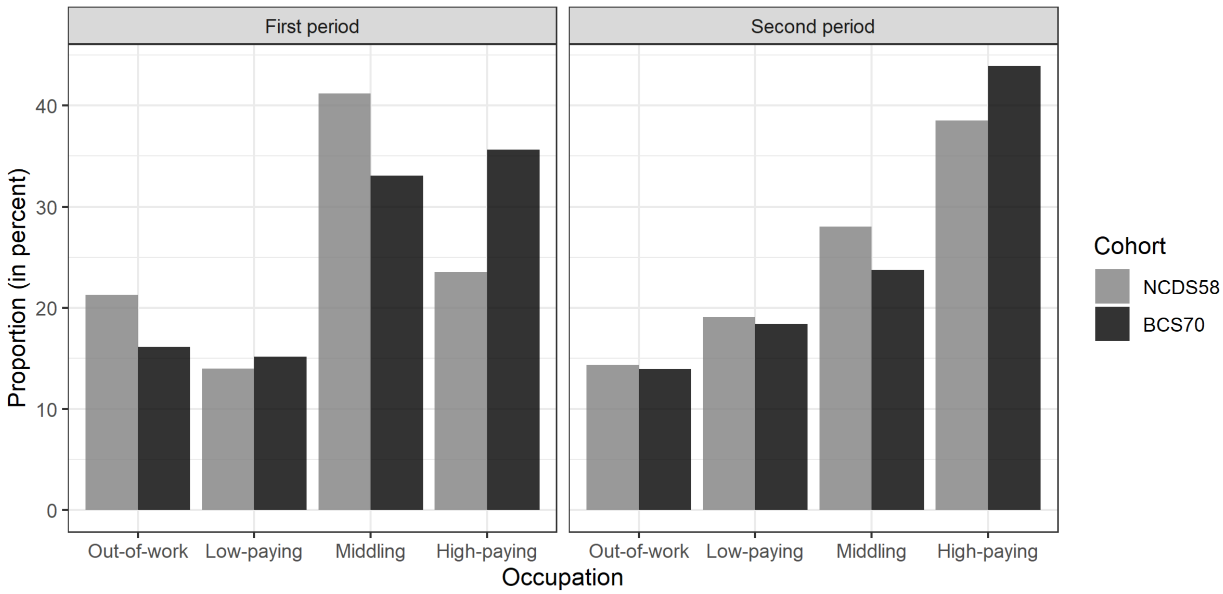
Once we restrict the data to those individuals for whom we have the key characteristics, i.e. parental income and occupations, our sample consists of 6,780 individuals in the NCDS58 and 7,983 in the BCS70, as reported in Table A.1.

[12] 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.

[13] 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.

[14] 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 2: 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 Employment polarization across two cohorts

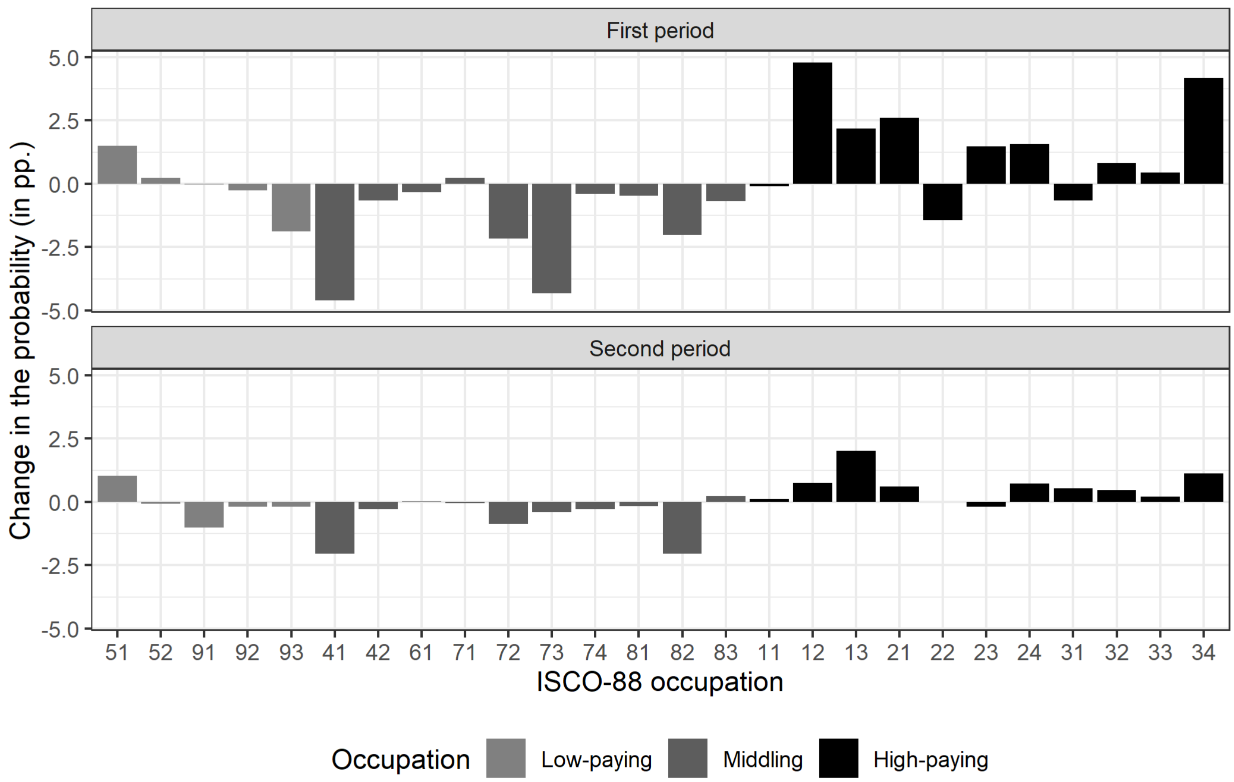
3.1 The structure of employment

We start by looking at the change in the distribution of occupations at ages 23/26 and 42 for both cohorts, reported in Figure 2.[15] 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. The differences between 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 3 performs a similar exercise using the ISCO-88 categories that we have grouped into our three broad categories. Occupations

[15] We report the proportion of individuals in each occupation for the two cohorts in Tables A.6 and A.7 in the appendix.

Figure 3: Change in the probability of being in each ISCO-88 occupation in both periods

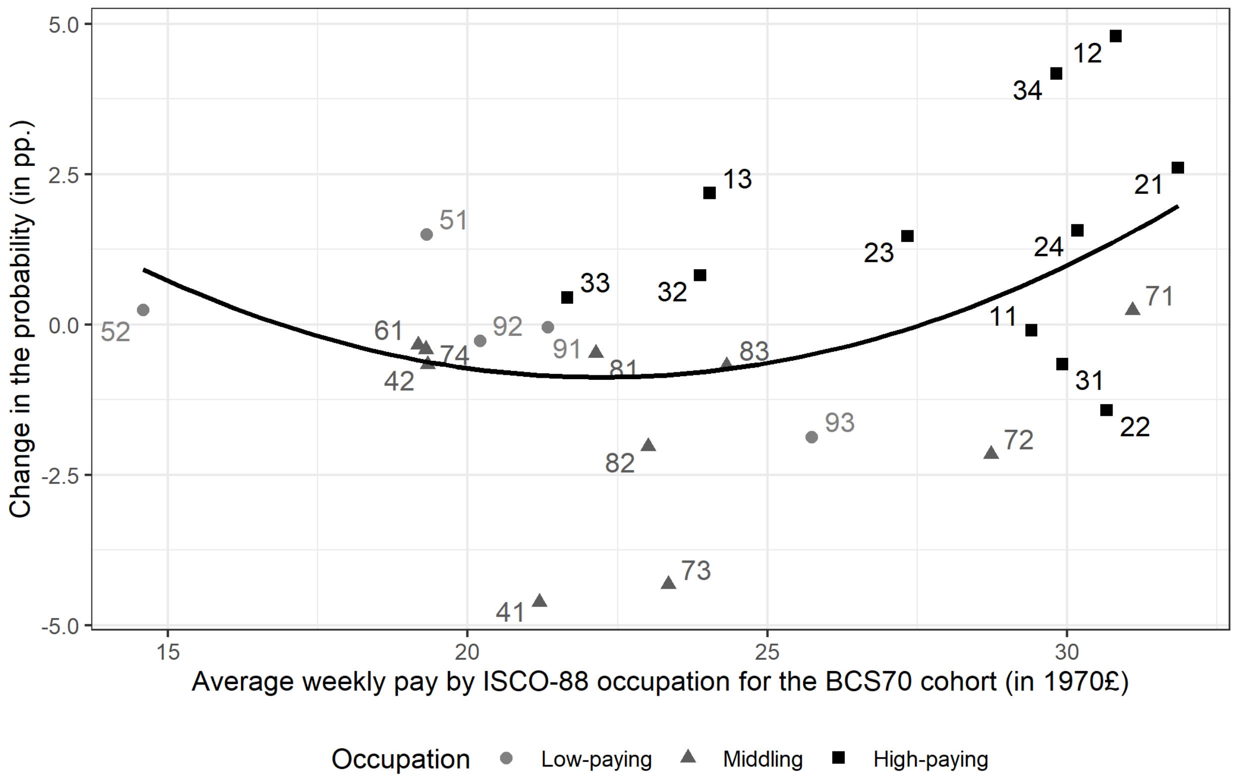


Notes: This figure presents the difference, expressed in percentage points, between the BCS70 and NCDS58 cohorts in terms of probability of being in each ISCO-88 occupation in both periods.

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 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 particularly marked. For low-paying occupations the changes have tended to be moderate—whether positive or negative—indicating that our result above of a small increase in the share of this broad category are not the result of averaging large positive and negative shifts.

A different way of thinking about polarization is to examine how occupations with different average pay have changed across the two cohorts. We hence compute the change in the share of individuals in each occupation when young and plot 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.

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



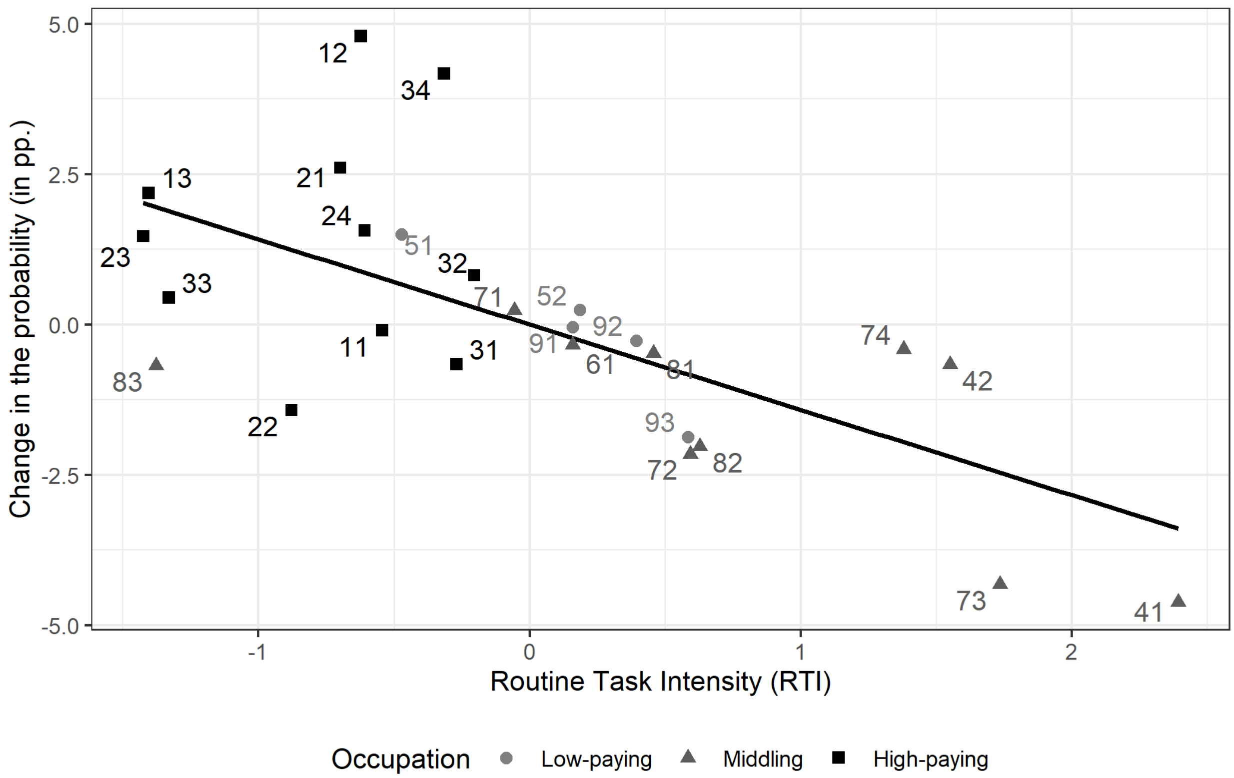
Notes: This figure presents the U-shaped relationship between the difference, expressed in percentage points, between the BCS70 and NCDS58 cohorts in terms of probability of being in each ISCO-88 occupation in the first period and the average weekly pay, expressed in 1970£, in this occupation for the BCS70 cohort.

As can be seen from the fitted curve displayed in Figure 4, 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.

Lastly we perform the same exercise but plotting the change in the share of each occupation for young individuals against the index for ”routine task intensity” or RTI scale provided by Mahutga et al. (2018). The downward slopping line in Figure 5 corresponds to the fitted curve implied by the data, and indicates that the change is negatively correlated with the degree of routinization. High-paying occupations (denoted with squares) tend to be at the bottom of the RTI scale, low-paying ones in the middle, and middling occupations at the bottom.

