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

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October 29, 2021

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 or 'class', 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 employment changes. The data indicates 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, as the younger cohorts displays a lower probability of moving from low-paying to middling jobs and a smaller share of young individuals in middling occupations, and hence with the potential to move upwards. Moreover, whatever the initial occupation, parental income has become more important, with those at the top (resp. bottom) of the parental-income distribution having a greater probability of experiencing an upgrading (resp. downgrading) of their occupation. That is, we observe a polarization of mobility.

Preliminary draft. Do not cite or distribute.

Keywords: Inter-generational mobility, Job polarization.
JEL Codes: to be filled.

*This work was supported by French National Research Agency Grants ANR-17-EURE-0020, ANR-18-CE41-0003-01, and by the Excellence Initiative of Aix-Marseille University - A*MIDEX.

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1 Introduction

A recent literature has document 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. Understanding what has driven such a decline is therefore crucial to policy makers in order to reassert equality of opportunity. Existing work has proposed several explanations for the reduction in mobility, focusing, for examples, on non-cognitive skills and the impact of geographical location, yet little attention has been paid to the role of entry occupations and the resulting career dynamics. 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, and argues that increased polarization in the labour market has been accompanied by a polarization of mobility. We use data on two mature British cohorts and exploit the fact that the younger cohort entered a much more polarized labour market than the older one to investigate the determinants of the probability of being in low-paying, middling or high-paying occupations at age 42. Notably, the data has information on individuals' labour market status both at the start of their career and as mature workers that allows us to identify employment dynamics and how they depend on parental income. We find that the reduction in the availability of middling jobs for young individuals has been a major factor in preventing the upwards (resp. downwards) social mobility for individuals from worse-off (resp. better-off) backgrounds. In the older cohort, those at the bottom of the parental income distribution experienced upwards inter-generational mobility by entering middling jobs and either remaining there or climbing to high-paying jobs. Employment polarization has made middling jobs scarce, thus drying up both mechanisms.

Our empirical analysis provides evidence on how changes in the structure of employment affect both inter- and intra-generational mobility and hence the overall extent to which economic privilege is transmitted across generations. To address this question, we use data from the National Child Development Study (NCDS58) and the British Cohort Study (BCS70). The surveys cover individuals born in, respectively, 1958 and 1970 for whom we have full

[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).

activity histories to the nearest month along with parental income and individual characteristics. 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 older one (Blanden et al. 2007, Nicoletti and Ermisch 2007, Blanden et al. 2013). Because we are interested in the structure of employment we focus on occupations, and define four occupational categories, low-paying, middling and high-paying jobs, in line with the employment polarization literature (Goos et al. 2014), as well as a category including those out-of-work.

Existing work on mobility has taken two approaches, either focusing on the correlation between the child's income or social status at age 40 and that of the parent or examining life-time dynamics independently of parental background. We argue that a key aspect of understanding inter-generational mobility is to examine entry jobs and how the extent to which individuals leave those jobs is affected by parental income. Our data allows to examine the relationship between parental income and child occupation at age 42, i.e. when mature, by looking at the intermediate role of the child's initial occupation, measured at age 23/26.[2] 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 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—changes in the role of parental income, parents' education and child education. We proceed in three steps which follow the main stages over the career of individuals. We start by estimating the impact of parental income and parents' education on child education; next we examine the determinants of the first-period occupation of the child, which is assumed to depend on education but also on parental income. Lastly, we consider 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. This last step allows us to compute a measure of intra-generation mobility by computing whether an individual moves upwards or downwards in the occupational scale between age 23/26 and 42. Our focus is the comparison between the result for the 1958 cohort, who entered the labour market when middling jobs were plentiful, and those for the 1970 cohort which faced greater job polarization.

Our analysis provides three main results. First, we find that occupational change over

[2] 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 (1970) having an interview at age 23 (26). We use these ages to measure early-career occupations.

the individual's lifetime, i.e. between age 23/26 and age 42, 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: first, the probability for those in low-paying occupations to move into middling ones has declined across cohorts; second, the fraction of individuals who start their careers in middling occupations —and hence have the potential to move into high-paying jobs— has fallen markedly. Consequently, for the younger cohort these two sources of upward mobility have weakened.

We also find an increased impact of family background at all the stages that determine an agent's occupation when mature. As has been established before, the effect of parental income on educational attainment has become stronger for the younger cohort.[3] What is novel is that we find an increased impact also when we look at initial occupation conditional on education, and at the occupation when mature controlling for both education and initial occupation. In fact, our results indicate that the direct effect of parental income on occupation has become more important over time and that of education less so. These results highlight the implications of the disappearance of middling jobs for mobility in the 1970 cohort. 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 cohort.

Lastly, our results indicate that on average intra-generational mobility has slightly declined for the 1970 cohort as compared to the older one. However, we find again large differences according to family background. For those at the top of the parental-income distribution upwards mobility 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 a polarization of mobility.

This paper 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.[4] Much of the focus has been on how individual characteristics affect income dynamics across generations, and three key aspects

[3]Examples of studies on parental impact on education in the UK are Crawford et al. (2016) and Blanden and Gregg (2004).

[4]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.

have been considered: education (Blanden and Macmillan 2014, Blanden and Macmillan 2016, Crawford et al. 2016, Neidhöfer et al. 2018), 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 individuals 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 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 there has been an increase in its impact. Notably, we find that for the younger cohort the transition from early to latter occupations is more dependent on parental income and less on education than is 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 latter has become more dependent on family background than it used to be.

Lastly, our paper adds to our understanding of the consequences of employment polarization,[5] which have been addressed by a large literature, not only in economics. For example, political scientists, such as Kurer and Palier (2019) have argued that changes in the structure of employment lie behind contemporary political disruptions. 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

[5]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).

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.[6] Surprisingly, the question of whether employment polarization affects mobility has been largely ignored. To our knowledge, the only exception is Hennig (2021), who shares with our work an interest in how the structure of employment affects 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 US data. In this framework, the occupation of a mature worker is determined exclusively by her educational choice; we hence complement it by adding an analysis of job-to-job transitions. Our results indicate 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, the polarization observed in the labour market has also spread to social mobility.

The paper is organised as follows. Section 2 presents the cohort data and describes the structure of employment along with occupational dynamics. Our empirical results are reported in section 3, starting with an analysis of the distribution of occupations amongst mature workers, which is then followed by a decomposition of the various stages. Section 4 concludes.

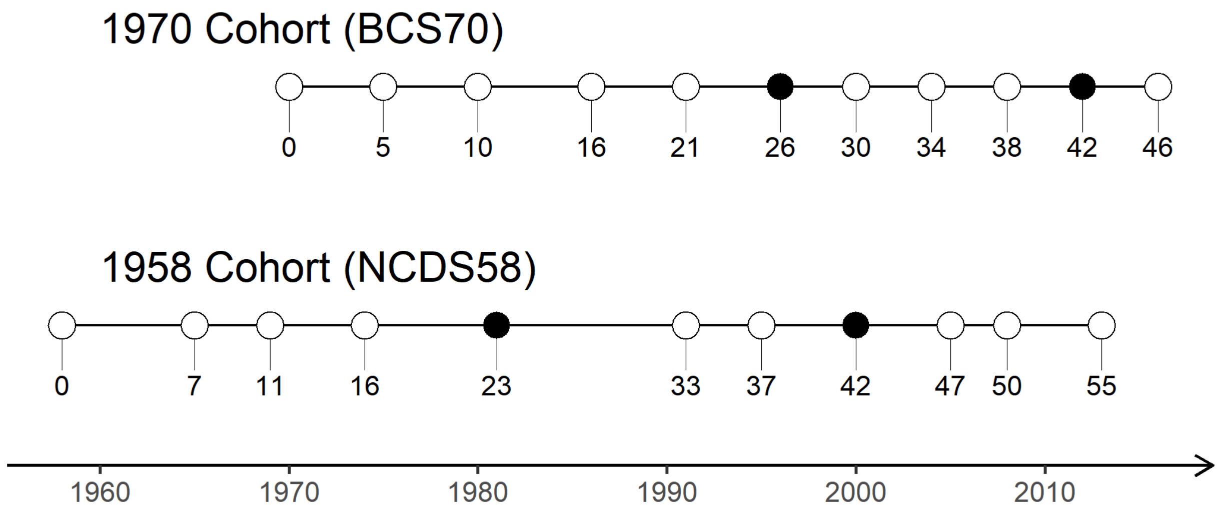
2 Data

2.1 Sample and variables

We use two mature British cohort studies that have been widely used by economists and sociologists to examine the extent of mobility in the UK. The National Child Development Study (NCDS58) is a cohort of individuals born during a given week in March 1958. The British Cohort Study (BCS70) is composed of individuals born during a given week in April 1970. Cohort members were born in England, Scotland, Wales and Northern Ireland and

[6] 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 disagree with the generalization that employment polarization necessarily results in greater earning inequality; 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.

participated to several interviews at different point in times over their life.

Figure 1 presents all the interviews at which cohort members may have answered and the corresponding year. We define the first period as the closest age to 25 years at which each cohort have been interviewed. Hence, we observe the NCDS58 cohort at age 23 and the BCS70 cohort at age 26. Both cohorts are interview at age 42, which we define as the second period.

Both cohorts studies provide the educational qualifications histories and the full activity histories to the nearest month. It includes occupations at the 3-digit level in the Standard Occupational Classification 1990 (SOC90) and the Standard Occupational Classification 2000 (SOC2000) along with the employment status. We focus on the following set of variables for which summary statistics are reported in Table A.1 in the appendix.

Income and wages. We have information on parental income, which is provided at the age of 16 years (of the child) for both cohorts. For the BCS70 cohort, it is also available at the age of 10 years. Thus, when both are available, we take the average, otherwise use the single one we observe. For the children, we observe wages, which are reported at each wave. We adjust for inflation using the consumer price index provided by the UK Office for National Statistics. The resulting monetary variables are all expressed in 1970 British pounds.

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.[7] 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.[8] 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 in the appendix.

Job characteristics. There are two dimensions of job characteristics in our dataset: occupations and employment status. 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). Socio-economic classes are constructed using three dimensions of employment: *i)* the occupation group; *ii)* the employment status; and *iii)* the number of employees in the workplace. However, such classification uses a definition of routine occupations that does not match that used in the job-polarization literature.[9] We hence cannot rely on the NS-SEC for our analysis and need to use another dimension of employment characteristics that focuses on the task content of occupations. Instead, we follow the job-polarization literature and focus on occupations derived from the SOC90 and SOC2000.

We classify ISCO-88 occupations into three categories: high-paying occupations, middling occupations and low-paying occupations. This classification is done according to the one proposed by Goos et al. (2014). Table A.2 in the appendix presents the classification. The ISCO-88 occupations are derived from the SOC90 and SOC2000 occupations that are available in our data using the CAMSIS project which provides files covering the occupational unit codes and translations. 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.

The employment status variable defines individuals as employed or self-employed. We

[7]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.

[8]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.

[9]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 a routine job following the definition of Autor et al. (2003) who define this type of job as a non-routine interactive job.

remove the self-employed from the analysis in order to focus on employees for whom it is easier to identify routinization.[10] Table A.3 in the appendix displays the shares of the various employment and occupational categories.

As has been shown in previous work, occupational categories are closely related to remuneration levels and educational attainment, and we document this for our data in Appendix A. Table A.4 reports the average weekly pay by occupation, and displays the expected correlation between occupations and pay. A comparison of education across the two cohorts is not straight forward as the overall educational attainment of the population has increased over time (see Figure A.1). The data are characterised by three features; see Table A.5. First, as expected, those in high-paying occupations have a high educational attainment, being in the top 25% of the educational distribution of their cohort. Second, the educational attainment of those in low-paying and middling occupations is much lower, and although the difference between the two groups is statistically significant its magnitude is very small, specially for mature individuals. Lastly, there is a remarkable stability across cohorts on the average educational profile in the various categories.

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) 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.