The various pieces of evidence in this section thus indicate that the strong polarization identified in cross-sectional data by previous work is also present when we focus on two

Figure 5: Change in the probability of being in each ISCO-88 occupation in the first period and routine task intensity



Notes: This figure shows the negative relationship between the difference, expressed in percentage points, between the BCS70 and NCDS58 cohorts in terms of probability of being in each ISCO-88 occupation in first period and the Routine Task Intensity (RTI) index from Mahutga et al. (2018).

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. In our data, polarization appears whether we use the RTI index to categorize occupations or when we look at average weekly pay.

3.2 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 1 reports the conditional probabilities of switching occupations between age 23/26 and age

Table 1: 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.

42.[16]

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 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 2, 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

[16] 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 appendix, and display the expected (large) difference between those on education and the rest of those out-of-work; see Table A.8.

hence be more likely to stay in their initial occupations. The importance of such changes for mobility will depends on the extent to which parental background matters for entry into each occupation and for the subsequent dynamics.

4 Patterns of mobility

4.1 Empirical specification

The evidence in Table 1 above indicates that mobility over the individual's lifetime is considerable, notably from middling to high-paying occupations. In order to understand the dynamics of inter-generational mobility we hence proceed in two steps. We start by estimating the impact of parental income on the child's probability to start her career in each occupation $j \in J = \{O, L, M, H\}$, 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 $j = \{L, M, H\}$ 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's characteristics (in our baseline specifications simply gender). Parental income is measured in log-standardized. All terms will be interacted with a dummy that equals one for those in the 1970 cohort (BCS70). Cross-term coefficients hence represent the change in the effect of the variable on the child's initial occupation. In the appendix, we also report the estimation of the four binomial logistic models that characterize the multinomial one.

We next consider the determinants of the probability of being in occupation $k \in K = \{O, L, M, H\}$ at age 42. The simplest specification, consistent with what is usually found in the literature would be to consider 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. Because we are interested in the role the initial occupations play, we suppose 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 $j \in J$ when young. That is, 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. As before, we estimate both second-period equations separately for the four occupations using binomial logistic regressions and report the results in the appendix.

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 model in which parental income determines education, which then determines first-period occupation, which in turn determines the second-period job. [17] 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.[18] We hence prefer to look exclusively at parental income, although we preform the three-step analysis in Appendix C.

Second, we have chosen to use for our core estimations a multinomial logistic model considering the four possible occupational outcomes. We have chosen as our reference outcome 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. Notably, 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.) but of comparable magnitude; see Table 1 above.

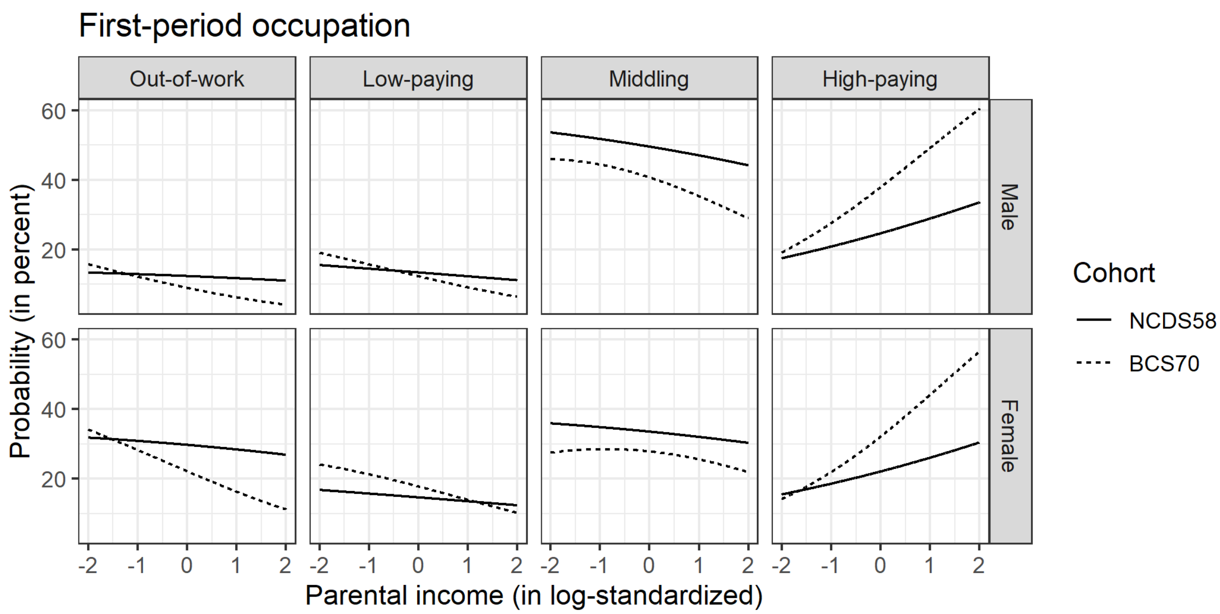
4.2 Initial occupations

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) using a multinomial logistic regression, as well as an equivalent binomial specification for the four occupation-types. The results are reported in the appendix, those for the binomial logits are reported in Table B.2 and the multinomial results in Table B.1.

[17] 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), Blanden and Macmillan (2014), Blanden and Macmillan (2016), Gregg et al. (2010) and Major and Machin (2018a).

[18] 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.

Figure 6: Probability of being in each occupation in first period, 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.

Logit coefficients are hard to interpret, hence to visualize the results Figure 6 displays the probability to be in each occupation when young as a function of parental income. The probabilities are computed according to the multinomial logistic regression from equation (1), reported in the appendix (see Table B.1).[19] The probabilities are reported separately for the two cohorts and for the two gender groups; 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 occupation. There is no effect on the probability of being out-of-work (see also Table B.2), a result that is not surprising given the various outcomes included in this category. 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. Starting with men, Table B.1 reports large changes across cohorts

[19] The results are qualitatively equivalent when using the binomial estimates. See the discussion in Appendix B.

in the coefficients on the direct effect of parental income, which are captured in the figures. For example, the coefficient doubles for high-paying occupations, increasing from 0.21 to 0.42, 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 C 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 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.[20]

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 are 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 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

[20] 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 (2018b) emphasize the changing role of education and the increasing importance of the "extra-investments" made by upper-middle class families, while Chetty et al. (2014a) show that neighborhood characteristics are extensively correlated with mobility, hence, being born in a family with more income in a context of spatial segregation would give access to a better social network, thus increasing the role of parental income in shaping mobility.

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 in 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 Where do mature individuals work?

4.3.1 Occupational outcomes at age 42

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 occupation, 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.

As before, we estimate this equation both separately for the four occupation-types as well as in a multinomial regression. The full results are reported in Tables B.3 and B.4 in the appendix, while Table 2 summarizes the multinomial results. As before, the reference category are those out of work. The first three regressions report the results when we do not consider the effect of initial occupation, while the last three report the specification that includes the first-period occupation, as well as initial occupations interacted with the BCS dummy.

Consider first the results when only parental income is included, as reported in columns (1). 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 raises the odds by 73% for the younger one.[21]

To illustrate the relationship between parental income and occupational dynamics, Figure 7 reports the *change* across the two cohorts in the probability of being in each occupational category at age 42. For each decile in the parental-income distribution, we report the proba-

[21]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 2: Probability of being in each occupation in the second period (multinomial)

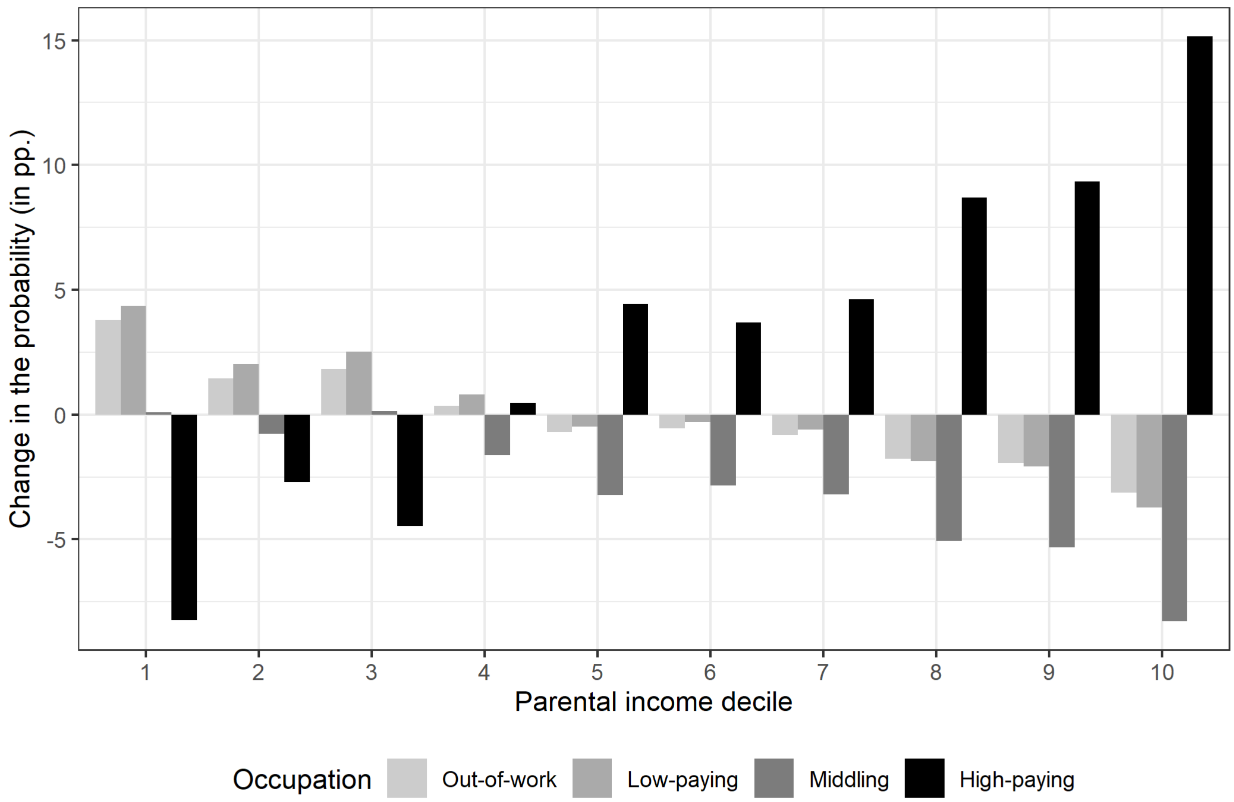
	Multinomial logit - Dep. var.: Second-period occupation					
	(1)			(2)		
	Low	Mid	High	Low	Mid	High
Par. inc.	0.01	0.04	0.19^{***}	0.02	0.05	0.14^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Par. inc. × BCS	0.05	0.15^{***}	0.36^{***}	0.05	0.11^{**}	0.25^{***}
	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(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. Control variables in all regressions include Intercept, BCS cohort, Female and Female × BCS; see Table B.3 in the appendix for these coefficients. 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.

bilities of being in each of the four occupations. The estimates used are those unconditional on first-period occupation (first three columns of Table 2) and hence capture the overall effect of family background. The figure hence indicates how the probability of being in, say, a high-paying occupation for the cohort born in 1970 has changed for a particular parental-income decile relative to what that probability was for those born in 1958.

Not surprisingly, for almost all parental-income categories the likelihood of being in a middling job has declined for the younger cohort. The exception are those in the first and third deciles, for whom there has been a small increase. Yet, whether this decline is offset by an increase in the probability of working in a low- or a high-paying occupation is strongly dependent on parental income. It is only for those in the fourth decile that we see the pattern observed in the aggregate data: a reduction in the share of middling jobs accompanied by an increase in that of both low- and high-paying ones. Everywhere else in the distribution

Figure 7: Change across cohorts in the probability of being in each occupation at age 42 (in percentage points)



Notes: This figure shows the difference, expressed in percentage points, between the BCS70 and NCDS58 cohorts in terms of probability of being in each type of occupation (out-of-work, low-paying, middling, high-paying) at age 42 according to the decile of the parental income distribution. Probabilities are computed for males in both cohorts at each parental income decile, according to the multinomial logistic regression reported in columns (1) of Table 2.

the changes in the share of high- and low-paying occupations are of opposite sign. For those in the top half of the parental-income distribution, the decline in the share of middling occupations has been accompanied by lower shares of individuals in both low-paying jobs and out of work and a higher share in high-paying occupations. The magnitude of these changes increases with parental income. For those in the top decile, the proportion of individuals in high-paying jobs rose by 15.1 pp., while that of those in middling fell by 8.3 pp. The bottom three deciles display an increase for out-of-work and low-paying and a decline for high-paying, irrespective of whether there was a positive or negative change in the share of middling jobs, though the magnitudes for the latter are small an all three cases.

Figure 7 is reminiscent of the analysis in Major and Machin (2018b), 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 (2018b), Figures 0.1 and 0.2). Our results indicate, not surprisingly, that the occupational structure is behind the observed changes in income mobility.

4.3.2 Intra-generational mobility and parental income

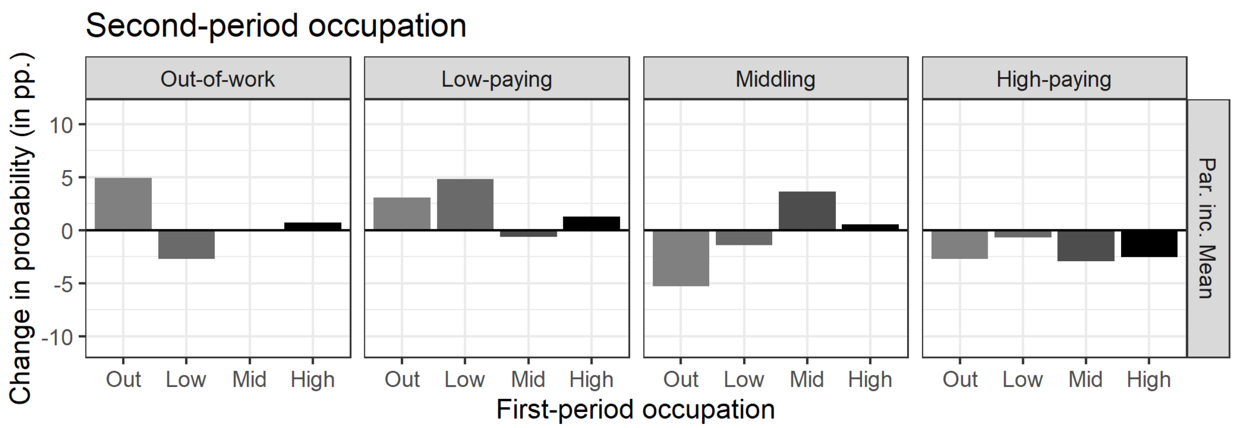
The marked change in the overall effect of parental income across the two generations can be due to changes in either how parental income impacts initial occupations or in its effect on mobility during the child's career, i.e. on intra-generational mobility. As we have seen above, the influence of parental 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.

The right panel of table Table 2 summarizes the multinomial results when we introduce in the regressions for occupation at 42 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). 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.

Because these coefficients are relative to out-of-work outcomes, they are not straightforward to interpret, hence we provide a graphical analysis. Figure 8 presents the change in the probability of being in each occupation in the second period for each first-period occupation (for males only).[22]. Changes in the probability are defined as the difference in probability between the two cohorts. Probabilities are computed using the multinomial regression in Table 2, at the mean of parental income. Each graph concerns a particular occupation at age 42, and each of the four bars represent the change in the probability of being in that occupation depending on the individual's first-period occupation.

[22] Equivalent figures for women are provided in appendix D—see Figure D.1

Figure 8: Change in probability to be in each occupation in the second period according to the first-period occupation (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, at the mean of the parental income distribution. Probabilities are computed for males in both cohorts according to the multinomial logistic regression reported in columns (2) of Table 2.

The changes are not large 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. The two graphs on the left provide evidence of 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 increased about 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 graph, 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 magnitudes being around 2.7 percentage points.

These changes do not capture the differences that may be due to parental background, which we have seen became more important for the younger cohort. Figure 9 hence performs the same exercise but computes the changes when parental income is 2-standard-deviations above and 2-standard-deviations below the mean, as well as reporting again the results obtained at the mean of parental income.

The fourth column of graphs, reporting changes in the probability of being in a high-paying occupation across cohorts, implies striking changes that are not apparent when looking only at the mean of parental income. For those at the top and the bottom of the parental

Figure 9: Change in probability to be in each occupation in the second period according to the 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, at several points of the parental income distribution (at -2 std., at the mean and at +2 std.). Probabilities are computed for males in both cohorts according to the multinomial logistic regression reported in columns (2) of Table 2.

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 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, 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, but the alternative outcome depends on parental income. The likelihood of remaining in the occupation has increased for those with average and with low parental income, by 4.8 pp. for the former and by 9.6 pp; for the latter, while for those at the top of the parental income distribution the declining 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 changes being strongly dependent on parental income.

An equivalent pattern is found when considering those who started in middling occupations. For low parental income, the probability of moving upwards declined and all others increased. At the mean of parental income, the likelihood of remaining in the occupation rose and all others fell, while for those at the top of the parental income distribution, accessing high-paying jobs became more likely at the expense of all other outcomes.

We summarize these results in Table 3. In order to provide a compact measure, 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 table reports changes in the probability of each type of mobility depending on the individual's initial occupation, assessed at several points of the parental income distribution as in the graphs above. The left panel of the table provides the results for men, the right panel for women.

Consider first the results for men. At the mean of parental income, persistence has increased and both upwards and downwards mobility have declined, for all individuals except those in high-paying occupations. For those in low-paying occupations the younger cohort has lost 2.13 pp. in upwards mobility, which amounts to a reduction of 3.7% as compared to the NCDS cohort.[23] For those starting in middling occupations there is a reduction of 2.95 pp. representing a decline of 8.3%. When we look at the top of the parental income distribution (top left panel) we find increases in both persistence for those in high-paying occupations and in upwards mobility for all other groups. Yet the most striking results are those at the bottom of the distribution of parental income, where upwards mobility has fallen by between 8.29 and 9.43 pp., and the probability of remaining in a high-paying job has fallen by over 10 pp. In contrast, at the top of the parental-income distribution, all individuals face more favourable outcomes in the younger than in the older generation: upwards mobility has increased for all groups and persistence in high-income jobs has risen.

[23]The probability of upward mobility for this cohort was 57.6%; see Table 2.

Table 3: Change in intra-generational mobility across cohorts

First-period occupation	Male Down	Male Persist	Male Up	Female Down	Female Persist	Female Up
		at +2 STD			*at +2 STD*	
Out-of-work		-0.57	0.57		-2.05	2.05
Low-paying	-4.41	-0.88	5.29	-6.88	-3.90	10.78
Middling	-3.84	-0.52	4.36	-9.82	-3.20	13.02
High-paying	-2.95	2.95		-10.19	10.19	
		at the Mean			*at the Mean*	
Out-of-work		4.92	-4.92		4.96	-4.96
Low-paying	-2.70	4.83	-2.13	-4.32	2.14	2.18
Middling	-0.70	3.65	-2.95	-3.68	-0.74	4.42
High-paying	2.54	-2.54		-3.25	3.25	
		at -2 STD			*at -2 STD*	
Out-of-work		11.27	-11.27		11.30	-11.30
Low-paying	-0.53	9.57	-9.04	-1.65	5.76	-4.11
Middling	3.29	5.41	-8.70	2.87	-0.74	-2.14
High-paying	10.92	-10.92		6.58	-6.58	

Notes: This Table summarizes the difference, expressed in percentage points, between the BCS70 and the NCDS58 cohorts in terms of type of mobility (down, persist, up) conditional on first period occupation (out-of-work, low-paying, middling, high-paying) at several points of the parental income distribution (at +2 std., at the mean, at -2 std.). These values are computed from the results obtained in Figure 9 for males and in Figure D.1 for females.

The right panel of Table 3 presents the results for women. Not surprisingly, the dynamics differ from those for men, as women of the older cohort where less likely to occupy middling and, especially, high-paying occupations than those in the younger cohort. For example, at the mean of the parental income distribution, persistence at the top and upwards mobility has increased for all women except those starting out-of-work. The results capture, however, the increase in the advantage that parental income confers in providing the means for upwards mobility. Note, specially, the very large increase in upwards mobility for women at the top of the parental income distribution.

The upwards/downwards intra-generational mobility measures are depicted graphically in Figures 10 and 11, 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, although in opposite directions for those at the bottom and at the top.

An equivalent pattern is observed for those that start their careers in middling occupations. 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 the magnitudes for those in the bottom decile 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. Table 3 captures, however, the advantage that parental income has on providing the means for upwards mobility. Figure 11 indicates that for those starting in high-paying and middling occupations we do not observe the same changes that we reported above for men. 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

Figure 10: Change in intra-generational mobility across cohorts (male only)

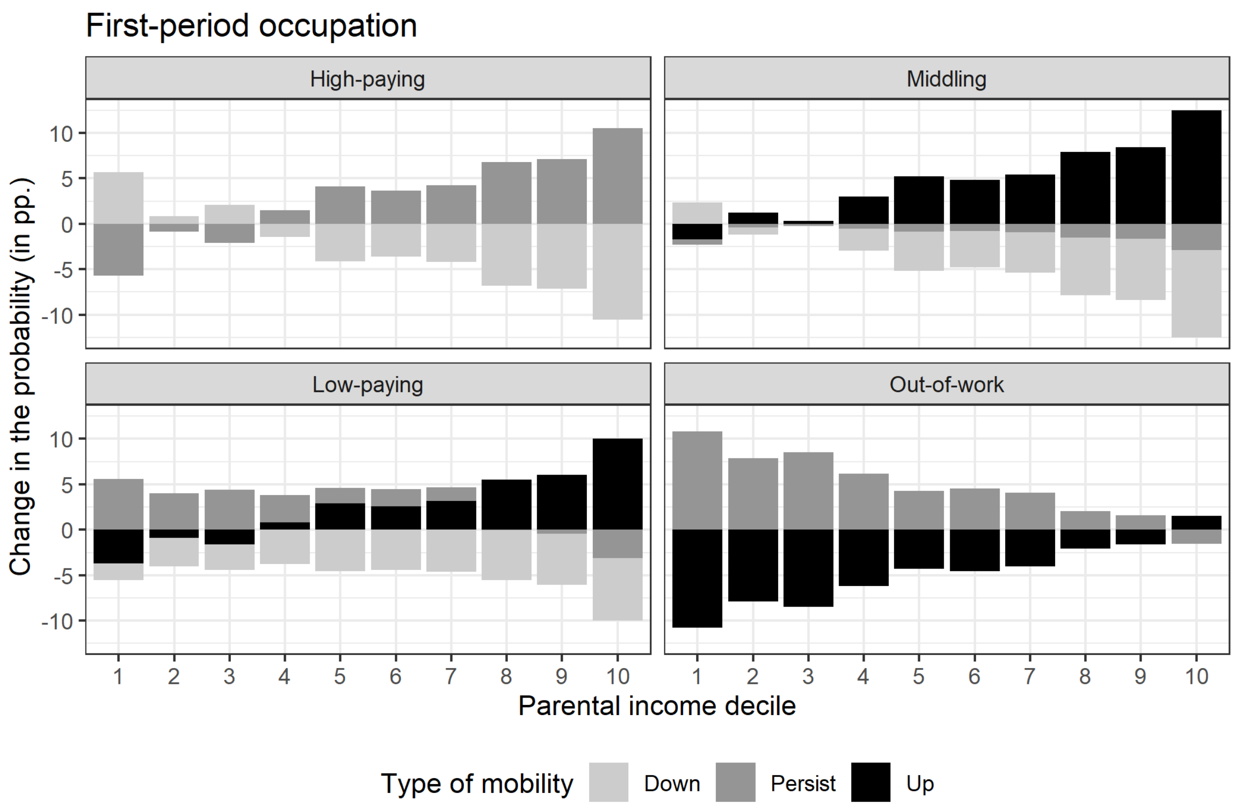
Notes: This figure presents the difference, expressed in percentage points, between the BCS70 and the NCDS58 cohorts in terms of type of mobility (down, persist, up) conditional on the first period occupation (out-of-work, low-paying, middling, high-paying) according to the decile of the parental income distribution. Probabilities are computed for males at each parental income decile, according to the multinomial logistic regression reported in columns (2) of Table B.3 in the appendix.

in the case of men (4th decile), indicating the tension between the general occupational upgrading of women and the decline in mobility observed for all workers coming from a less well-off background. The results for those out of work broadly mimic those for men.

4.3.3 The trade-off between parental income and initial occupation

Our results indicate that, conditional on first period occupation, the role of parental income in determining occupational outcomes has increased. At the same time, as is clear from the regressions, initial occupations are also important to determine outcomes at age 42. In particular, those who started their careers in middling have a probability to move to high-paying occupations that is about 7 pp. higher than those who started in a low-paying occupation (see Table A.8). Similarly, entering the labour market in a middling occupation implies a likelihood to be in such an occupation at age 42 at least 20 pp. higher than

Figure 11: Change in intra-generational mobility across cohorts (female only)



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 females at each parental income decile, according to the multinomial logistic regression reported in columns (2) of Table B.3 in the appendix.

entering in a low-paying job. We would hence like to assess to what extent parental income compensates for past occupations.

We compare the probability to be in a middling occupation at age 42 for two individuals who started in different initial occupations, middling and low-paying, and compute the additional parental income that the latter would need to have in order to compensate the advantage given by starting work in a middling occupation. To do so, we define the ratio between the two probabilities

$$\frac{p_M^M}{p_M^L} = \frac{p_O^M}{p_O^L} \exp\Big(\eta_{MM} - \eta_{ML} + \beta_{3M}(Y^M - Y^L)\Big), \tag{4}$$

where p_k^j is the probability of being in occupation k in second period conditional on having started in occupation j, and Y^L and Y^M are, respectively, the parental income of the individual starting in a low-paying occupation and of that starting in a middling occupation.

For both cohorts, we derive the parental income $Y^c = Y^L - Y^M$ such that the two individuals are as likely to be in a middling occupation at age 42, i.e. $p^M_M = p^L_M$. Thus,

$$Y^c \equiv \frac{\eta^c}{\beta^c} = \frac{\eta^c_{MM} - \eta^c_{ML} - \log(p^M_O/p^L_O)}{\beta^c_{3M}}, \tag{5}$$

where p^M_O and p^L_O are evaluated at the mean of the parental income distribution. We interpret Y^c as the additional parental income that an individual in cohort c starting in occupation L needs in order to be as likely as one starting in occupation M to be in a middling occupation when mature. Thus, η^c captures the degree of persistence in M, whereas β^c reflects the effectiveness of parental income in moving into a middling occupation in second period. The greater the degree of persistence in M, the greater the parental income required to compensate the advantage given by the first-period occupation, i.e. $\partial Y^c/\partial \eta^c > 0$. The greater the effectiveness of parental income, the smaller the parental income required to compensate, i.e. $\partial Y^c/\partial \beta^c < 0 \; \forall \Delta\beta > 0$.