Lastly, since individuals give their address at each interview, we also have a location history according to the interviews' response. We focus our interest 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

[10] The data also provide information on the employment status of employees, which are divided into three categories according to their status: employee, foreman/supervisor or manager. This is an additional dimension that we intend to explore in future work.

rely on the Standard Statistical Regions (SSR).[11]

Once we restrict the data to those individuals for whom we have the key characteristics, i.e. parental income, child education and occupations, our sample consists of 6,761 individuals in the NCDS58 and 7,795 in the BCS70, as reported in Table A.1.

2.2 The structure of employment

The focus of our analysis are occupational outcomes. We hence start by looking at the change in the distribution of occupations at age 42 between both cohorts, reported in Figure 2 separately for men and women (in percentage points).[12] For both genders there is an increase across generations in the probability of working in a high-paying occupation and a decline in that of working in a middling-paying occupation, with the change being particularly large for young individuals. The share of low-paying jobs exhibits much smaller changes, declining slightly (being stable) for young (mature) men and increasing (declining) for young (mature) women. 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.

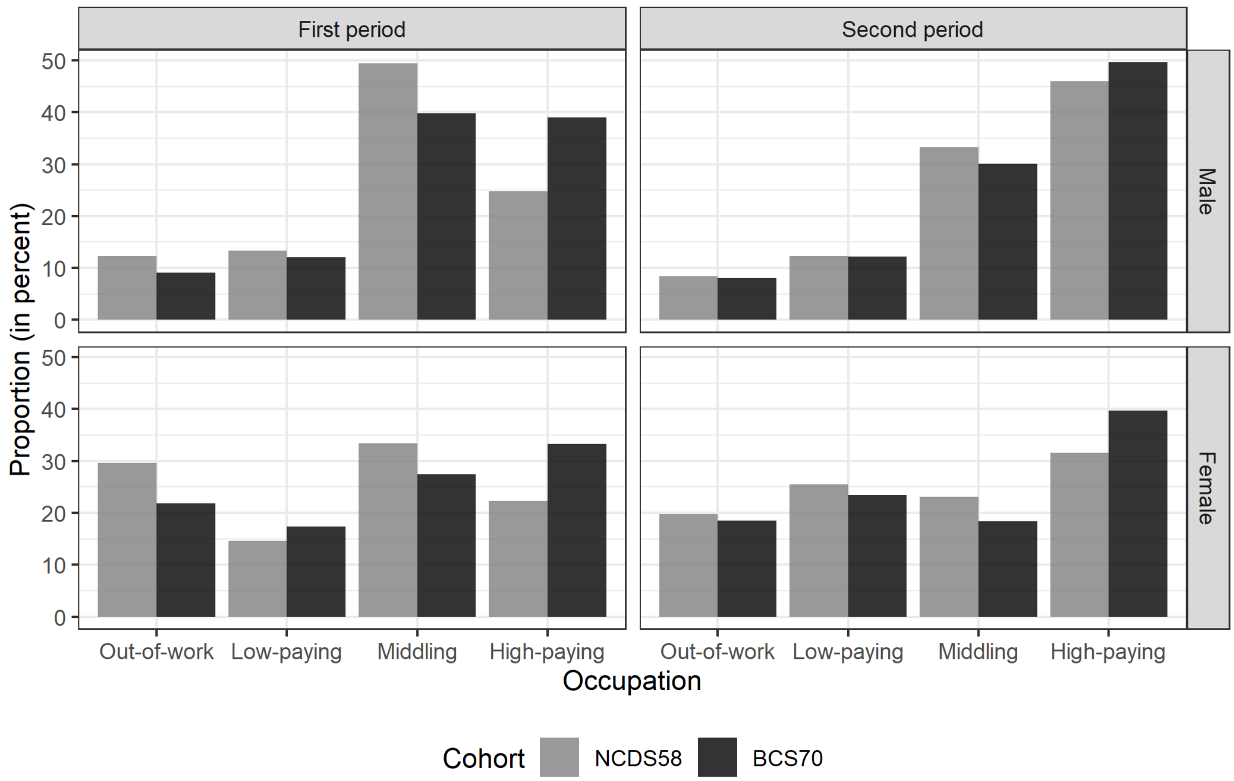
To better understand these dynamics, Figure 3 performs a similar exercise (for men and women together) using the ISCO-88 categories that we have grouped into our three broad categories. Occupations are depicted in light gray for those we place in the lo-paying category, in dark grey for those in the 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. Interestingly, 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

[11] The categories are (from the south to the north): South West, South East, Wales, East Anglia, West Midlands, East Midlands, North West, Yorkshire and Humberside, North and Scotland. We define a last region named Abroad regrouping people living abroad and in Northern Ireland.

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

Figure 2: Occupation distribution across cohorts



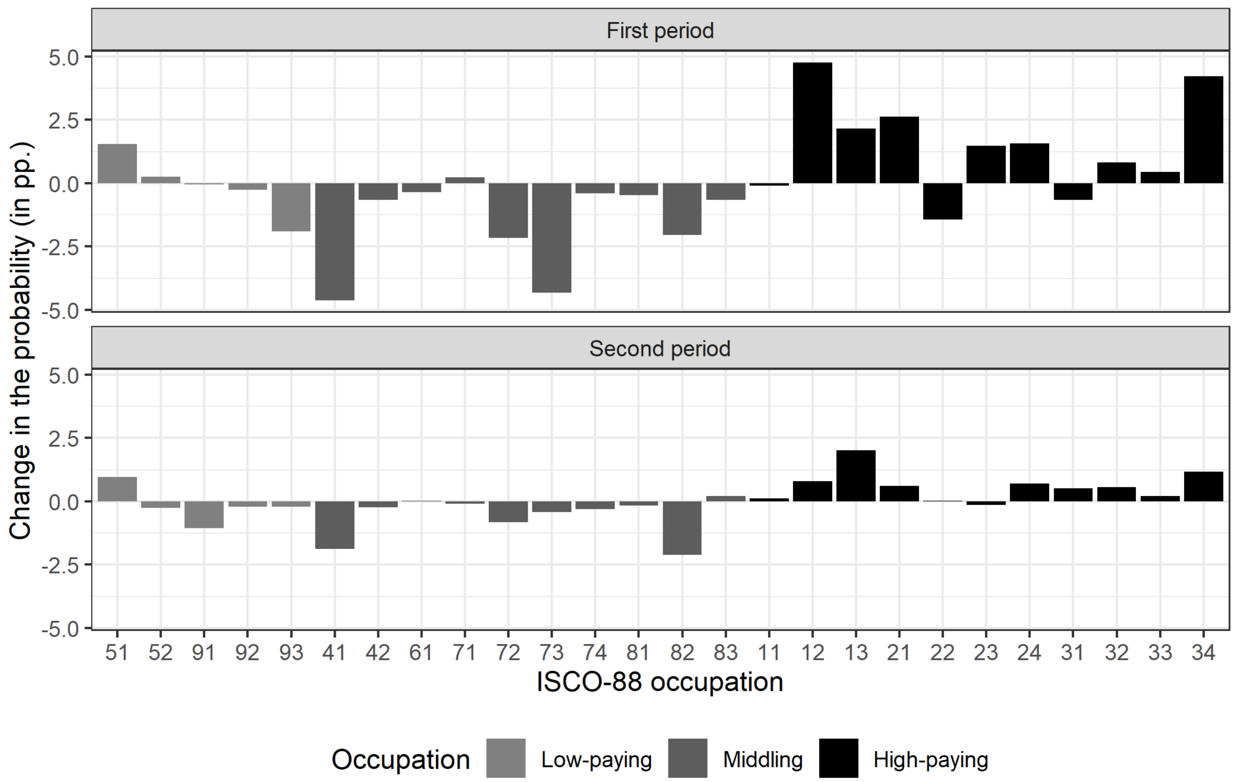
Notes: This figure reports the proportion of individuals in each type of occupation (out-of-work, low-paying, middling, high-paying) for the NCDS58 and BCS70 cohorts according to the period and gender.

our category of low-paying (circle), middling (triangle) or high-paying (square) occupations. 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 3: Change in the probability of being in each ISCO-88 occupation in both periods



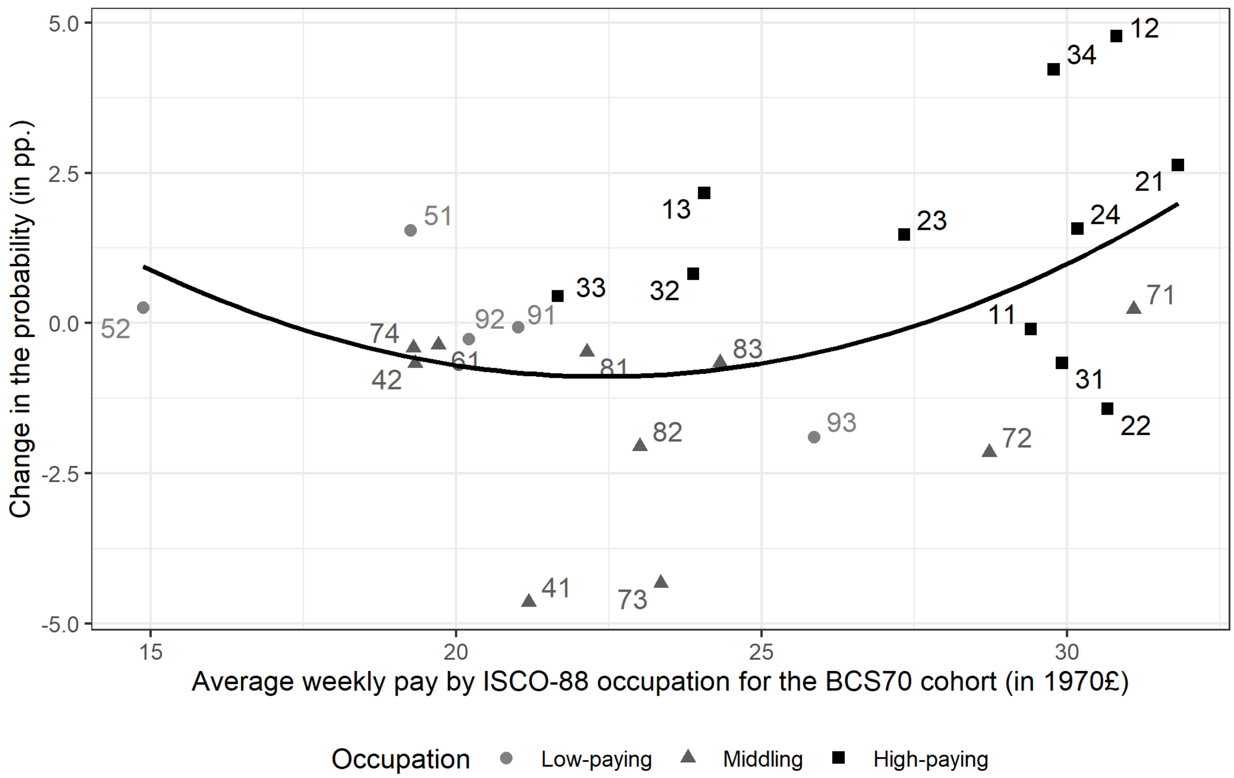
Notes: This figure presents the difference, expressed in percentage points, between the BCS70 and NCDS58 cohorts in terms of probability of being in each ISCO-88 occupation in both periods.

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.