This difference in parental income reflects the value conferred by being in a certain first-period occupation—compared to parental income—for mobility across occupations. Taking the ratio between Y^{70} and Y^{58}, we obtain the *change across cohorts in the relative advantage* such that

$$\Delta Y \equiv \frac{Y^{70}}{Y^{58}} = \frac{\Delta\eta}{\Delta\beta} \tag{6}$$

where $\Delta\eta = \eta^{70}/\eta^{58}$ captures the effect of the change in the degree of persistence and $\Delta\beta = \beta^{70}/\beta^{58}$ reflects the effect of the change in the role of parental income. Both affect the worth of the first-period occupation in opposite ways. The greater the change in the degree of persistence, the greater the change in parental income needed to compensate, hence, the greater the relative worth of first-period occupation, i.e. $\partial\Delta Y/\partial\Delta\eta > 0$. The greater the change in the effectiveness of parental income, the smaller the change in the parental income to compensate, hence, the smaller the relative worth of first-period occupation, i.e. $\partial\Delta Y/\partial\Delta\beta < 0 \; \forall \Delta\beta > 0$.

Table 4 presents the decomposition of the relative advantage of first-period occupation—compared to parental income—for upward mobility. We consider three cases: the difference in reaching a middling occupation for those starting in low-paying or in middling occupations (left panel), the difference in reaching a high-paying occupation for those starting in high-paying or in middling occupations (middle panel), and the difference in reaching a high-paying occupation for those starting in low-paying or in high-paying occupations (right panel).

Table 4: Relative advantage of the first-period occupation with respect to parental income

	$p_M^M = p_M^L$			$p_H^H = p_H^M$			$p_H^H = p_H^L$		
	Y	η	β	Y	η	β	Y	η	β
BCS70	4.63	0.73	0.16	2.13	0.84	0.39	2.25	0.89	0.39
NCDS58	13.11	0.60	0.05	5.47	0.79	0.14	6.24	0.90	0.14
Δ	0.35	1.22	3.45	0.39	1.07	2.74	0.36	0.99	2.74
Δ (η constant)	0.29	1.00	3.45	0.37	1.00	2.74	0.37	1.00	2.74
Δ (β constant)	1.22	1.22	1.00	1.07	1.07	1.00	0.99	0.99	1.00

Notes: This table presents the relative advantage of the first-period occupation with respect to parental income for upward mobility. Y corresponds to the parental income that an individual in cohort c needs in order to compensate for having started one occupational category below, η captures the degree of persistence, whereas β captures the effectiveness of parental income. Coefficients for the NCDS58 and BCS70 cohorts are computed for males using Table B.3 in the appendix. Δ rows refer to the ratio between the BCS70 and NCDS58 under three specifications: the actual ratio, the ratio keeping η constant, and the ratio keeping β constant.

Consider first the relative effect of initial occupations versus parental income for the NCDS58. Because parental income is standardized, the figures reported for Y^{70} represent the standard deviations needed to compensate the difference when starting in the various initial occupations (computed at the mean of parental income.). For the three cases we report, the additional income required is between 5.47 and 13.11 standard deviations. Such large magnitudes imply that it was hard for parental income to compensate the advantage conferred by a more favourable initial occupation, and, in the case of the probabilities of being in a middling occupation at age 42 (p_M^M and p_M^L, left panel) only a massive difference in parental income could compensate the advantage that being in a middling occupation at 23 conferred. When we compare these figures with those for the BCS70, we can see that the additional income required to compensate the most favourable occupation is between 2.13 and 4.63 standard deviations, magnitudes that amount to about a third of those needed for the older cohort.

The bottom two lines allow us to understand what is driving this change. We compute the ratio Y^{70}/Y^{58} by keeping constant, i.e. at the value it had for the NCDS58, either η or β. Recall from equation (5) that η captures the degree of persistence in an occupation, whereas β reflects the advantage to move upwards conferred by parental income. The three cases we examine display the same pattern. When we keep η constant we obtain a change in the relative importance of parental income that is very close to the actual one, indicating that changes in persistence have played a minor role. In contrast, keeping β constant results in values of ΔY that are around or above 1. That is, what is driving the differences across cohorts in the advantage that parental income affords relative to initial occupations is the direct effect of the former rather than any changes in persistence associated with the latter.

These results indicate that there has been a major change in the relative roles that entry jobs and parental background play in determining the occupational outcomes of mature individuals. For the older cohort, the advantage conferred by entry occupations could only be offset by vast amounts of parental income; for the younger one, the latter has become much more able to offset the career advantages conferred by early career experiences.

5 Evidence for UK regions

5.1 Mobility at the regional level

The geography of mobility has received increasing attention over the past few years, following the seminal work of Chetty et al. (2014a) using a vast dataset for the US.[24] The findings imply large variations in the degree of intergenerational income mobility across locations, with the probability of someone born in a household in the bottom quintile moving to the top quintile being three times higher in the most than in the least mobile locations. Recent work by Bell et al. (2019) finds regional differences are also large in Britain. Such results raise the question of whether our findings so far are the result of movements of population across regions that exhibit different degrees of mobility. Our data is not ideal to focus on regional differences. There are two reasons for this. First, the geographical units are large, consisting of 10 regions and hence not allowing us to identity very local effects.[25] Second, sample sizes at the regional level are small, implying that insignificant coefficients may be due to lack of statistical power. Nevertheless, estimating mobility patterns across the 10 regions separately allows us to see whether the changes we have identified hold within these large regions.

We hence run the same multinomial regressions as above but at the regional level.[26] Table 5 presents the coefficients on parental income obtained when we regress second period occupation on parental income, i.e. the specification in columns (1) of Table 2. We report results for the three occupations, giving two coefficients, with "Par. Inc." capturing the effect

[24]See also Chetty and Hendren (2018a,b) as well as studies for Sweden (Heidrich 2017), Norway (Butikofer et al. 2018), Canada (Connolly et al. 2019), Australia (Deutscher and Mazumder 2020) and Italy (Acciari et al.).

[25]Bell et al. (2019) consider the 32 NUTS2 regions, while Chetty et al. (2014a) focuse on considerably smaller locations.

[26]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.

of parental income for the NCDS58 cohort and "Par. Inc. $\times$ BCS" the increase in that effect for the BCS70 cohort. As before, we need to recall that these are the coefficients relative to the probability of being out-of-work (see also Figures D.2 and D.3 in the appendix).

Recall that our main result at the national level was that parental impact had a significant effect on the likelihood to be in a high-paying occupation, and that this effect was three times as large for those born in 1970 as compared to those born in 1958. When we split the data we find that for the vast majority of regions (7/10) parental income exhibits insignificant coefficients for the older cohort. Only in the North West, the South East and the West Midlands do we find a significant coefficient on parental income. Note, however, that out of the seven regions for which the coefficient is not significant, 4 of them have magnitudes close to the 0.19 point estimate we obtained at the national level. The lack of significance can then be due to a lack of statistical power given the limited number of observations, per region and also in certain region-occupation cells. In any case, the point estimates differ considerably across regions, with three being close to zero (North, Wales, Yorkshire and Humberside) and two well above the national estimate (North West and West Midlands), pointing at important differences in the role of parental income across locations. When we consider 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 (eg. North West) and much larger in others. These results indicate that the increase in the importance of parental income across cohorts holds at the regional level.

5.2 Regional mobility and employment polarization

Our estimates above also indicate that the dynamics of the impact of parental income on occupational outcomes vary across regions, with the change across generations being much larger in some than in others. This raises the question of whether the magnitude of these changes is correlated to the degree of employment polarization observed at the regional level.

To address this question we construct a measure of regional polarization. We do this by using data from the Labour Force Survey (LFS). As argued above, our cohort data consists of small regional samples and thus measures of regional polarization based on that data may not capture well the actual changes in the structure of employment. The LFS allows us to exploit much larger samples and hence provide more accurate measures of polarization.

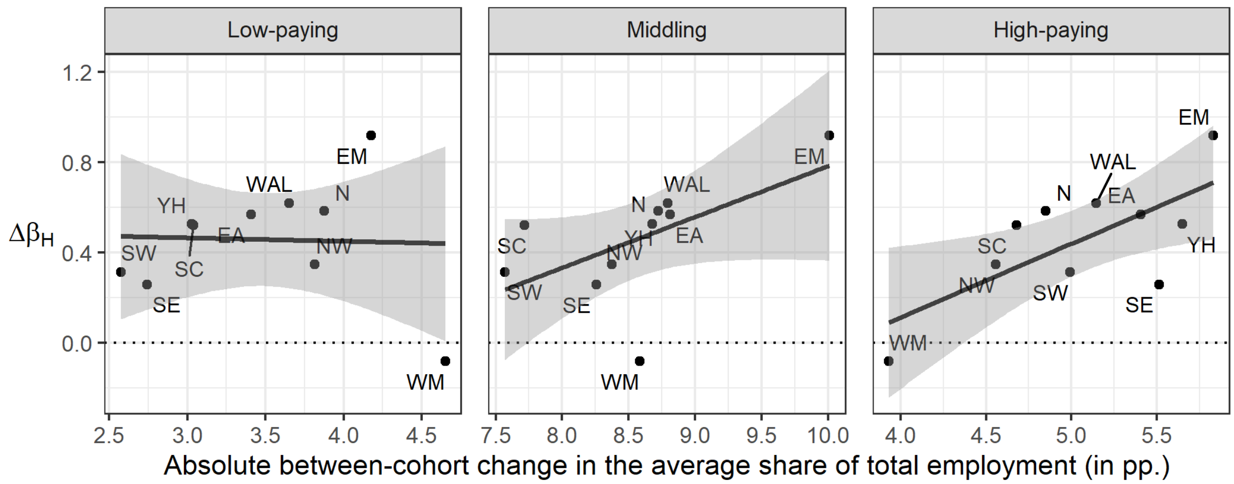
When computing the extent of polarization we face two concerns. First, as shown in the appendix, the share of middling employment has fallen in all regions, but whether this has occurred at the expense of low-paying or high-paying occupations varies. For this reason, rather than focusing exclusively on the share of middling jobs we consider changes in the share of jobs in all three occupations. Second, we need to define the job 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 observe the NCDS58 cohort in 1981 and 2000; we hence suppose that members of that cohort are in competition for jobs with individuals that were born in the 5 years before or 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 then measure the extent of polarization as changes in occupational shares between the 1953-63 cohort and the 1965-75 one. Appendix A.2 gives details on the LFS data and our measures of polarization, and shows that all regions exhibited an increase in polarization (see Figure A.7).

To capture changes in mobility in region r, we consider the between-cohort change in the role of parental income for being in a high-paying occupation, namely, $\Delta\beta^r_H$. These coefficients correspond to the "Par. Inc. $\times$ BCS" coefficients from Table 5.

Figure 12 displays the correlation between regional mobility and regional polarization. Our measures of polarization are the changes, across the two cohorts, in the share of each category in total employment, in percentage points. The three panels report, in the horizontal axis, these changes in absolute value. 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 is the one corresponding to the linear regression line. Consider the right-most graph. The upward slope indicates that regions where the 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 by more are also those where parental impact became stronger. The left-hand graph, which depicts the correlation between the change in the coefficient and the change in the share of low-paying occupations, and displays a flat schedule.[27]

[27]Figure D.4 in the appendix presents equivalent graphs for the change in the coefficients on parental income in the probability of being in middling and low-paying occupations, namely, $\Delta\beta_M$ and $\Delta\beta_L$. We obtain broadly similar results in the two cases,

Figure 12: 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).

5.3 Discussion

Our results point at the possibility that the greater role of parental income in determining occupational outcomes be related to the increase in employment polarization faced by the two cohorts we study. In this subsection we discuss two mechanisms why greater polarization may lead to lower social mobility.

A first possibility, explored by Hennig (2021), is that the disappearance of middling jobs reduces the incentives to acquire education by those coming from less well-off families. In Hennig's model, education is a function of parental bequests and future wages. As middling jobs become scarce the probability of landing such jobs falls, reducing the expected wage. Those with high bequests (and hence a low cost of education) will continue to invest in education; those with low bequest (and thus a high cost of education) prefer not to do so. Investing is no longer optimal as the cost is too high relative to the now lower probability of getting a middling job, and hence those from less well-off households simply aim at getting a low-paying job which requires no investment. As a result, educational outcomes become more polarized, which in turn generates less social mobility.

This mechanism is supported by the analysis of American data in Hennig (2021) and is consistent with our findings that parental income has become more important in determining initial occupations (as well as with the results on education presented in Appendix C).

However, it implies no intra-generational mobility, as educational investments determine once and for all the occupation of the individual. Yet, our results indicate that part of the reduction in mobility that we identify occurs through the fact that, for a given initial occupation, the effect of parental income on subsequent outcomes has increased.

A possible explanation for this result is based on the idea that different occupations have different information contents. Suppose that individuals differ both in parental income and innate ability. The latter is not initially observable but may be observed at the end of the first period of employment. Suppose also that while high-paying and middling jobs reveal the ability of the individual, low paying jobs do not. Consider, for simplicity, an economy with two levels of parental income such that those with low-parental income are initially randomly allocated to either low-paying or middling jobs, and those with high parental income to high-paying or middling jobs. When middling jobs are abundant, a large number of individuals from low-income households will occupy these jobs and reveal their ability. As a result, those with high ability will be promoted into high-paying jobs. These jobs will be liberated by demoting those with high-parental income who have revealed to be low ability and who will consequently occupy a middling job in the second period. Mobility will be large and will be driven by the intra-generational changes in occupations.

Consider now a scenario with only a small number of middling jobs. The majority of those from low-income backgrounds will start their careers in low-paying jobs, and hence there will be few individuals for whom ability is revealed by being in a middling job in the first period. Only a few will be promoted into high-paying occupations and as a consequence only few of those who started in high-paying occupations will be demoted. The result will be a lower degree of mobility.

6 Conclusion

A vast literature has discussed the consequences of job polarization for wage inequality. In contrast, little is known about whether the change in the employment structure has also had an impact on social mobility. This paper raises such question using British data for two cohorts for which we have information for parents and children.

Our empirical approach consists in examining the occupational outcomes of children in the two cohorts, taking into account parental characteristics. Crucially, 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. An important aspect of our analysis it that, since we have data for children at various ages, 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. We then examine how parental income affects the various steps that determine the child's outcome at age 42. Our results indicate that the role of parental income in determining occupations has increased, both for first-period occupation and for the transition towards better-paid occupations. For example, the fortunes of those who start in low-paying jobs differ considerably across generations. For the older cohort, a considerable fraction moved into middling jobs, but this probability has fallen markedly for the younger cohort. At the same time, the probability for those who start in low-paying jobs to move into high-paying jobs has remained roughly stable on average, but this average hides the fact that it has considerably increased for those with high-income parents and declined for those from low-income backgrounds.

Although our data does not allow us to establishing causality, the changes we identify are suggestive that as middling jobs have been eroded, parental income has become more important in determining occupational outcomes. Our analysis of regional mobility patterns supports this possibility, as we find that regions where polarization rose the most are also those where *immobility* increased the most. Our results hence suggest that the structure of employment affects not only the distribution of income but also its persistence across generations, indicating that the polarization of the labour market may have resulted in a polarization of mobility.

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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Appendices

A Data and summary statistics

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

A.1 Cohort studies

We start by describing additional variables that will be used in the robustness analysis.

Education. We observe both child and parental education as time-invariant variables. To define the child education variable, we take the highest academic qualification ever obtained from the educational qualifications history.[28] For parental education such information is not available, hence we use the age at which each parent left full-time education as a proxy. All education variables are ranked at the cohort level in peer-inclusive downward-looking ranking.[29] This approach is particularly suited to the period, given the massive expansion of secondary and higher education that occurred between the two cohorts; see Figures A.1 and A.2.

Family characteristics. A number of family characteristics are available in our data. 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 for both cohorts, and create a dummy variable 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)

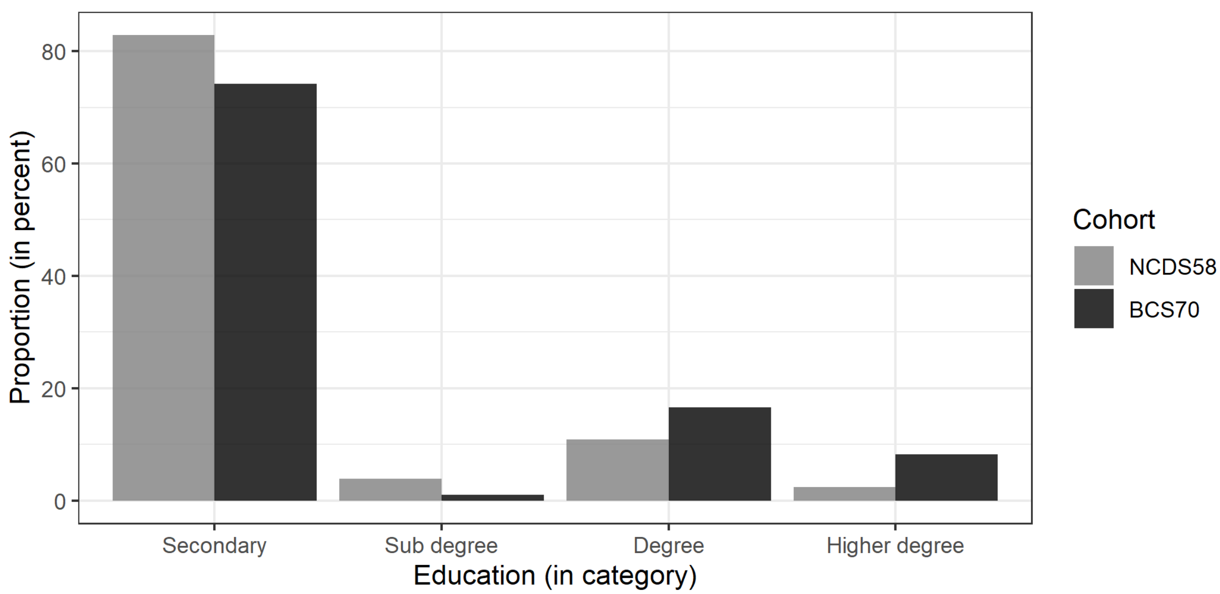
[28] There are 11 categories which are (from the lowest to the highest): no qualifications; less than O-level; less than 5 O-levels; 5+ O-levels; 1 A-level and less than 5 O-levels; 1 A-level and 5+ O-levels; 2+ A-levels and less than 5 O-levels; 2+ A-levels and 5+ O-levels; Sub degrees; Degree - lower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

[29] 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, e.g. of education. See, for example, Jenkins (2020) for an application of this ranking.

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 A.1 reports the summary statistics for the individual data. Given that the overall educational attainment of the population has increased considerably across the two cohorts, Figure A.1 presents the distribution of the child's education for both cohorts. We have regrouped child education into four categories for ease of exposition. As expected, educational attainment has increased across the cohorts. The proportion of individuals with a higher degree has more than doubled. Figure A.2 presents the distributions of education for fathers and mothers.

Figure A.1: 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.

A.2 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 and collects data on labour market status and, since 1993, wages. The LFS was conducted every two years until 1983, then annually until 1992, and quarterly since then. It 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

Table A.1: Summary statistics - Individual data

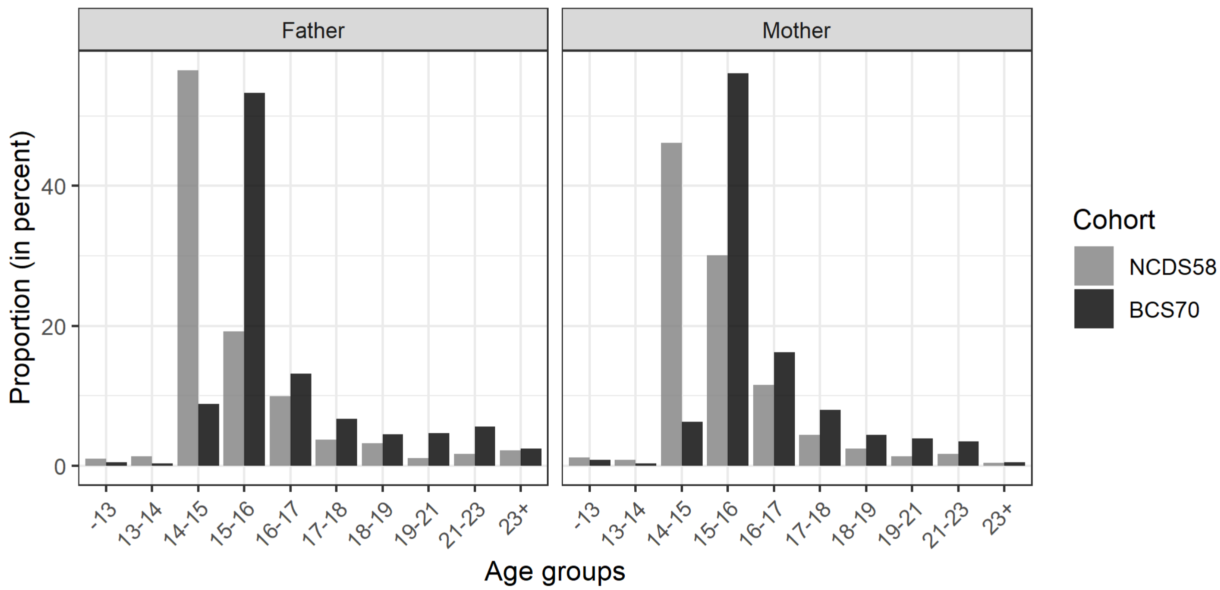
	N = 14763							
Variable	Mean	SD	Min	Q1	Median	Q3	Max	NA
Child								
BCS Cohort	0.54	0.50	0.00	0.00	1.00	1.00	1.00	0
Female	0.52	0.50	0.00	0.00	1.00	1.00	1.00	0
Education - Secondary	0.75	0.43	0.00	1.00	1.00	1.00	1.00	216
Education - Sub degree	0.03	0.16	0.00	0.00	0.00	0.00	1.00	216
Education - Degree	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.

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 for the period 1981 to 2012, these being the years de-

Figure A.2: 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.

fined 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.

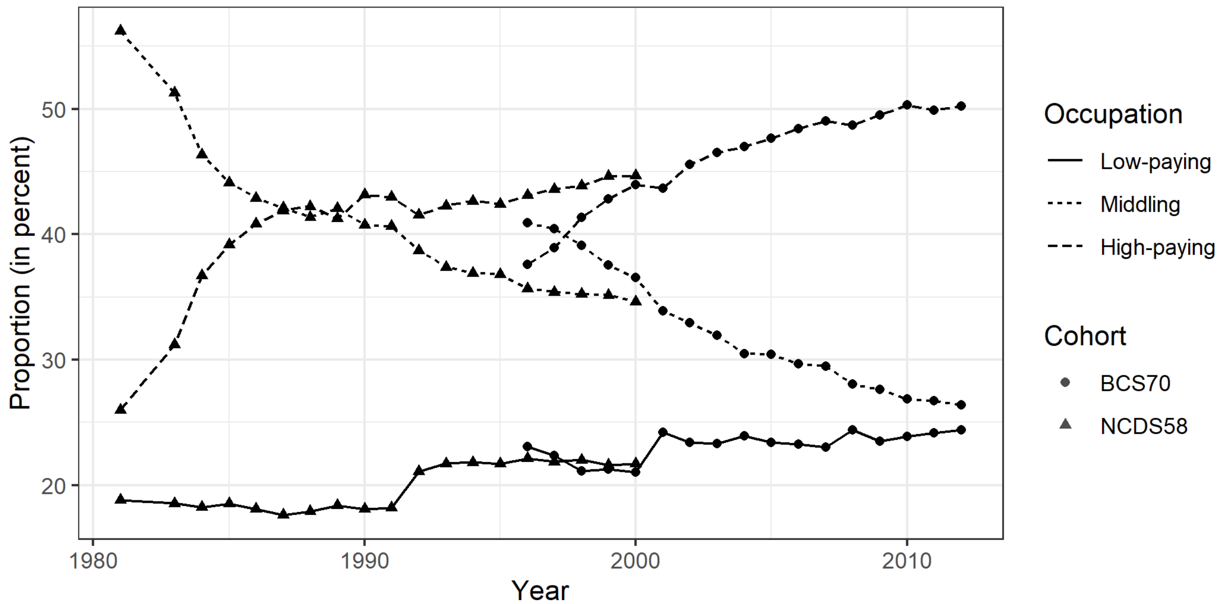
Figure A.3 shows the extent of job polarization at the national level. The share of middling jobs has declined by over 20 percentage points from 1981 to 2012. This reduction has been offset by an increase in the share of high-paying occupations by 16 percentage points over the same period, whereas the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

A.3 Occupational classification

Table A.2 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).

Table A.3 displays the shares of the various activity status and occupational categories. Table A.4 reports the average weekly pay by occupation. Weekly pay is more concentrated

Figure A.3: Job polarization at the national level (Labour Force Survey)



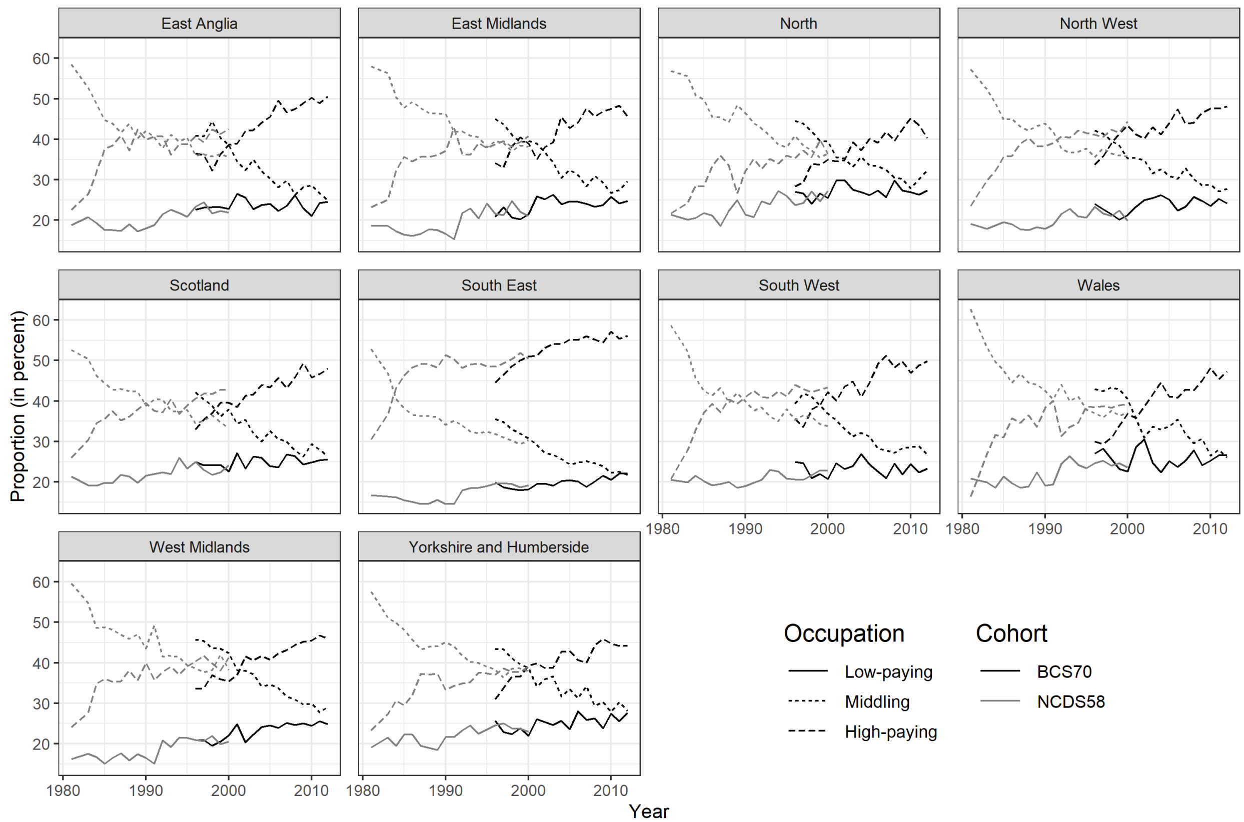
Notes: This figure presents the job polarization at the national level using the Labour Force Survey data from 1981 to 2012.