2.3 Occupational dynamics

While the literature on inter-generational mobility has traditionally focused on the outcomes of children when they are mature, we are interested in the occupational dynamics through which individuals reach a particular outcome. To illustrate why this is important, Table 1 reports the conditional probabilities of switching occupations between age 23/26 and age

Figure 4: Change in the probability of being in an occupation in the first period and average weekly pay



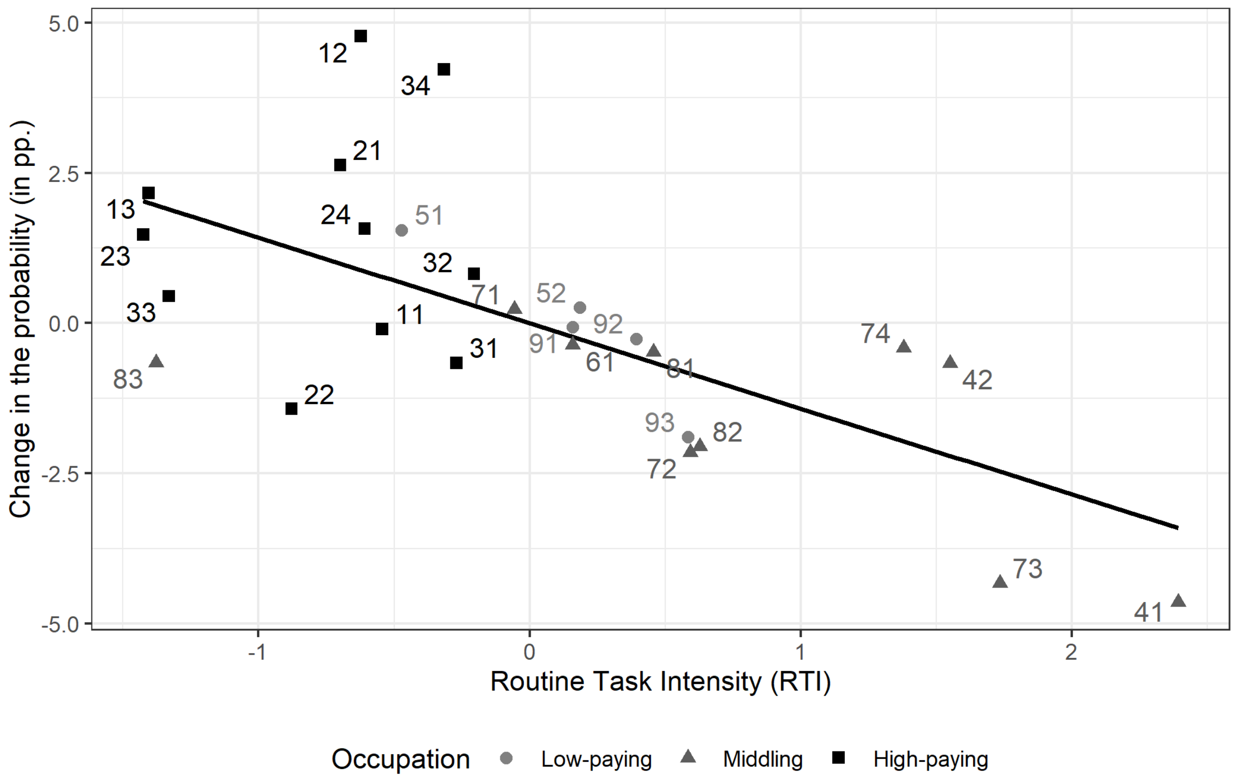
Notes: This figure presents the U-shaped relationship between the difference, expressed in percentage points, between the BCS70 and NCDS58 cohorts in terms of probability of being in each ISCO-88 occupation in the first period and the average weekly pay, expressed in 1970£, in this occupation for the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

42.[13]

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, 31% 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

[13]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.

Figure 5: Change in the probability of being in an 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).

Table 1: Conditional probabilities of changing occupations (in percent)

	BCS70				NCDS58			
Occupation	Out	Low	Mid	High	Out	Low	Mid	High
Out-of-work	32.5	25.4	14.9	27.2	27.2	24.8	20.7	27.3
Low-paying	13.7	44.4	17.8	24.1	16.3	39.9	20.3	23.4
Middling	10.3	13.9	44.7	31.1	10.3	15.5	43.3	30.9
High-paying	8.2	8.1	11.1	72.6	8.5	8.1	12.3	71.1

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.

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.

3 Empirical results

3.1 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. This raises the question of to what extent transitions across occupations, and in particular the disappearance of middling jobs, are an important aspect determining the occupational outcomes of mature individuals. In order to understand the dynamics of inter-generational mobility, and in particular the impact of parental income, we hence proceed in three steps. We start by estimating the impact of parental income and parents' education on child education, and consider the following specification

$$E_i^c = \pi + \gamma Y_i^p + \phi_f E_i^f + \phi_m E_i^m + \psi X_i + u_i, \tag{1}$$

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. All four variables are measured in peer-inclusive downward-looking ranking. X_i are individual characteristics and u_i the error term. Parental income and education are also interacted with a dummy variable that equals one when an individual is in the 1970 cohort (BCS) and zero otherwise. Cross-term coefficients hence represent the change in the effect of the variable on the child's education.

The second step consists in examining the determinants of an individual's probability to start her career in occupation j. Defining $p_{i(j)}$ $\forall j \in \{O, L, M, H\}$ as the probability that individual i starts in occupation j, we suppose that this probability is given by the following logit model:

$$\text{logit}(p_{i(j)}) = \alpha + \gamma Y_i^p + \phi E_i^c + \psi X_i + v_i, \tag{2}$$

where Y_i^p is parental income, E_i^c the child's education and X_i are individual characteristics. All terms are interacted with a dummy that equals one for those in the 1970 cohort (BCS). We estimate this equation both separately for the four occupation-types -out-of-work (O), low-paying (L), middling (M) and high-paying (H)- and using a multinomial logistic regression.

Lastly, we consider the determinants of the probability of being in occupation k at age 42. We suppose that it is given by

$$\text{logit}(p_{i(k)}) = \alpha + \sum_j \eta_j \mathbb{1}_j + \gamma Y_i^p + \phi E_i^c + \psi X_i + \epsilon_i, \tag{3}$$

where $\mathbb{1}_j$ is a dummy variable that equals one when an individual was in occupation j when young. That is, we suppose that as well as depending on education and parental income, the occupation of mature workers depends on their job at the start of their career. As before, we estimate this equation both separately for the four occupations as well as in a multinomial regression.

3.2 Where do mature individuals work?

We start by running a regression equivalent to those generally used in the literature on mobility. We hence consider the probability of a mature (i.e. aged 42) individual being in each of the four occupational categories conditional exclusively on gender and parental income, allowing the coefficients to vary between the older and the younger cohort. Table 2 reports the results obtained when running a binomial logit regression on each of the four categories we consider.[14] Parental income has been standardized, so that the mean and variance are 0 and 1 for the two cohorts.

As expected, parental income matters, with a higher income making it more likely that the individual is in a high-paying occupation and less likely that he is either of the other three categories. The effect of parental income increases considerably for the BCS70 cohort, with the coefficient being between two and three time higher for the younger cohort. While a one-standard-deviation increase in parental income used to raise the odds to be in a high-paying occupation by 18% for the older cohort, this same increase raises the odds by 55% for the younger one.[15] Conversely, a one-standard deviation increase in parental income reduces the odds to be in a low-paying occupation by 23% for the 1970 cohort against only 8% for their elders.

To illustrate the relationship between parental income and occupational dynamics, Figure 6 reports the *change* across the two cohorts in the probability of being in each occupational category at age 42. It 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 group relative to what that probability was for those born in 1958. Not surprisingly, for all parental-income categories the likelihood of being in a middling job has declined for the younger cohort (with the exception of those in the first decile). Yet, whether this decline is offset by an increase in the probability of working in a low- or a high-paying occupation is highly dependent on parental income. Polarization is only apparent for those in the fourth decile, with those at the bottom of the parental-income distribution seeing a decline in both the likelihood of being

[14] We also run a multinomial logistic regression, see Table D.4 in the appendix.

[15] These coefficients are obtained by taking the exponential of the change in log odds, i.e. $\exp(0.17) = 1.185$ and $\exp(0.17 + 0.27) = 1.553$.

Table 2: Probability of being in each occupation in the second period

	Binomial logit - Dep. var.: Second period occupation			
	Out-of-work	Low-paying	Middling	High-paying
Intercept	-2.39^{***}	-1.97^{***}	-0.70^{***}	-0.16^{***}
	(0.06)	(0.05)	(0.04)	(0.04)
BCS cohort	-0.08	-0.02	-0.15^{***}	0.13^{***}
	(0.09)	(0.07)	(0.05)	(0.05)
Female	0.98^{***}	0.89^{***}	-0.51^{***}	-0.61^{***}
	(0.08)	(0.07)	(0.05)	(0.05)
Female × BCS	-0.03	-0.11	-0.15^{**}	0.21^{***}
	(0.11)	(0.09)	(0.08)	(0.07)
Par. inc.	-0.09^{***}	-0.08^{***}	-0.06^{**}	0.17^{***}
	(0.03)	(0.03)	(0.03)	(0.03)
Par. inc. × BCS	-0.21^{***}	-0.18^{***}	-0.08^{**}	0.27^{***}
	(0.05)	(0.04)	(0.04)	(0.04)
Pseudo R^2	0.04	0.03	0.02	0.03
Log Likelihood	-5646.72	-6775.16	-8155.80	-9558.17
Num. obs.	14556	14556	14556	14556

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 child education in peer-inclusive ranking, both are standardized at the cohort level. The corresponding multinomial logistic regression is reported in the appendix, see table D.4.

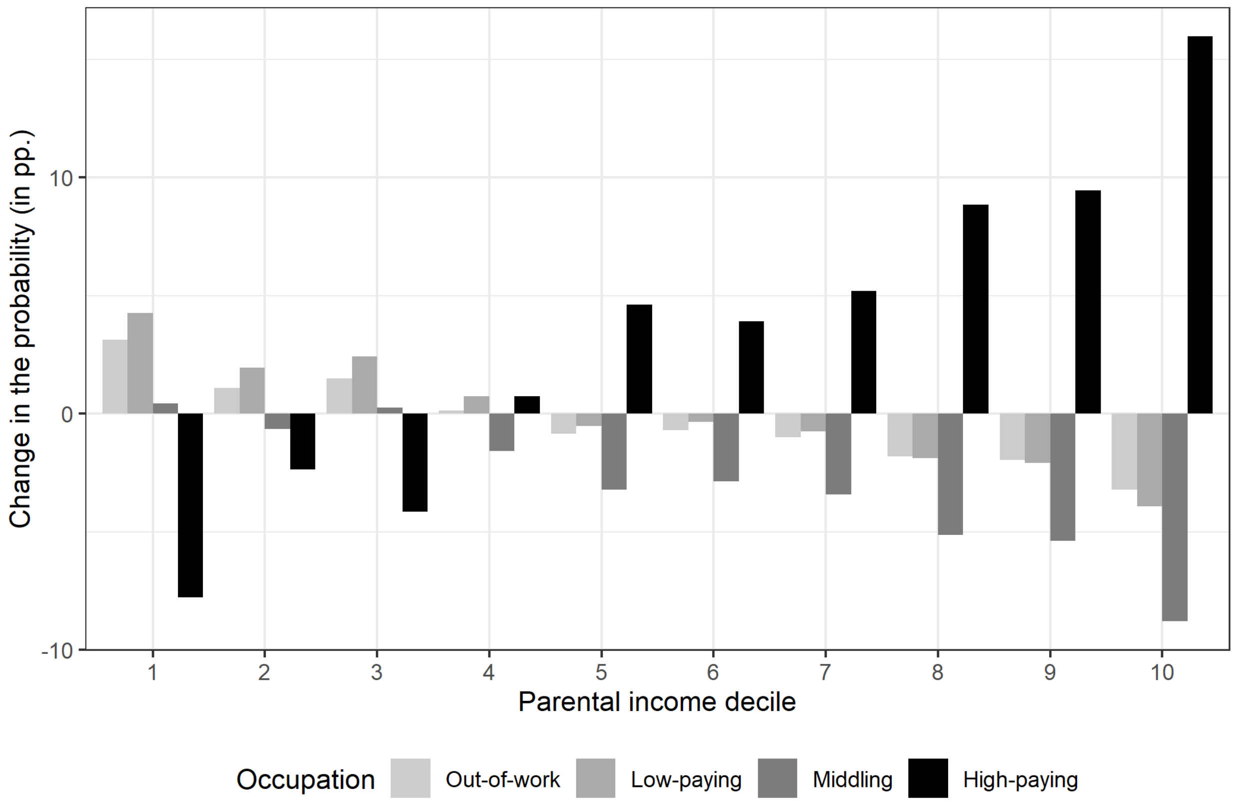
in middling and in high-paying jobs. In contrast, those in the top half of the distribution witnessed an increased probability of being in high-paying occupations at the expense of all other outcomes, with the effect being stronger the wealthier the parents are.

3.3 Initial occupation

In order to understand the dynamics of inter-generational mobility, this section estimates the impact of parental income on child education, before looking at the determinants of first-period occupations. The next section considers how the occupation of mature individuals is affected by their education and their initial occupation.

Table 3 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

Figure 6: 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 D.4 in the appendix. See below for details.

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 cohort 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.

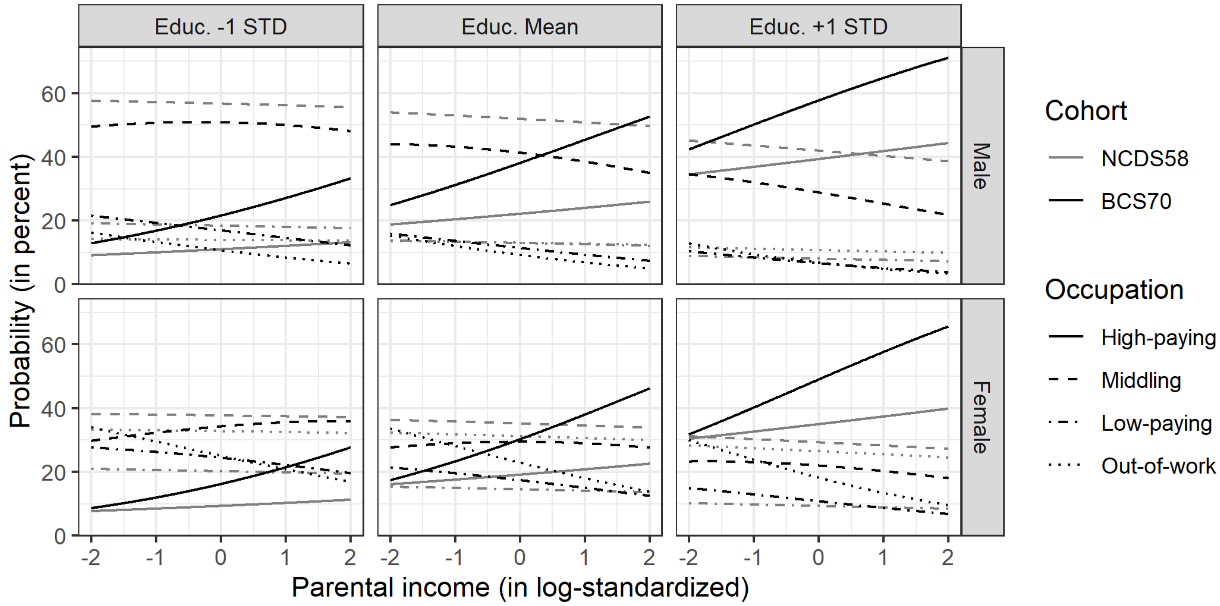
Consider now the determinants of an individual's probability to start her career in occupation j, with $j = \{O, L, M, H\}$. We estimate equation (2) both separately for the four occupation-types -out-of-work (O), low-paying (L), middling (M) and high-paying (H)- and using a multinomial logistic regression. The results for the binomial logits are reported in Table D.1 in the appendix, while the multinomial results are summarized in Table 4 (see Table D.2 for the full results).

Parental income is a key determinant of initial occupation, increasing the probability to be in a high-paying occupation relative to the other three categories. In the appendix we show that, as expected, much of the effect of parental income occurs through education; see Tables D.1 and D.2. The change across cohorts of the coefficients on the direct effect of parental income, reported in the first two lines of Table 4 are massive. The coefficient increases from 0.10 to 0.23 for high-paying occupations, while the probability of being in a low-paying or middling occupation, which was not affected by parental income once education was accounted for, is positively correlated with income for the younger cohort. This results indicate that for those born in 1958 most of the transmission across generations was occurring through access to education (which has the expected signs, increasing the probability of working in a high-paying occupation and reducing the others with the effect being insignificant for middling occupations). In contrast, for the BCS70 cohort, the impact of parental income through education is magnified by a direct effect on occupational outcomes. Noting that there is no significant change in the impact of education across the two cohorts and recalling that the two variables are normalized, our estimates indicate that while for the older cohort the effect of parental income on the likelihood of being in a high-paying occupation was equivalent to only 13% of that of education, for the younger cohort it is 60%.

To visualize these effects, Figure 7 displays the probability to be in each occupation when young as a function of parental income, in both cohorts.[16] The probabilities are reported separately for the two gender groups and for three levels of the child's education - the average and plus/minus one standard deviation of education. Concerning men, three results are striking. As far as high-paying occupations are concerned, we see a gap between the two cohorts that increases with parental income for all levels of the child's education. In other words, even when we control for education, parental income became more important in affecting the likelihood of getting into the top occupations. One possible explanation for this is that non-cognitive skills have become more important and that they are positively associated with the household's income; alternatively, parental income could be a proxy for the child's social network, either its size or 'quality', which in turn has become more

[16]Figure E.1 in the appendix depicts the same probability according to the child's education level at several points of the parental income distribution. The probabilities are computed according to the multinomial logistic regression, reported in the appendix (see table D.2).

Figure 7: Probability of being in each occupation at 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, at several points of the child education distribution (at -1 std., at the mean and at +1 std.). Probabilities are computed for males and females in both cohorts according to the multinomial logistic regression reported in columns (2) of Table D.2 in the appendix.

important in determining access to jobs.[17]

Second, for the older cohort the schedules for low-paying or out-of-work are roughly flat, indicating that only education mattered, yet they exhibit a considerable downward slope for the younger cohort, again highlighting the increased role of parental income. Lastly, the evolution of the probability of being in a middling-paying occupation for the BCS70 is particularly surprising: for those with high educational attainment, the relationship between parental income and this probability is strongly decreasing, for those with average education, it is decreasing but less steep, and for those with low education it is roughly flat (it actually exhibits a slightly hump-shaped pattern). In all cases, the probability of getting middling jobs has fallen across cohorts, but, except for those with low education, the reduction has been greater the higher parental income is. This has several implications. First, the share of those with low education getting these jobs has fallen overall, pushing these individuals

[17]See, for example, Blanden et al. (2007), using the same data as us and, showing a strengthening of the relationship between parental income and non-cognitive skills between both cohorts. Chetty et al. (2014a) shows 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.

towards worse employment conditions. Second, while for the older cohort lack of education was an equalizing factor (those with scarce qualifications fared similarly irrespective of their background), for the younger cohort parental income has become a substitute for education implying that low-education youngsters have very different outcomes depending on their background.

The results for women are more mixed but the key patterns are confirmed. Notably, for the younger generation parental income has a stronger effect on the probability of getting a high-paying job than was the case for the older cohort. The data also indicate that for women with low education, the probability of getting a middling-job is increasing in parental income. For the older cohort, low levels of education implied getting a middling job with a high probability (close to 40%) irrespective of parental income. For the younger generation those with low parental income have witnessed a drop in this probability of around 10 pp., making them more likely to have no job or be in a low-paying occupation; however, as parental income increases the probability of having a middling job rises.

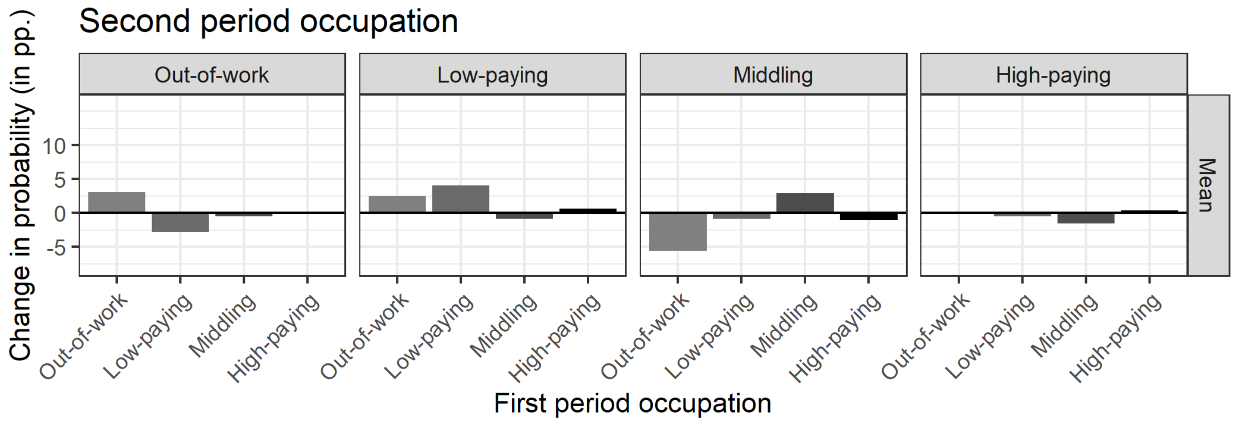
3.4 Parental income and the occupation of mature individuals

Consider now the determinants of the probability of being in occupation k at age 42, as given by equation (3). Recall that we suppose that as well as depending on education and parental income, the occupation of mature workers depends on their job at the start of their career. As before, we estimate this equation both separately for the four occupation-type as well as in a multinomial regression. The full results are reported in Tables D.3 and D.4 in the appendix, and summarized in Table 5.

As we saw above, parental income has a large impact on occupational outcomes at age 42, with the coefficient more than doubling across cohorts. Table 5 indicates that this effect occurs largely through education. However, for the BCS70 cohort the relative impacts on the likelihood to be in a high-paying occupation have changed, with parental income becoming more important (an increase in the coefficient from 0.08 to 0.39) and own education less (with the coefficient going from 0.97 to 0.76) than for the NCDS58 cohort.

Consider next the role played by initial occupation. 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 (second panel) and the coefficients for BCS70 indicate the change in the log-odds between both cohorts (third 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,

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 and child education distribution. Probabilities are computed for males in both cohorts according to the multinomial logistic regression reported in columns (3) of the table D.4 in the appendix.

with the coefficients on the diagonal being large and highly significant. Note that being in a middling-occupation when implies not only a high probability of being in that occupation when mature (coefficient of 1.44) but also a high probability of moving to a high-paying occupation (coefficient of 0.90). When we compare the impact of initial occupation across the cohorts (third panel) there are only two significant changes. 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. For those who started in middling occupations, persistence increased.

Figure 8 presents the change in the probability of being in each occupation in the second period depending on the first-period occupation (for males only). [18]. Changes in the probability are defined as the difference in probability between the two cohorts. Probabilities are computed using the multinomial regression in Table D.4, at the mean of parental income and child education. 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.