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).

Occupations are also characterized by different educational requirements. Note, however, that a comparison across the two cohorts is not straight forward as the overall educational attainment of the population has increased, as seen in Figure A.1. Because of these changes, Table A.5 reports average education by occupation using the peer-inclusive downward-looking ranking. As well as our three employment categories we also report the educational attainment of those who are not in employment, splitting this category into those in full time education and the rest of those who are out-of-work (unemployed or not participating).[30] When we do not split this category we find that average education is rather high, this being the combination of the low attainment of those not participating or unemployed

[30] In our data, child education is time invariant because we consider the highest qualification ever obtained. Although some individuals may still appear in the occupational category full-time education, their educational level is the one they will obtain in the future.

Figure A.4: 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 data from 1981 to 2012.

and the high attainment of those still in education.

A.4 Structure of employment

Table A.6 presents the probability to be in each occupation at both periods, for both cohorts. The first-period probabilities indicate that BCS70-cohort individuals are about 7.9 pp. less likely to start in middling occupations, while they are about 12.4 pp. more likely to start their careers in a high-paying occupation. The probabilities with those in education in a separate category, hence not included in out-of-work, are reported in Table A.7. Table A.8 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 A.5 presents the change in the frequencies of second period occupation according to the average weekly pay for the BCS70 cohort. Figure A.6 displays the negative relationship between the probability of being in each second-period occupation according to its routine task intensity.

Table A.2: Overview of ISCO-88 occupation codes and routine task intensity

		RTI	
Code	**Occupation**	**GMS**	**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.

Lastly, Figure A.7 reports the change in polarization in each of the regions obtained from the LFS.

Table A.3: Summary statistics - Cohort data per period

	NCDS58 - N = 6780				BCS70 - N = 7992			
	First period		Second period		First period		Second period	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Activity - Employee	0.74	0.44	0.74	0.44	0.78	0.42	0.72	0.45
Activity - Self-employed	0.05	0.21	0.12	0.33	0.06	0.24	0.14	0.35
Activity - Unemployed	0.05	0.23	0.02	0.14	0.02	0.16	0.02	0.14
Activity - in Education	0.02	0.15	0.01	0.08	0.03	0.16	0.00	0.06
Activity - Inactive	0.14	0.34	0.12	0.32	0.11	0.31	0.11	0.32
Occupation - High-paying	0.24	0.42	0.39	0.49	0.36	0.48	0.44	0.50
Occupation - Middling	0.41	0.49	0.28	0.45	0.33	0.47	0.24	0.43
Occupation - Low-paying	0.14	0.35	0.19	0.39	0.15	0.36	0.18	0.39
Occupation - Out-of-work	0.19	0.39	0.14	0.34	0.13	0.34	0.14	0.34
Occupation - in Education	0.02	0.15	0.01	0.08	0.03	0.16	0.00	0.06
Pay	19.06	7.23	30.35	24.20	25.21	16.47	36.01	25.54

Notes: This table provides summary statistics for individual time-variant data from the BCS70 and NCDS58 according to the period.

Table A.4: Average weekly pay by occupation (in 1970£)

	First period		Second period	
Occupation	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.5: Average education by occupations

	First period		Second period	
Occupation	NCDS58	BCS70	NCDS58	BCS70
Out-of-work	0.55	0.51	0.54	0.54
	(0.01)	(0.01)	(0.01)	(0.01)
Education	0.89	0.79	0.84	0.62
	(0.01)	(0.01)	(0.03)	(0.05)
Low-paying	0.54	0.52	0.52	0.51
	(0.01)	(0.01)	(0.00)	(0.00)
Middling	0.58	0.54	0.55	0.53
	(0.00)	(0.00)	(0.00)	(0.00)
High-paying	0.74	0.72	0.73	0.70
	(0.01)	(0.00)	(0.00)	(0.00)

Notes: This table presents the average education, expressed in peer-inclusive downward-looking ranking, in each first- and second-period occupations for the NCDS58 and BCS70 cohorts. Standard errors between parentheses.

Table A.6: Probability of being in each occupation at both periods, for both cohorts (in percent)

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

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

Table A.7: 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

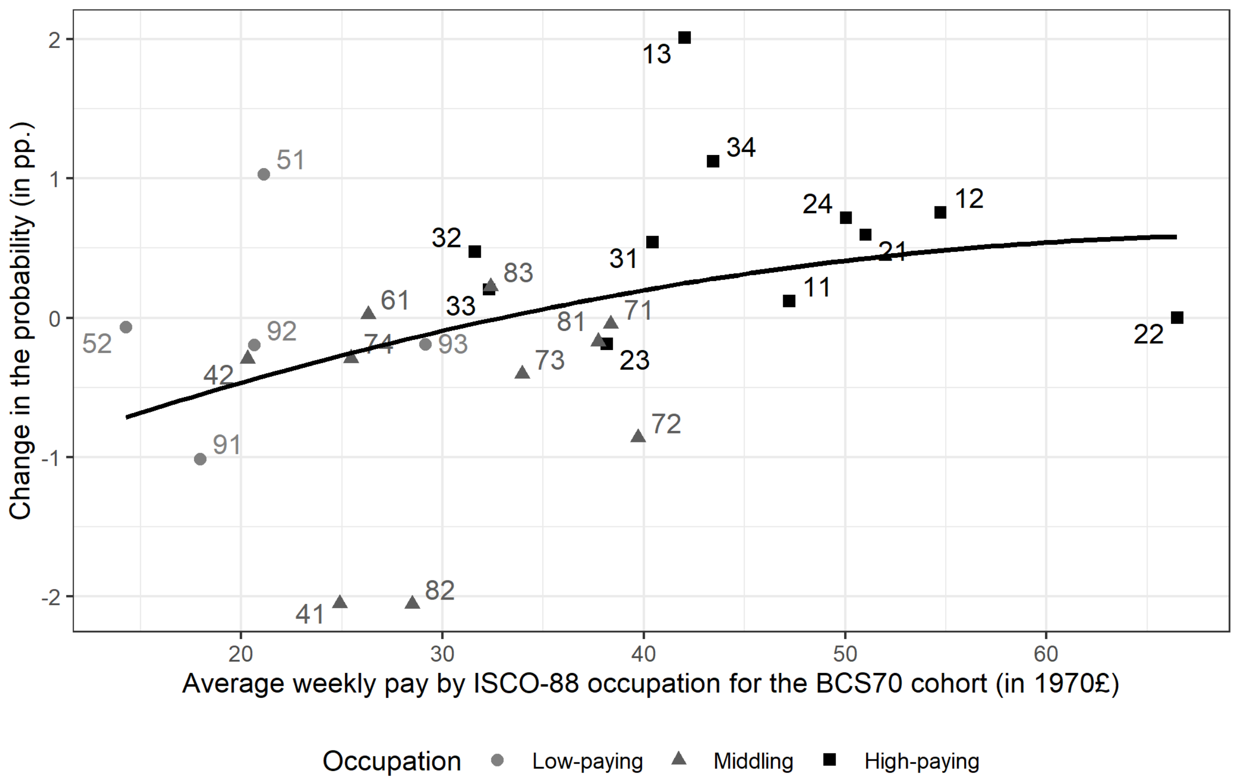
Notes: This table shows the probability, expressed in percent, of being in each first- and second-period occupation for the BCS70 and NCDS58 cohorts. Differences between both cohorts, expressed in percentage points, are reported in the last column of both periods.

Table A.8: 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

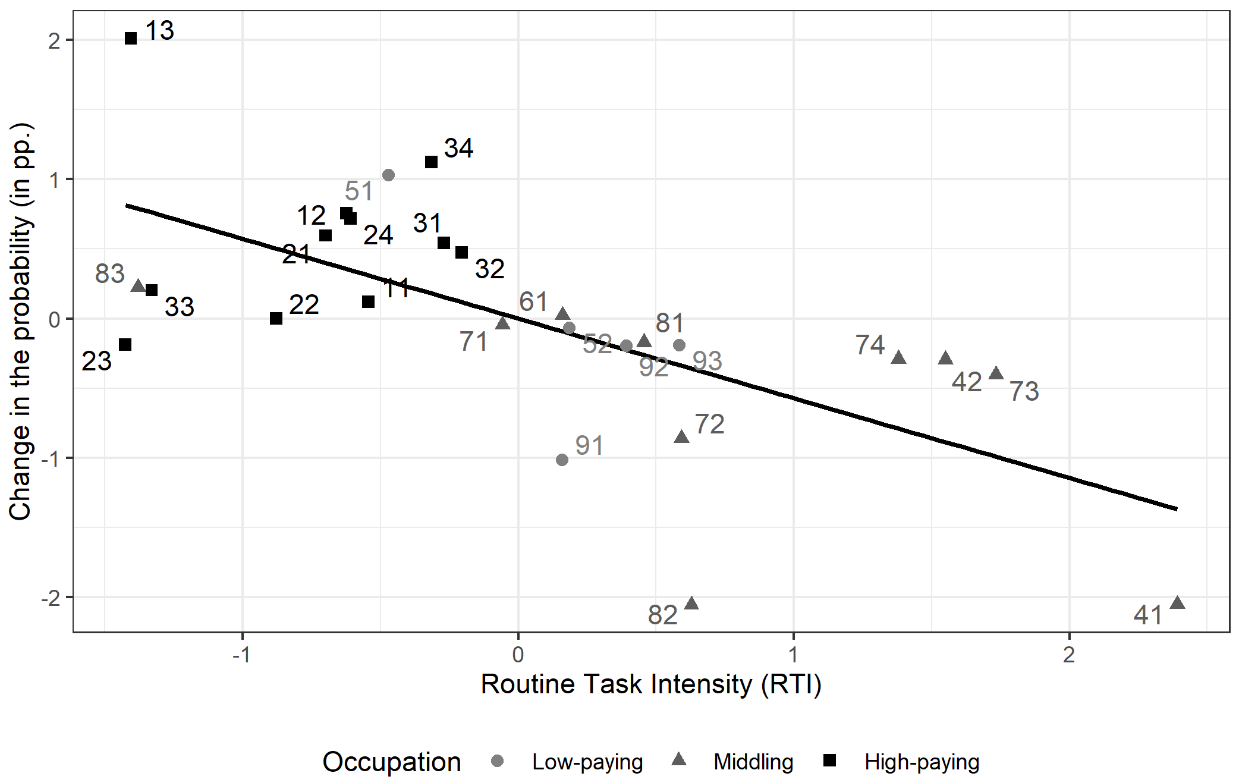
Notes: Conditional probabilities with people in education included in out-of-work are reported in the paper, see table 1.

Figure A.5: Change in the probability of being in an occupation in the second period and average weekly pay



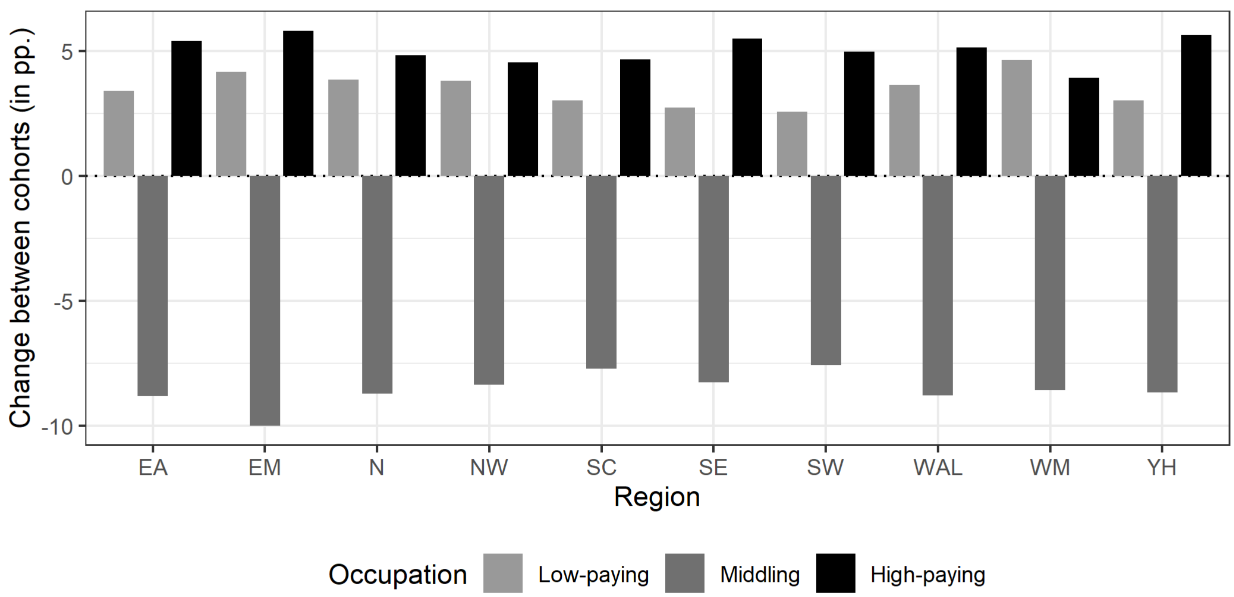
Notes: This figure presents the positive relationship between the difference, expressed in percentage points, between the BCS70 and NCDS58 cohorts in terms of probability of being in each ISCO-88 occupation in second period and the average weekly pay, expressed in 1970£, in this occupation for the BCS70 cohort.