The changes are not large at the top of the distribution. Notably, the fourth graph, reporting changes in the probability of being in a high-paying occupation, implies that although the probability of being in such an occupation has increased for individuals who

[18]Equivalent figures and tables to those presented in the rest of this section but for women are provided in the Appendix. See Figures E.2 and E.3 and Table 7

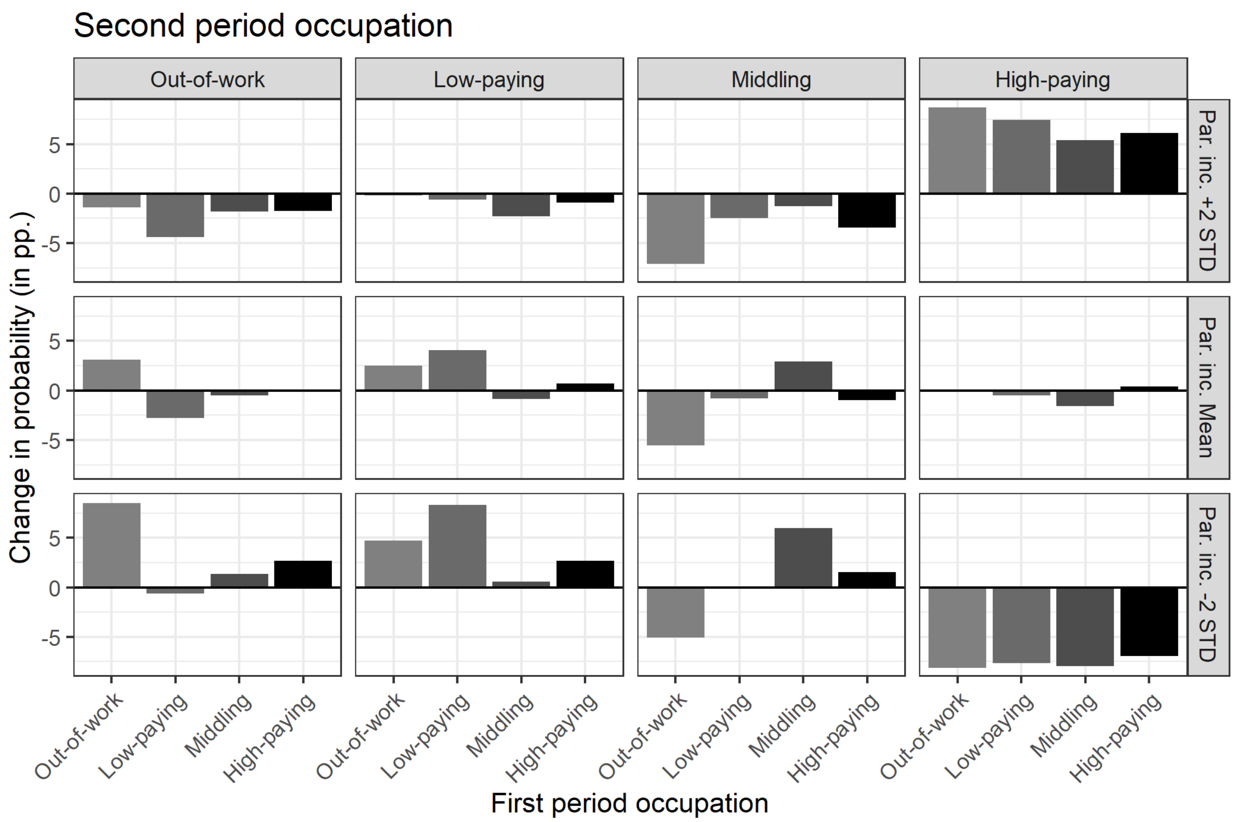
started in a high-paying job and declined for the others, the magnitudes are small, less than one percentage point. Larger changes are observed in other categories. The probability of being in a middling occupation in late career has increased by almost 3 pp. for those who started in such occupation but declined for all other groups. 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 3.1 pp., and although the probability of being in a low-paying occupation at 42 has increased about 2.5 pp. this has occurred at the expense of moving into middling jobs with a decline about -5.55 pp.

These changes do not capture the differences that may be due to parental background, which we have seen became more important -as measured by its direct effect- 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 income distribution the changes are large and of opposite sign. Notably, for those who started in any occupation other that high-paying and who came from a household with parental income 2-standard-deviations below the mean, the reduction in the probability is between 6.9 and 8.1 pp.; even those who started in high-paying occupations are less likely to remain there if parental income is low. In contrast, when parental income is 2-standard-deviations above the mean there are large increases in the likelihood of remaining or moving to the top, with those who started in a low-paying occupation experiencing an increase of 7.5 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 pp. for the former and by 8 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 lower persistence and 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.

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.) and at the mean of the child education distribution. Probabilities are computed for males in both cohorts according to the multinomial logistic regression reported in columns (3) of the table D.4 in the appendix.

The analysis we have just performed considers the direct effect of parental income, but as is well established and we have seen above, much of this effect occurs through its impact on the child's education. We hence examine the change in the probability to be in each occupation for different positions in the distribution of the child's education, depicted in Figure 10, (again for males only).[19] The middle row of graphs is again that depicted in Figure 8 for average parental income and child's education, while the top and bottom rows depict the results for individuals which are one-standard-deviation above and below the mean

[19] As before, changes are defined as the difference in probability between the cohorts, and probabilities are computed from the multinomial logistic regression reported in the appendix (see table D.4) for an individual with the cohort-average parental income.

Figure 10: Change in probability to be in each occupation in the second period according to the first-period occupation and child education (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 child education distribution (at +1 std., at the mean and at +1 std.) and 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 (3) of the table D.4 in the appendix.

of child's education.[20].

Although the changes are again much larger at the top and bottom than at the mean, they imply that the effect of education on mobility during the individual's career has diminished. In terms of the likelihood of moving into high-paying occupations, those at the top of the education distribution are less likely to move to or stay for the younger than for the older cohort irrespective of their initial occupation. The opposite occurs for those with low educational achievement. The disappearance of middling jobs has reduced both the probability of those starting in low-paying occupations to upgrade their occupation to

[20]Looking at two standard deviations is not particularly interesting in the case of education since individuals are bunched at the bottom (secondary schooling) and top (higher degree) of the distribution, contrary to parental income where dispersion is much greater and we have a long right-tail

middling and for those starting there to remain for low and average educational levels, but increased it for those at the top of the education distribution. For the younger cohort, those starting in low-paying jobs experienced an increase in the likelihood of remaining in that occupational category between 3.88 and 6.72 pp. depending on their level of schooling.

We summarize these results in Tables 6 and 7. 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 and child education distributions as in the graphs above.

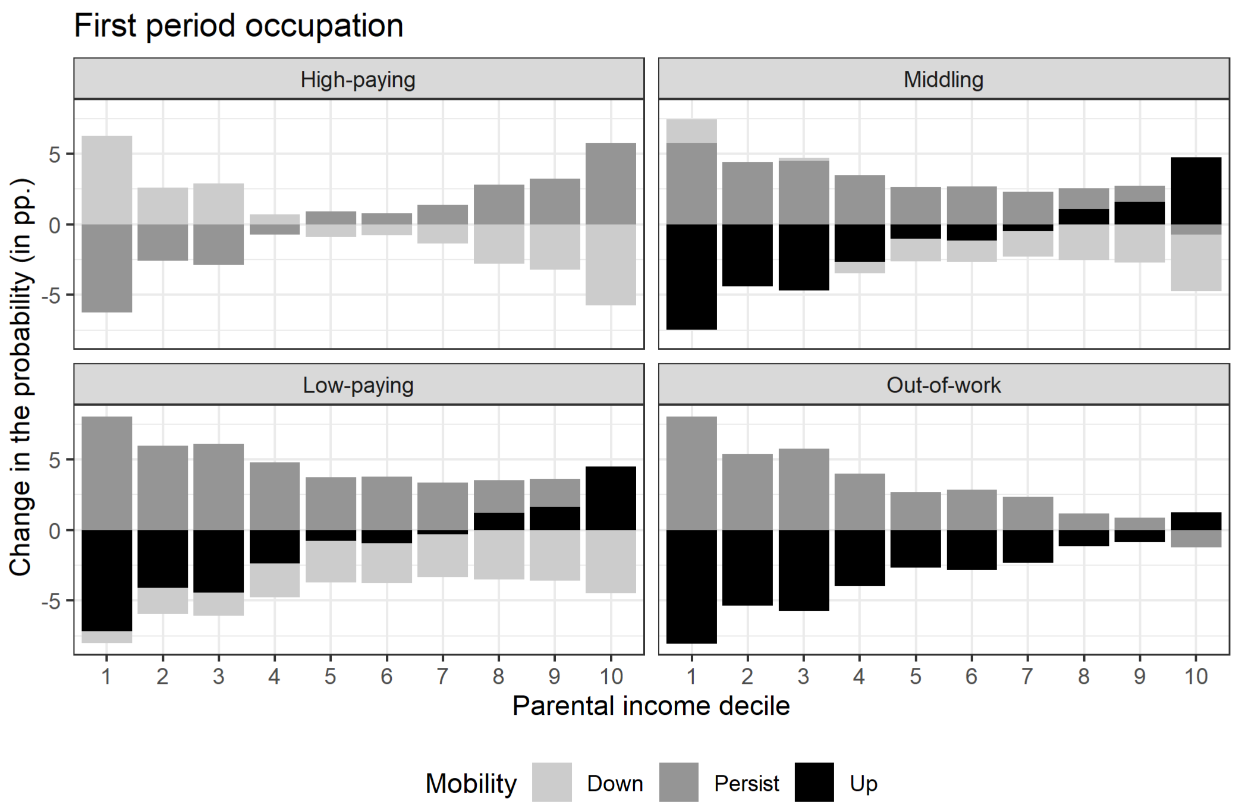
Table 6 presents the results for men. Consider first the role of parental income. At the mean, persistence has increased and both upwards and downwards mobility have declined, irrespective of the initial occupation. For those in low-paying occupations the younger cohort has lost 1.31 pp. in upwards mobility, which amounts to a reduction of 5% as compared to the NCDS cohort.[21] For those starting in middling occupations there is a reduction of 1.56 pp. representing a decline of 12%. When we look at the top of the parental income distribution (top left panel) we find large 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 7.69 and 8.50 percentage points, and the probability of remaining in a high-paying job has fallen by 6.9 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. When we consider the effects at different points of the education distribution, we find that the advantage conferred by education has declined, with upwards mobility falling for those at the top of the educational distribution.

These results are depicted graphically in Figure 11

Table 7 presents equivalent results for women. 12

[21] The probability of upward mobility for this cohort was 24%; see Table 2.

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



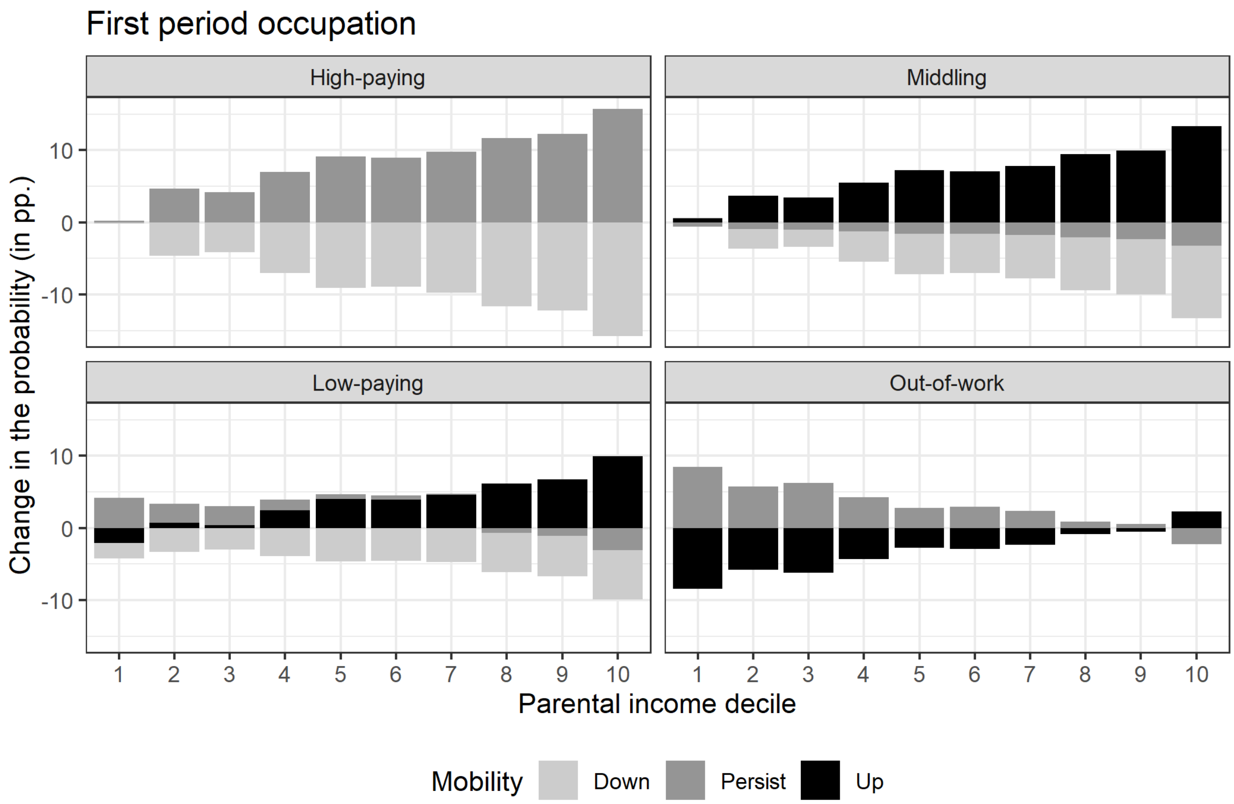
Notes: This figure presents the difference, expressed in percentage points, between the BCS70 and the NCDS58 cohorts in terms of type of mobility (down, persist, up) conditional on the first period occupation (out-of-work, low-paying, middling, high-paying) according to the decile of the parental income distribution. Probabilities are computed for males with average education in both cohorts at each parental income decile, according to the multinomial logistic regression reported in columns (3) of the table D.4 in the appendix.

4 Conclusion

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

Our empirical approach consists of examining the occupational outcomes of children in the two cohorts, taking into account parental characteristics. An important aspect of our analysis it that, since we have data fort children at various ages, we can identify to what extent mobility is driven by an improvement in the occupation at which the child enters the labour market or by going up the occupational ladder during her work-life. 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

Figure 12: 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 with average education in both cohorts at each parental income decile, according to the multinomial logistic regression reported in columns (3) of the table D.4 in the appendix.

more polarized labour market.

The data indicates two major changes across generations. First, we find that the share of individuals who start their careers in middling occupations has declined markedly between the older and the younger cohort. Second, the probability of those who start in low-paying occupations to move into middling jobs has also fallen. As a result, two sources of occupational mobility seem to have weakened. We then examine how parental income affects the various steps that determine the child's outcome at age 40, focusing on changes across the two cohorts. Our results show that the role of parental income in determining occupations has increased, and that the difference across the two cohorts is only partly due to a greater effect of parental characteristics on educational attainment, with the rest being driven largely by the type of entry job that the child holds (conditional on education). In fact, our results indicate that not only there are fewer middling entry jobs, but also that parental income has become more important in having access to those jobs. Lastly, the fortunes of those who start in low-paying jobs differ considerably across generations. For the older cohort, a considerable fraction moved onto 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 to high-paying jobs has increased, yet only for those with high-income parents.

These results highlight that as middling jobs were eroded, the natural progression from low-paying into middling-paying, and eventually into high-paying occupations, has become less likely. Moreover, not only has the likelihood of upwards mobility during the individual's work-life decreased, it has also become more dependent on parental income. These results hence indicate that the structure of employment affects not only the distribution of income but also its persistence across generations and raise major policy concerns as they indicate that the fragmentation of the labour market enhances social fragmentation.

Table 3: Determinants of the 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)
Female	0.07^{***}	0.06^{***}	0.07^{***}	0.05^{**}	0.05^{**}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Parental income	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)
BCS cohort	-0.03	-0.05^{**}	-0.05^{**}	-0.11^{***}	-0.05
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Female × BCS	0.02	0.03	0.02	0.00	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Parental income × BCS	0.11^{***}	0.11^{***}	0.08^{***}	0.05^{**}	0.06^{***}
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Father's educ. × BCS		-0.10^{***}	-0.07^{***}	-0.04^{*}	-0.03
		(0.02)	(0.02)	(0.02)	(0.02)
Mother's educ. × BCS		-0.03	-0.02	-0.03^{*}	-0.05^{**}
		(0.02)	(0.02)	(0.02)	(0.02)
Father's soc. class × BCS			-0.06^{***}	-0.04^{**}	-0.05^{**}
			(0.02)	(0.02)	(0.02)
Number of siblings × BCS					0.08^{***}
					(0.02)
Eldest child × BCS					-0.01
					(0.04)
Parents' interest in education				Yes	Yes
Region FE				Yes	Yes
R^2	0.04	0.09	0.11	0.18	0.18
Adj. R^2	0.04	0.09	0.11	0.17	0.18
Num. obs.	20722	17354	13901	11814	10509

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Male in the NCDS58 cohort is the referent group. Parental income is in logarithm then standardized, see below. 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. Estimate without standardized variables is also reported in the appendix, see table C.1.

Table 4: Probability of being in each occupation at first period (multinomial)

	Multinomial logit - Dep. var.: First period occupation		
	Low-paying	Middling	High-paying
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	0.03	-0.04	-0.05
	(0.07)	(0.05)	(0.06)
Num. obs.	14556	14556	14556

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 child education in peer-inclusive ranking, both are standardized at the cohort level. Control variables in all regressions include Intercept, BCS cohort, Female and Female × BCS; see table D.2 in the appendix for these coefficients.

Table 5: Probability of being in each occupation in the second period (multinomial)

	Multinomial logit - Dep. var.: Second period occupation					
	(2)			(3)		
	Low	Mid	High	Low	Mid	High
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	−0.03	−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**	0.62***	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.	14556	14556	14556	14556	14556	14556

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. Control variables in all regressions include Intercept, BCS cohort, Female and Female × BCS; see table D.4 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.

Table 6: Change in intra-generational mobility across cohorts (male only)

	Type of mobility according to					
	Parental income			Child education		
First period occupation	Down	Persist	Up	Down	Persist	Up
	at +2 STD			*at +1 STD*		
Out-of-work		-1.41	1.41		3.87	-3.87
Low-paying	-4.38	-0.59	4.96	-1.16	4.96	-3.80
Middling	-4.11	-1.29	5.41	0.34	7.66	-8.00
High-paying	-6.12	6.12		2.96	-2.96	
	at the Mean			*at the Mean*		
Out-of-work		3.10	-3.10		3.10	-3.10
Low-paying	-2.76	4.07	-1.31	-2.76	4.07	-1.31
Middling	-1.36	2.93	-1.56	-1.36	2.93	-1.56
High-paying	-0.37	0.37		-0.37	0.37	
	at -2 STD			*at -1 STD*		
Out-of-work		8.50	-8.50		2.85	-2.85
Low-paying	-0.65	8.34	-7.69	-3.67	3.52	0.15
Middling	1.98	5.96	-7.95	-2.60	-0.70	3.31
High-paying	6.90	-6.90		-6.36	6.36	

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 the 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.) and the child education distribution (at +1 std., at the mean, at -1std.) for males only. These values are computed from the results obtained in figures 9 and 10.

Table 7: Change in mobility across cohorts (female only)

	Type of mobility according to					
	Parental income			Child education		
First period occupation	Down	Persist	Up	Down	Persist	Up
	at +2 STD			*at +1 STD*		
Out-of-work		-2.50	2.50		3.63	-3.63
Low-paying	-6.69	-3.94	10.63	-3.61	1.87	1.74
Middling	-10.38	-3.73	14.11	-2.93	0.89	2.05
High-paying	-16.22	16.22		-2.18	2.18	
	at the Mean			*at the Mean*		
Out-of-work		3.23	-3.23		3.23	-3.23
Low-paying	-4.43	0.93	3.50	-4.43	0.93	3.50
Middling	-5.15	-1.47	6.62	-5.15	-1.47	6.62
High-paying	-8.44	8.44		-8.44	8.44	
	at -2 STD			*at -1 STD*		
Out-of-work		8.88	-8.88		3.99	-3.99
Low-paying	-1.88	4.45	-2.57	-4.16	1.35	2.81
Middling	0.49	-0.59	0.10	-5.42	-2.11	7.53
High-paying	0.57	-0.57		-13.51	13.51	

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 the 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.) and the child education distribution (at +1 std., at the mean, at -1std.) for females only. These values are computed from the results obtained in figures E.2 and E.3.

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Appendices

A Data descriptives and summary statistics

This appendix presents data descriptives and summary statistics, and provides additional tables and figures about the structure of employment and the observed job polarization in the data.

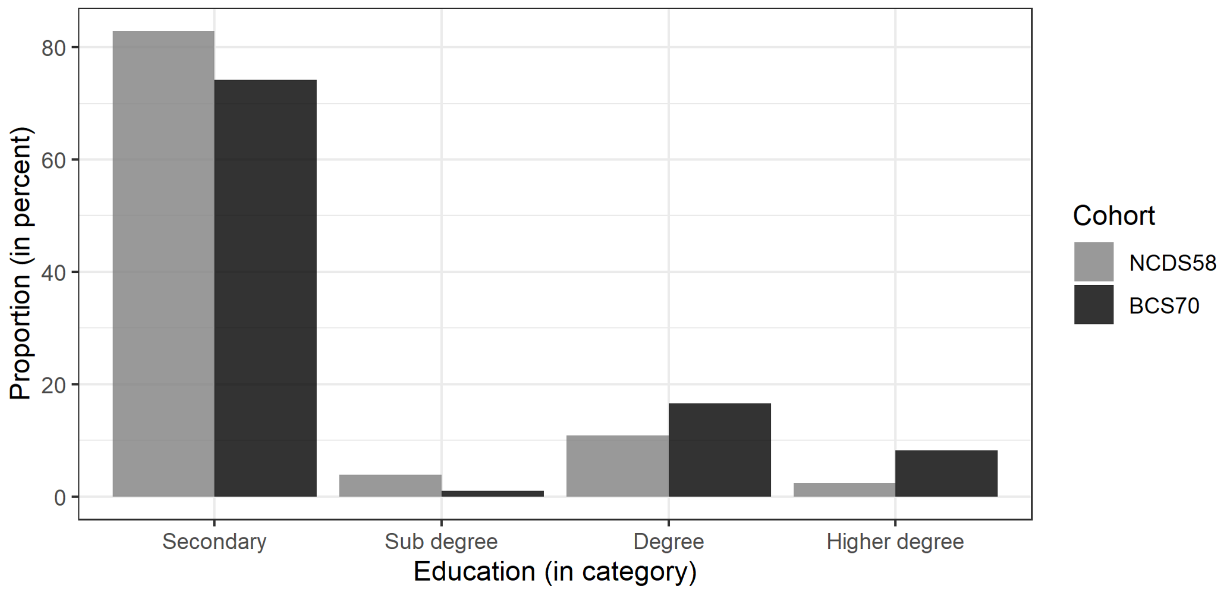
Table A.1 reports the summary statistics for the individual data. Given that the overall educational attainment of the population has increased considerably across the two cohorts, Figure A.1 presents the distribution of the child's education for both cohorts. We have regrouped child education into four categories for ease of exposition. As expected, educational attainment has increased across the cohorts. The proportion of individuals with a sub-degree has more than doubled, while the proportion of individuals with a higher degree has been multiplied by 1.58. Figure A.2 presents the distributions of education for fathers and mothers. For parental education, we use the age at which each parent left full-time education.