Figure A.6: Change in the probability of being in an occupation in the second period and routine task intensity



Notes: This figure shows the negative relationship between the difference, expressed in percentage points, between the BCS70 and NCDS58 cohorts in terms of probability of being in each ISCO-88 occupation in second period and the Routine Task Intensity (RTI) index from Mahutga et al. (2018).

Figure A.7: Between-cohort change in the average share of total employment over the life-cycle of both cohorts (at the regional level)



Notes: This figure presents the job polarization at the regional level using the Labour Force Survey data from 1981 to 2012.

B Logistic regressions

This appendix provides the regression tables for both period occupations under the multinomial and the binomial 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 from equation (1) for the first-period occupation. Table B.2 reports the coefficients regressions for the equivalent *binomial* specification.

Each of these two estimation methods has advantages and disadvantages. Consider first the binomial logit in Table B.2. Each regression compares the probability of being in occupation j relative to the other three outcomes. In some cases, the regression is easy to interpret. For example, the regression for out-of-work compares this outcome relative to a composite of all three other occupations, i.e. being in employment. The coefficients on the Out-of-work column then tell us that for the NCDS58 cohort parental income had no effect on being out-of-work, while for the BCS70 it had a negative and significant effect. For low-paying occupations we find that parental income reduces the likelihood to be in the occupation, with the effect being three times as high for the BCS70 than for the NCDS58. The 4th column indicates that parental income increases the probability of being in a high-paying occupation (as compared to the other three outcomes) for both cohorts, although the coefficient is twice as high for the younger cohort. The interpretation of the regressions becomes harder for middling occupations as the alternative not-being-in-middling-occupations includes outcomes that are better and outcomes that are worse than middling. We find a moderate effect of parental income (-0.07) and no significant change across cohorts. Yet this may be the result of differential effects for moving up or down the occupational scale.

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. That is, when considering coefficients one needs to keep in mind the dynamics for the out-of-work outcome as captured by the Out-of-work column in Table B.2.

The results for the multinomial estimation reported in Table B.1 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. The negative slopes reported in Figure 6 are the combination of a large decline in the coefficient on parental income for those out-of-work (see the coefficient on Par. inc. × BCS in the first column in Table B.2) and the positive but smaller coefficients on the first two columns of Table B.1.

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.

B.2 Second-period occupation

Table B.3 reports the coefficients of the *multinomial* logistic regression for second-period occupation. Table B.4 reports the coefficients regressions for the equivalent *binomial* specification.

Table B.2: 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 B.3: Probability of being in each occupation in the second period (multinomial)

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

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Out-of-work occupation in second period is the base outcome of the multinomial logistic regression. 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.

Table B.4: 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.

C Accounting for education

This section replicates our core analysis but considers a three-step process in which we also account for education. We start by estimating the impact of parental income on child education, and consider the following linear specification:

$$E_i^c = \alpha_4 + \beta_4 Y_i^p + \phi_f E_i^f + \phi_m E_i^m + \gamma_4 X_i + u_i, \tag{7}$$

where E_i^c is the child's education, Y_i^p parental income, and E_i^f (resp. E_i^m) is the father's (resp. mother's) education. Education variables are measured in peer-inclusive downward-looking ranking. X_i are individual characteristics and u_i the error term. All terms are interacted with a dummy that equals one for those in the 1970 cohort (BCS70). Table C.1 summarizes the coefficients for the determinants of child's education.

Table C.1 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. As expected, the effect of parental income is strong. Moreover, it almost doubles across the two cohorts, increasing from 0.13 for the older cohort to 0.24 for the BCS. The next four columns sequentially introduce other possible determinant of education such as parental education, father's social class and number of siblings. The effect of parental income is reduced as these controls are added to the regression; however, the doubling of the coefficient on parental income across cohorts remains robust.

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, and much of the effect of income identified in column (1) is capturing the effect of these factors. 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.

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

Consider the determinants of an individual's probability to start her career in each of the occupations j, with $j = \{O, L, M, H\}$. Comparing these results with those in Table B.1 we see that, as far as high-paying occupations go, much of the effect of parental income occurs through education (or unobserved characteristics correlated with education). When we compare the two cohorts, the most important result is that while the direct effect of

Table C.1: 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.

parental income has increased across cohorts (by the same magnitude as when we did not control for education), that of education has not.

Concerning the occupation of mature workers, Table C.3 reports regressions in which it depends on education as well as on parental income and the initial job. The coefficients on

Table C.2: 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 education less 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 to cohorts.

Table C.3: 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

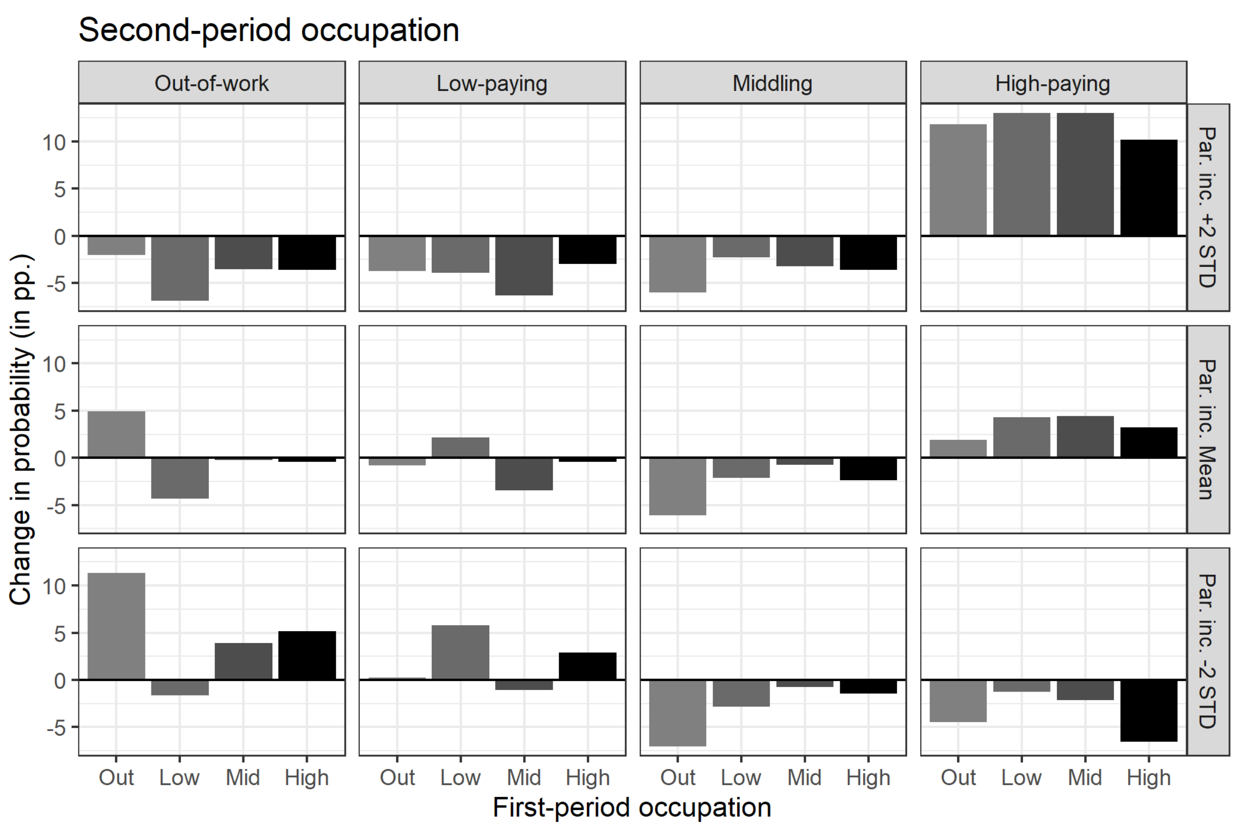
Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Out-of-work occupation in second period is the base outcome of the multinomial logistic regression. Male in the NCDS58 cohort in out-of-work occupation in first period is the referent group. Parental income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

D Additional material

This appendix provides various additional figures and tables to complete the analysis.

Figure D.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 only.

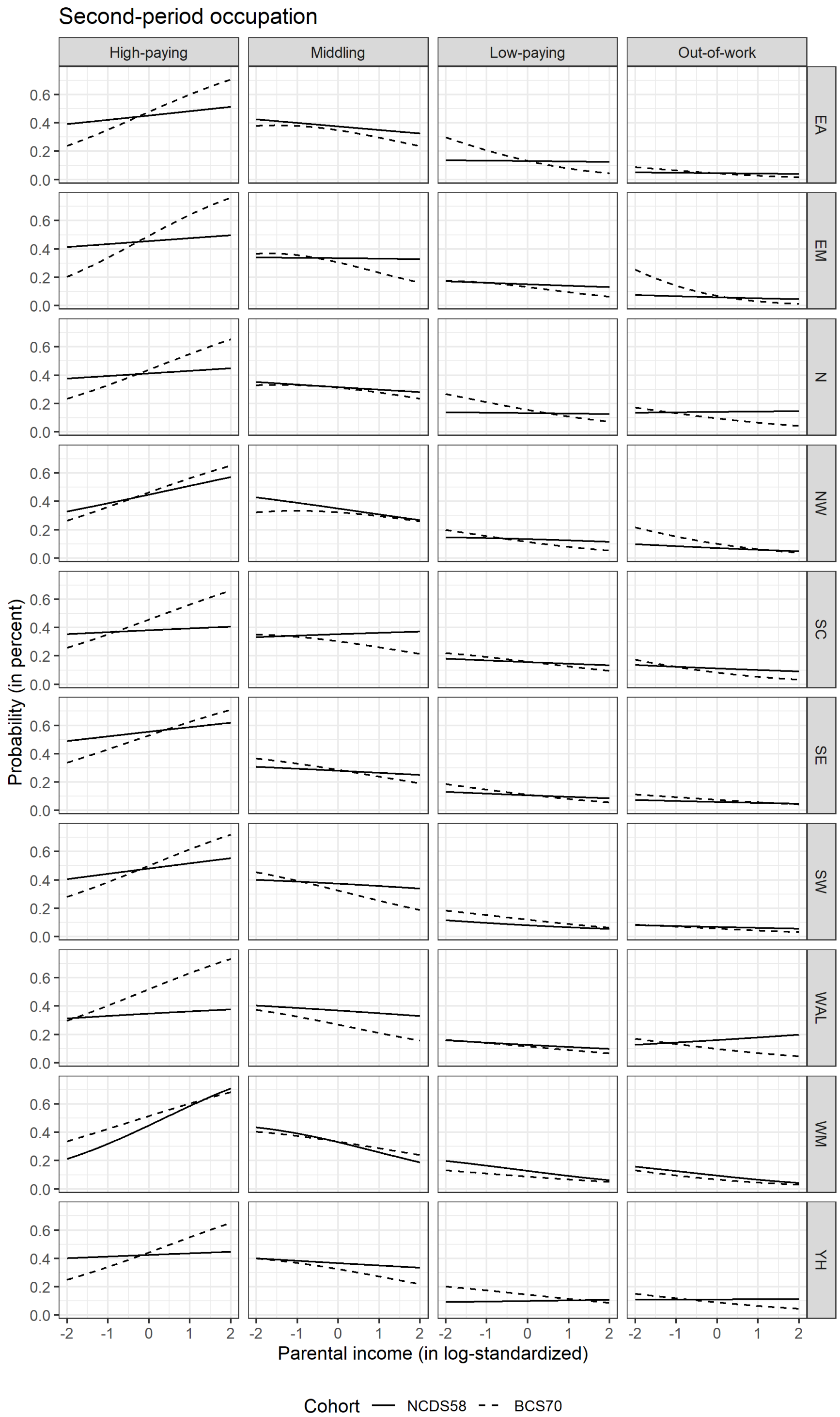
Figure D.1: Change in probability to be in each occupation in the second period according to the first-period occupation and parental income (female only)



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, at several points of the parental income distribution (at -2 std., at the mean and at +2 std.). Probabilities are computed for females in both cohorts according to the multinomial logistic regression reported in columns (2) of Table 2.