Table A.1: Summary statistics - Individual data

	N = 14556							
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	0.53	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	0
Education - Sub degree	0.03	0.16	0.00	0.00	0.00	0.00	1.00	0
Education - Degree	0.16	0.36	0.00	0.00	0.00	0.00	1.00	0
Education - Higher degree	0.06	0.24	0.00	0.00	0.00	0.00	1.00	0
Household								
Parental income	30.42	14.61	1.47	19.27	27.87	37.55	115.35	0
Sibling size	2.64	1.37	1.00	2.00	2.00	3.00	12.00	1692
Eldest child	0.56	0.50	0.00	0.00	1.00	1.00	1.00	1692
Mother								
Age	24.23	6.29	8.00	20.00	24.00	28.00	58.00	1525
Age left school	16.35	1.49	13.00	15.00	16.00	17.00	22.00	1560
Int. in educ. - Very interested	0.48	0.50	0.00	0.00	0.00	1.00	1.00	2257
Int. in educ. - Moderate interest	0.32	0.47	0.00	0.00	0.00	1.00	1.00	2257
Int. in educ. - Cannot say	0.11	0.31	0.00	0.00	0.00	0.00	1.00	2257
Int. in educ. - Little interest	0.09	0.28	0.00	0.00	0.00	0.00	1.00	2257
Father								
Age	27.20	7.07	11.00	22.00	26.00	31.00	67.00	1997
Age left school	16.42	1.79	13.00	15.00	16.00	17.00	22.00	2110
Int. in educ. - Very interested	0.37	0.48	0.00	0.00	0.00	1.00	1.00	2912
Int. in educ. - Moderate interest	0.24	0.43	0.00	0.00	0.00	0.00	1.00	2912
Int. in educ. - Cannot say	0.29	0.45	0.00	0.00	0.00	1.00	1.00	2912
Int. in educ. - Little interest	0.11	0.31	0.00	0.00	0.00	0.00	1.00	2912
Social class	3.02	0.93	1.00	2.00	3.20	3.20	5.00	2974
Occupation - High-paying	0.27	0.45	0.00	0.00	0.00	1.00	1.00	2665
Occupation - Middling	0.52	0.50	0.00	0.00	1.00	1.00	1.00	2665
Occupation - Low-paying	0.17	0.37	0.00	0.00	0.00	0.00	1.00	2665
Occupation - Out-of-work	0.04	0.20	0.00	0.00	0.00	0.00	1.00	2665

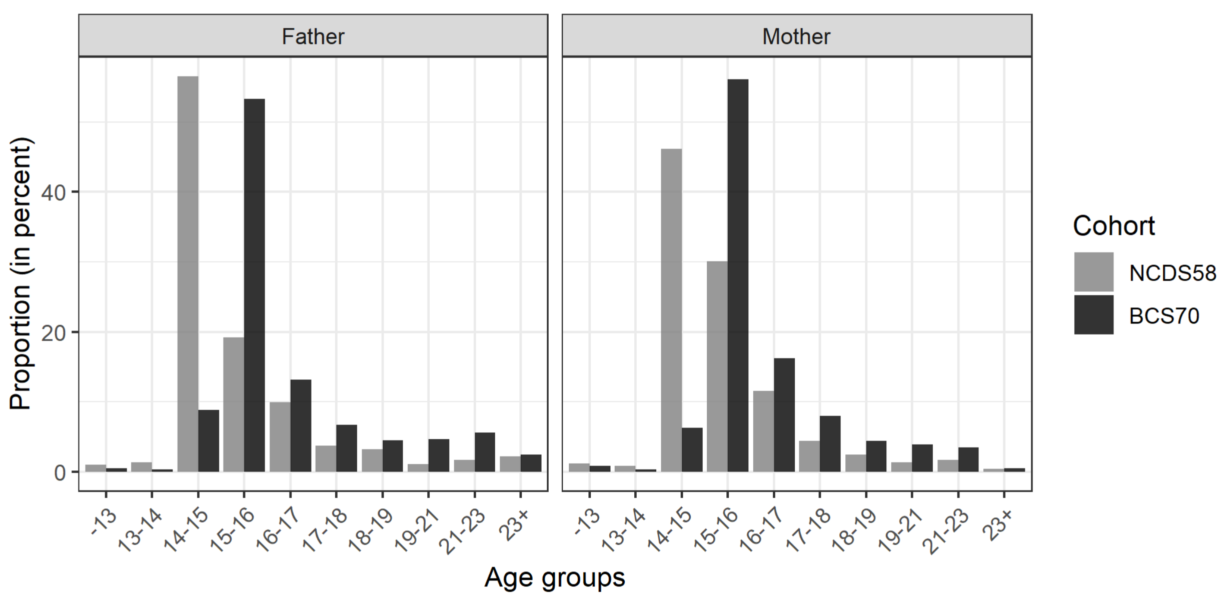
Notes: This table provides summary statistics for individual time-invariant data from the BCS70 and NCDS58 cohorts.

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.

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.

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.

Table A.2 describes the classification of occupations 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 employment and occupational categories.

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

	NCDS58 - N = 6761				BCS70 - N = 7795			
	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	0.41	0.72	0.45
Activity - Self-employed	0.05	0.21	0.12	0.32	0.06	0.24	0.14	0.35
Activity - Unemployed	0.05	0.23	0.02	0.14	0.02	0.15	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	0.13	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	25.20	16.47	36.13	25.56

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

Table A.4 reports the average weekly pay by occupation. Weekly pay is more concentrated for young individuals than for mature ones, as wages tend to grow faster with age for those in high-paying occupations. The table indicates that the average pay has increased for every type of occupation between both cohorts. The change across cohort of pay at age 42 is roughly the same for the three categories, lying between 14 and 15%. In contrast, for young individuals, the change has been much larger for those in high-paying occupations (50%) than for the other two groups (13 and 20%, respectively, in low-paying and middling occupations).

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).[22] 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

[22]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.

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

	First period		Second period	
Occupation	NCDS58	BCS70	NCDS58	BCS70
Low-paying	17.05	19.33	17.75	20.23
	(0.30)	(0.61)	(0.39)	(0.38)
Middling	19.59	23.43	25.26	29.11
	(0.16)	(0.34)	(0.45)	(0.40)
High-paying	19.51	29.23	40.82	46.72
	(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)
in-Education	0.89	0.79	0.84	0.62
	(0.01)	(0.01)	(0.03)	(0.05)
Low-paying	0.54	0.51	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.

and the high attainment of those still in education.

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 6 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 also reported in table A.7

Figure A.3 presents the change in the frequencies of second period occupation according to the average weekly pay for the BCS70 cohort. Figure A.4 displays the negative relationship

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	15.9	21.3	-5.4	13.6	14.3	-0.7
Low-paying	14.9	14.0	0.9	18.2	19.1	-0.9
Middling	33.2	41.2	-7.9	23.8	28.0	-4.2
High-paying	35.9	23.5	12.4	44.3	38.5	5.8

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.

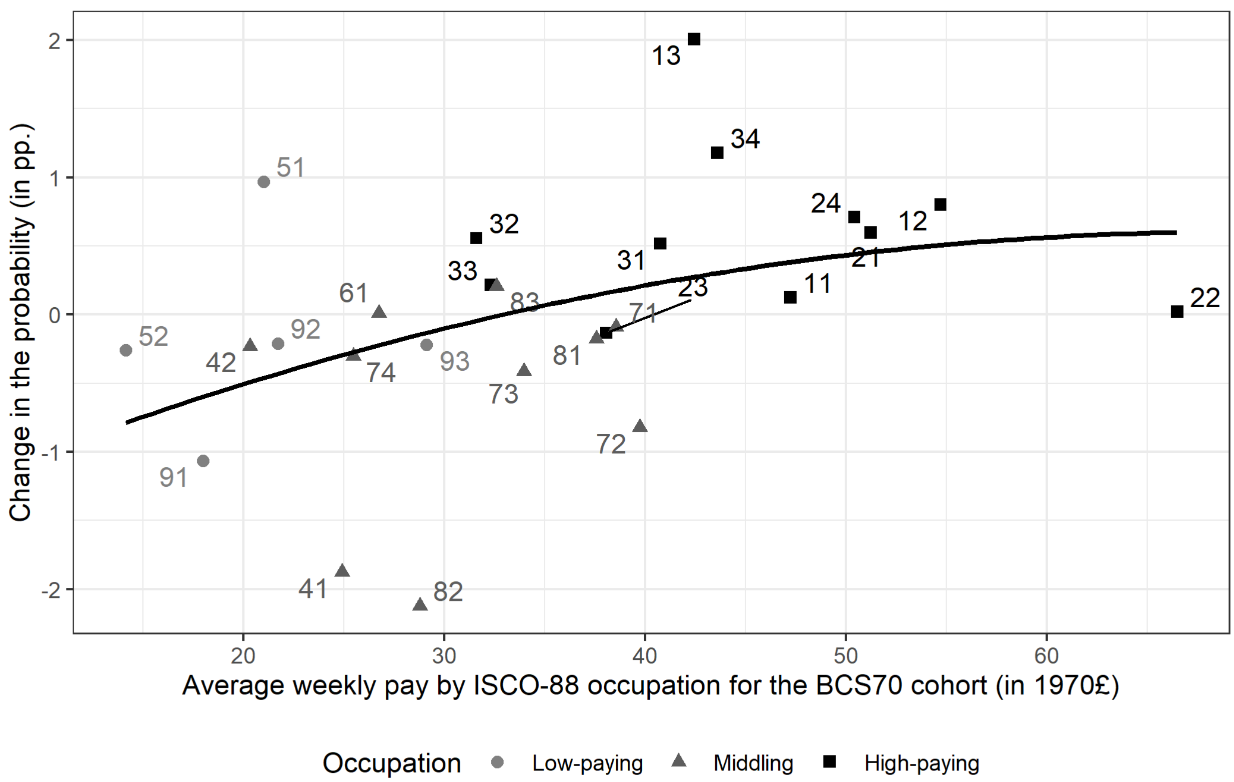
Table A.7: Probability to be in each occupation at both periods, isolating those in-education (in percent)

	First period			Second period		
Occupation	BCS70	NCDS58	Δ	BCS70	NCDS58	Δ
Out-of-work	13.1	19.1	-5.9	13.3	13.7	-0.4
in-Education	2.8	2.2	0.5	0.3	0.6	-0.3
Low-paying	14.9	14.0	0.9	18.2	19.1	-0.9
Middling	33.2	41.2	-7.9	23.8	28.0	-4.2
High-paying	35.9	23.5	12.4	44.3	38.5	5.8

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.

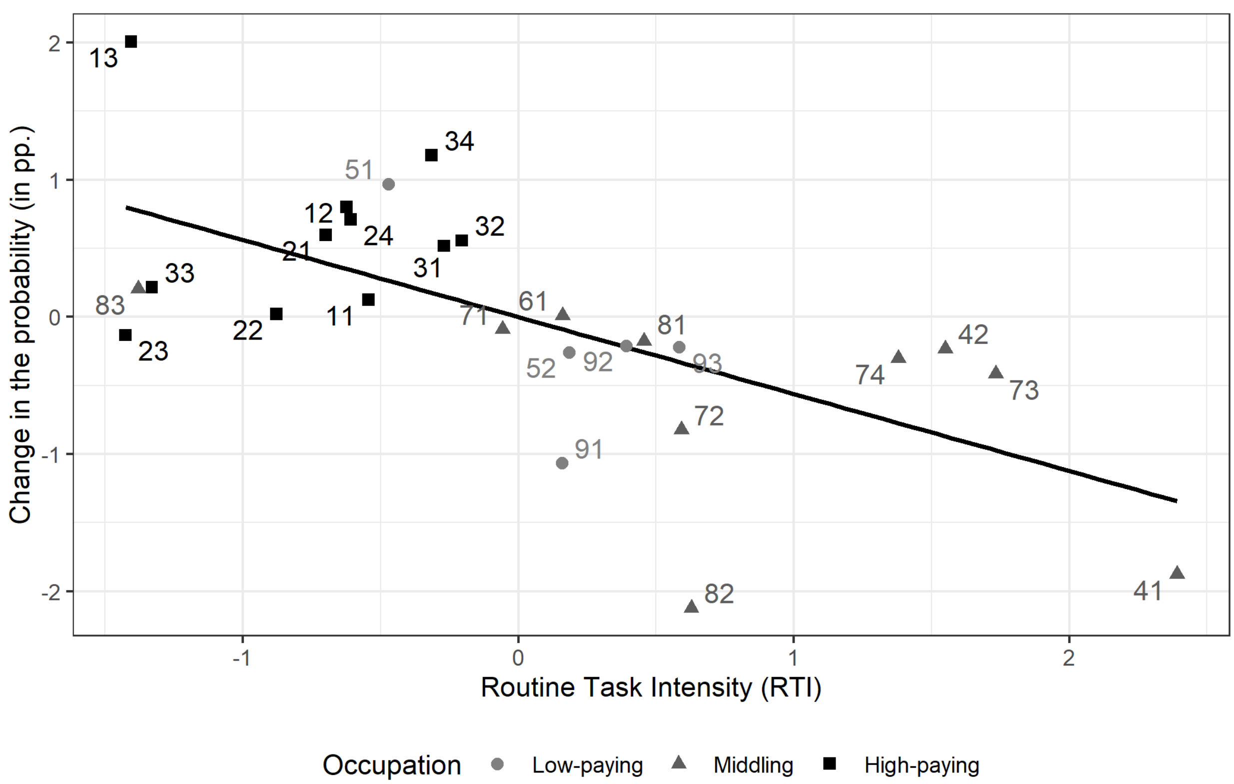
between the probability of second period occupation according to the routine task intensity.