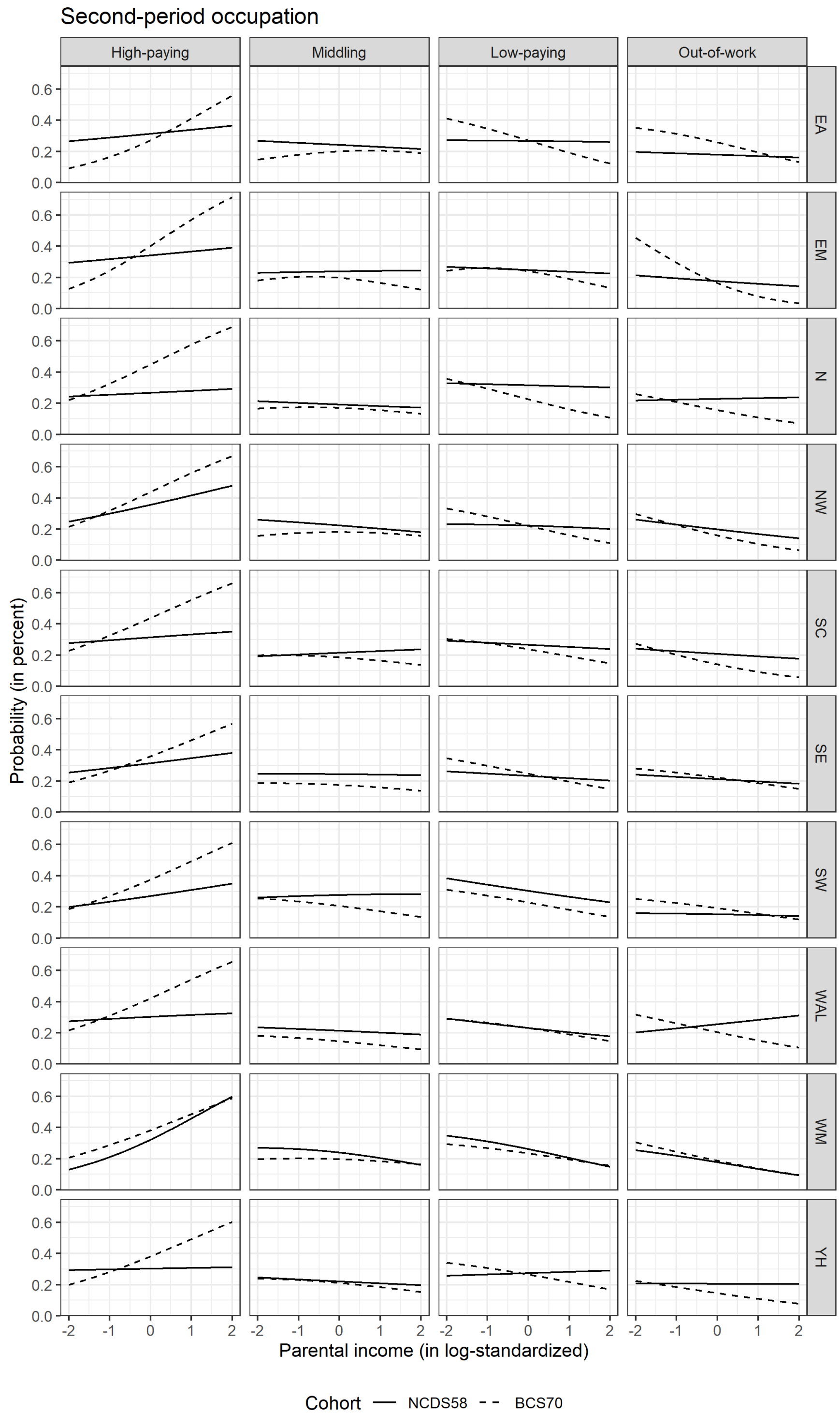
Figures D.2 and D.3 depict the probabilities of being in each second period occupation according to parental income at the regional level, for men and women respectively. Figure D.4 depicts the correlation between the change in the parental income coefficient for second-period occupations and the change in job polarization at the regional level.

Figure D.2: Probability of being in each occupation at second period according to parental income at the regional level (male only)



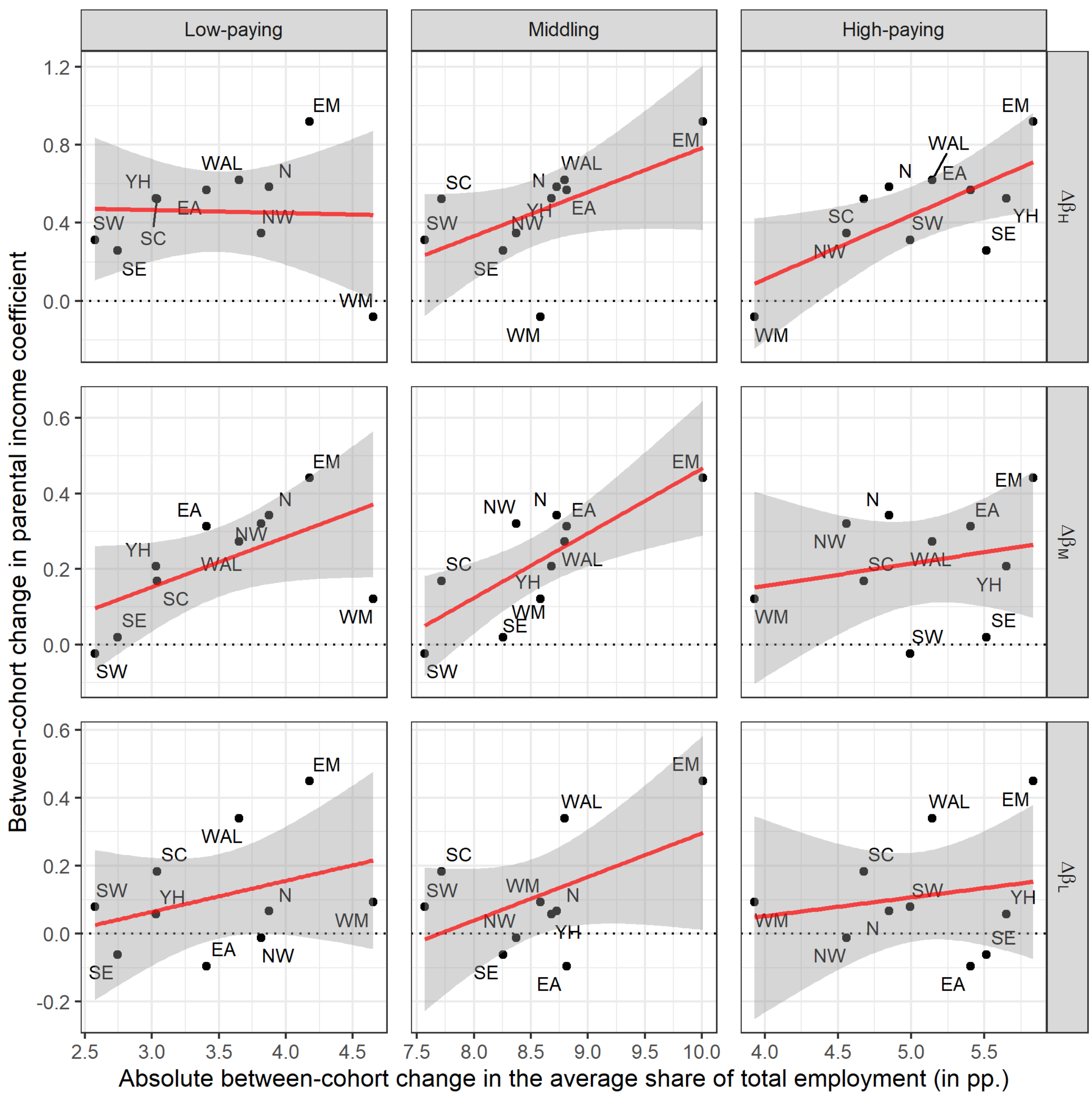
Notes: This figure presents the probability, expressed in percent, of being in each type of occupation (out-of-work, low-paying, middling, high-paying) in second period according to parental income, in log-standardized, for each region. Probabilities are computed for males in both cohorts according to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

Figure D.3: Probability of being in each occupation at second period 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 according to the multinomial logistic regressions reported in Table 5.

Figure D.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).

E Robustness checks

E.1 Squared parental income

This appendix provides a robustness check on the role of squared parental income. We consider the non-logarithmic parental income although standardized. Table E.1 shows the coefficients of the multinomial logistic regression for the probability of being in each first-period occupation. Table E.2 shows the coefficients of the multinomial logistic regression for the probability of being in each second-period occupation. Table E.3 shows the coefficients of the multinomial logistic regression for the probability of being in each second-period occupation according to first-period occupation.

Table E.1: Probability of being in each occupation in first period (Squared-parental-income robustness check)

	Multinomial logit - Dep. var.: First-period occupation					
	(1)			(2)		
	Low	Mid	High	Low	Mid	High
Intercept	0.08	1.39^{***}	0.69^{***}	0.06	1.38^{***}	0.66^{***}
	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
BCS cohort	0.23^{**}	0.12	0.76^{***}	0.29^{***}	0.25^{***}	0.90^{***}
	(0.10)	(0.08)	(0.09)	(0.11)	(0.09)	(0.09)
Female	-0.79^{***}	-1.27^{***}	-1.00^{***}	-0.79^{***}	-1.27^{***}	-1.00^{***}
	(0.09)	(0.07)	(0.08)	(0.09)	(0.07)	(0.08)
Female × BCS	0.25^{**}	-0.01	-0.07	0.25^{**}	-0.02	-0.07
	(0.12)	(0.10)	(0.11)	(0.12)	(0.10)	(0.11)
Par. inc.	-0.03	0.02	0.28^{***}	-0.04	0.02	0.26^{***}
	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)
Par. inc. × BCS	0.09	0.20^{***}	0.35^{***}	0.11	0.28^{***}	0.46^{***}
	(0.06)	(0.05)	(0.05)	(0.07)	(0.06)	(0.06)
Par. inc.^{2}				0.02	0.01	0.03
				(0.03)	(0.02)	(0.02)
Par. inc.^{2} × BCS				-0.06	-0.14^{***}	-0.15^{***}
				(0.04)	(0.03)	(0.03)
Num. obs.	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 is the referent group. Parental income is standardized at the cohort level and squared parental-income is the square of the standardized parental income.

Table E.2: Probability of being in each occupation in second period (Squared-parental-income robustness check)

	Multinomial logit - Dep. var.: Second-period occupation					
	(1)			(2)		
	Low	Mid	High	Low	Mid	High
Intercept	0.37^{***}	1.37^{***}	1.69^{***}	0.45^{***}	1.46^{***}	1.72^{***}
	(0.08)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)
BCS cohort	0.03	−0.05	0.11	0.06	0.03	0.22^{**}
	(0.11)	(0.09)	(0.09)	(0.12)	(0.10)	(0.10)
Female	−0.13	-1.22^{***}	-1.24^{***}	−0.12	-1.22^{***}	-1.24^{***}
	(0.09)	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)
Female × BCS	−0.04	−0.12	0.17	−0.05	−0.13	0.17
	(0.13)	(0.12)	(0.11)	(0.13)	(0.12)	(0.11)
Par. inc.	−0.02	0.02	0.25^{***}	−0.01	0.03	0.25^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Par. inc. × BCS	0.03	0.12^{**}	0.28^{***}	0.09	0.22^{***}	0.39^{***}
	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
Par. inc.^{2}				-0.08^{***}	-0.09^{***}	−0.02
				(0.03)	(0.03)	(0.02)
Par. inc.^{2} × BCS				−0.02	-0.07^{*}	-0.11^{***}
				(0.04)	(0.04)	(0.03)
Num. obs.	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 is standardized at the cohort level and squared parental-income is the square of the standardized parental income. 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.

Table E.3: Probability of being in each occupation in second period (Squared-parental-income robustness check)

	Multinomial logit - Dep. var.: Second-period occupation					
	(1)			(2)		
	Low	Mid	High	Low	Mid	High
Intercept	−0.10	0.44^{***}	0.82^{***}	−0.03	0.52^{***}	0.85^{***}
	(0.11)	(0.10)	(0.10)	(0.11)	(0.11)	(0.10)
BCS cohort	−0.09	-0.49^{***}	-0.34^{**}	−0.05	-0.42^{***}	-0.25^{*}
	(0.15)	(0.15)	(0.14)	(0.16)	(0.15)	(0.14)
Female	−0.01	-0.98^{***}	-1.14^{***}	−0.00	-0.98^{***}	-1.14^{***}
	(0.10)	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)
Female × BCS	−0.10	−0.09	0.27^{**}	−0.11	−0.10	0.26^{**}
	(0.13)	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)
Par. inc.	−0.01	0.02	0.19^{***}	0.01	0.04	0.19^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Par. inc. × BCS	0.03	0.09	0.18^{***}	0.09	0.17^{***}	0.27^{***}
	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)
Par. inc.^{2}				-0.08^{***}	-0.09^{***}	−0.03
				(0.03)	(0.03)	(0.02)
Par. inc.^{2} × BCS				−0.02	−0.04	-0.08^{**}
				(0.04)	(0.04)	(0.03)
Change with respect to the referent group as first period occupation (Out-of-work)						
Low-paying	1.00^{***}	0.31^{**}	0.14	1.00^{***}	0.31^{**}	0.14
	(0.12)	(0.13)	(0.13)	(0.12)	(0.13)	(0.13)
Middling	0.50^{***}	1.47^{***}	0.81^{***}	0.51^{***}	1.48^{***}	0.82^{***}
	(0.11)	(0.10)	(0.10)	(0.11)	(0.10)	(0.10)
High-paying	0.06	0.52^{***}	1.94^{***}	0.07	0.53^{***}	1.95^{***}
	(0.14)	(0.14)	(0.12)	(0.14)	(0.14)	(0.12)
Change between cohorts						
Low. × BCS	0.47^{***}	0.66^{***}	0.56^{***}	0.46^{***}	0.65^{***}	0.55^{***}
	(0.17)	(0.19)	(0.18)	(0.17)	(0.19)	(0.18)
Mid. × BCS	0.03	0.57^{***}	0.27^{*}	0.01	0.54^{***}	0.25^{*}
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
High. × BCS	0.19	0.39^{**}	0.18	0.17	0.37^{**}	0.16
	(0.19)	(0.19)	(0.16)	(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. Male in the NCDS58 cohort in out-of-work occupation in first period is the referent group. Parental income is standardized at the cohort level and squared parental-income is the square of the standardized parental income. 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.

E.2 First-period age

This appendix provides a robustness check about the difference in terms of age in the first period between both cohorts. Tables E.4 and E.5 show the coefficients of the multinomial logistic regressions for the probability of being in each occupation in first and second periods, when both cohorts are either 23 or 26 years old and compare them to their respective baseline estimates from Tables B.1 and B.3.

Table E.4: Probability of being in each occupation in first period (First-period age robustness check)

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

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Out-of-work 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. Columns (Base) correspond to the baseline estimate from table B.1. Columns (Age 23) estimate the same regression with first-period occupation at the age of 23 for both cohorts. Columns (Age 26) estimate the same regression with first-period occupation at the age of 26 for both cohorts.

Table E.5: Probability of being in each occupation in second period (First-period age robustness check)

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

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Out-of-work 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. Columns (Base) correspond to the baseline estimate from columns (2) in table B.3. Columns (Age 23) estimate the same regression with first-period occupation at the age of 23 for both cohorts. Columns (Age 26) estimate the same regression with first-period occupation at the age of 26 for both cohorts.