Figure A.3: 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.4: 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).

Table A.8: Conditional probabilities of changing occupations during the career (in percent)

	BCS70					NCDS58					Δ				
Occupation	Out	Educ	Low	Mid	High	Out	Educ	Low	Mid	High	Out	Educ	Low	Mid	High
Out-of-work	35.6	0.7	28.5	15.7	19.5	28.3	0.8	27.0	22.2	21.7	7.3	-0.1	1.5	-6.5	-2.1
in-Education	14.0	0.5	10.7	11.2	63.7	10.7	0.0	5.3	8.0	76.0	3.3	0.5	5.4	3.2	-12.3
Low-paying	13.4	0.3	44.4	17.8	24.1	15.8	0.5	39.9	20.3	23.4	-2.4	-0.2	4.5	-2.6	0.7
Middling	10.0	0.3	13.9	44.7	31.1	9.8	0.5	15.5	43.3	30.9	0.2	-0.2	-1.6	1.4	0.2
High-paying	8.0	0.2	8.1	11.1	72.6	7.7	0.8	8.1	12.3	71.1	0.3	-0.6	0.0	-1.3	1.5

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

B Decomposing changes

To understand changes in the occupations of mature individuals we consider a decomposition of the probability of being in a high paying occupation at age 42. Let $P_c^t(i)\ \forall i \in \{H, M, L, O\}\ \forall c \in \{A, B\}$ be the probability to be in occupation i at time t for an individual in cohort c.

The probability to be in a high-paying occupation at age 42 for an individual in cohort c depends both on the share in each occupation when he is young, $P_c^t(i)$, and on the conditional probability to be in occupation j at time 2 conditional on being in occupation i at time 1, $P_c^t(j|i)$, where $i \in \{H, M, L, O\}$ is the first-period occupation. The probability for a mature individual to be in a high-paying occupation can hence be written as

$$P_c^2(H) = \sum_i P_c^2(H|i) \times P_c^1(i).$$

The change in the probability of being in a high-paying occupation can then be written as

$$\Delta P^2(H) \equiv P_B^2(H) - P_A^2(H) = \sum_i \Delta P^1(i) \times P_A^2(H|i) + \sum_i \Delta P^2(H|i) \times P_B^1(i). \quad (4)$$

There are hence two sources of variation in the probability to be in high-paying occupation when mature: changes in the distribution of first-period occupations, captured by the first term in equation (4), and changes in the conditional probabilities of changing occupations during the career, captured by the second term.

Table B.1 presents the decomposition in equation (4) of the change in the probability of being in a high-paying occupation when mature. The overall change is 5.8 pp., of which 5.1 points (i.e. 88.3% percent) are due to the change in initial probabilities. The columns in the table compute the contribution to $\Delta P^2(H)$ of changes in each occupational category, whether because the share of individuals initially in that category has changed or because the probability of transiting to a high-paying occupation has changed. Three effects dominate.

Table B.1: Change in probability of being in a high-paying occupation when mature

	Occupations				
	All	Out-of-work	Low-paying	Middling	High-paying
Overall change	5.8				
(in %)	15.0				
Contribution due to...					
Initial probabilities	5.1	-1.5	0.2	-2.5	8.8
(as % of total)	88.3	-25.3	3.6	-42.4	152.4
Transition probabilities	0.7	-0.0	0.1	0.1	0.5
(as % of total)	11.7	-0.4	1.7	1.3	9.1

Notes: This table quantifies the respective roles of initial and transition probabilities in the probability change of being in a high-paying occupation at the age of 42 between both cohorts. Coefficients are rounded to one digit.

First, as far as the contribution of transition probabilities is concerned, most of its impact is due to a change of 0.5 pp. in the probability of those who started in high-paying occupations to remain in that category. The bulk of the effect is, however, due to a change in the initial distribution of occupations, with a strong negative impact from the fact that fewer individuals start their careers in middling occupations and a large positive effect due to more youngsters starting in high-paying ones.

Two mechanisms are thus in operation.The higher share of individuals in high-paying occupations is due to both more workers entering the labour market in a high-paying occupation and a greater likelihood of remaining in the occupation. These two mechanisms together would have increased the share of workers in high-paying occupations by 8.8 points. This effect is partially offset by the reduction in the fraction of young individuals employed in middling occupations, which reduces the share in high-paying occupations by 2.5 points. This is a large effect, almost a third of the positive effect, the reason being that those starting in middling occupations have a high probability of moving upwards (of over 30% as we saw above). In fact, if the distribution of initial occupations had remained the same and the only difference between the two cohorts had been the transition probabilities, we would have observed an increase in the share of individuals in high-paying occupations of 0.7 instead of the 5.8 pp. we actually observe.

Similar decompositions for low-paying and middling occupations are reported in tables B.2 and B.3; see below. We also consider the same analysis with people in education as an occupation and not included in out-of-work. Tables A.7 and A.8 report the absolute and conditional probabilities. Tables B.4, B.5 and B.6 present the counterfactual decompositions

Table B.2: Change in probability of being in a low-paying occupation when mature

	Occupations				
	All	Out-of-work	Low-paying	Middling	High-paying
Overall change	-0.9				
(in %)	-4.9				
Contribution due to...					
Initial probabilities	-1.2	-1.3	0.4	-1.2	1.0
(as % of total)	127.3	141.9	-38.3	131.3	-107.6
Transition probabilities	0.3	0.1	0.7	-0.5	0.0
(as % of total)	-27.4	-11.0	-71.5	56.3	-1.1

Notes: Coefficients in percent are rounded to one digit.

for, respectively, the low-, mid- and high-paying occupations. The results we report below indicate that the reduction by 4.2 pp. of the share of mature individuals in middling occupations is due, roughly, two thirds to changes in initial probabilities to be in that category and one third to changes in transitions, notably to a reduction in the likelihood that those out-of-work and in low-paying occupations move into middling ones.

Overall our results indicate that the reduction in the availability of middling jobs had two effects. First, an important source of upwards mobility - the transition from middling to high-paying jobs- has become less important as fewer individuals start in those jobs. Second, middling jobs were often the end-outcome for those starting in low-paying occupations or in unemployment, but as their number has shrunk this mechanism has also become weaker. The overall effect is that there is greater persistence of initial occupations. We turn next to what determines an individual's initial occupation and to what extent parental background matters.

This appendix provides the additional counterfactual decompositions for the low-paying and middling, based on the same methodology of Table B.1. Table B.2 and B.3 present the change in probability of being in a low-paying and middling occupations when mature.

Table B.3: Change in probability of being in a middling occupation when mature

	Occupations				
	All	Out-of-work	Low-paying	Middling	High-paying
Overall change	-4.2				
(in %)	-14.8				
Contribution due to...					
Initial probabilities	-2.8	-1.1	0.2	-3.4	1.5
(as % of total)	68.5	26.8	-4.4	83.0	-36.9
Transition probabilities	-1.3	-0.9	-0.4	0.4	-0.4
(as % of total)	31.5	22.2	9.2	-10.8	10.9

Notes: Coefficients in percent are rounded to one digit.

Table B.4: Change in probability of being in a low-paying occupation when mature

	Occupations					
	All	Out	Educ	Low	Mid	High
Overall change	-0.9					
(in %)	-4.9					
Contribution due to...						
Initial probabilities	-1.4	-1.6	0.0	0.4	-1.2	1.0
(as % of total)	152.8	170.5	-3.1	-38.3	131.3	-107.6
Transition probabilities	0.5	0.2	0.1	0.7	-0.5	0.0
(as % of total)	-52.8	-20.7	-15.8	-71.5	56.3	-1.1

Notes: Coefficients in percent are rounded to one digit.

Table B.5: Change in probability of being in a middling occupation when mature

	Occupations					
	All	Out	Educ	Low	Mid	High
Overall change	-4.2					
(in %)	-14.8					
Contribution due to...						
Initial probabilities	-3.0	-1.3	0.0	0.2	-3.4	1.5
(as % of total)	72.3	31.6	-1.0	-4.4	83.0	-36.9
Transition probabilities	-1.1	-0.8	0.1	-0.4	0.4	-0.4
(as % of total)	27.7	20.6	-2.1	9.2	-10.8	10.9

Notes: Coefficients in percent are rounded to one digit.

Table B.6: Change in probability of being in a high-paying occupation when mature

	Occupations					
	All	Out	Educ	Low	Mid	High
Overall change	5.8					
(in %)	15.0					
Contribution due to...						
Initial probabilities	5.7	-1.3	0.4	0.2	-2.5	8.8
(as % of total)	98.6	-22.1	7.1	3.6	-42.4	152.4
Transition probabilities	0.1	-0.3	-0.3	0.1	0.1	0.5
(as % of total)	1.4	-4.9	-5.8	1.7	1.3	9.1

Notes: Coefficients in percent are rounded to one digit.

C Determinants of education

This appendix provides the alternative specifications for estimating determinants of the child's education from equation (1). Table C.1 shows the estimated coefficients for non-standardized education using as explanatory variable non-standardized parental income. Table C.2 (resp. table C.3) presents determinants of the standardized (resp. non-standardized) child's education with father's occupation as an explanatory variable.

Table C.1: Determinants of the (non-standardized) child's education (according to parental income)

	Linear regression - Dep. var.: Education (in PIR)				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.50^{***}	0.31^{***}	0.29^{***}	0.34^{***}	0.35^{***}
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Female	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{**}	0.01^{**}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Parental income	0.04^{***}	0.02^{***}	0.02^{***}	0.02^{***}	0.02^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Father's education		0.22^{***}	0.16^{***}	0.10^{***}	0.10^{***}
		(0.01)	(0.02)	(0.02)	(0.02)
Mother's education		0.12^{***}	0.11^{***}	0.09^{***}	0.10^{***}
		(0.01)	(0.01)	(0.01)	(0.01)
Father's soc. class			0.13^{***}	0.09^{***}	0.09^{***}
			(0.01)	(0.01)	(0.01)
Number of siblings					-0.01^{***}
					(0.00)
Eldest child					0.01^{***}
					(0.01)
BCS cohort	-0.16^{***}	-0.05^{***}	-0.02	-0.02	-0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Female × BCS	0.00	0.01	0.00	0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Parental income × BCS	0.05^{***}	0.05^{***}	0.04^{***}	0.02^{***}	0.03^{***}
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Father's educ. × BCS		-0.14^{***}	-0.09^{***}	-0.05^{***}	-0.05^{**}
		(0.02)	(0.02)	(0.02)	(0.02)
Mother's educ. × BCS		-0.03	-0.02	-0.03^{*}	-0.05^{**}
		(0.02)	(0.02)	(0.02)	(0.02)
Father's soc. class × BCS			-0.04^{***}	-0.03^{**}	-0.03^{**}
			(0.01)	(0.01)	(0.01)
Number of siblings × BCS					0.01^{***}
					(0.00)
Eldest child × BCS					-0.00
					(0.01)
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. Education variables and the father's social class variable are defined in peer-inclusive ranking. Estimate with standardized variables is reported in table 3.

Table C.2: Determinants of the child's education (according to father's occupation)

	Linear regression - Dep. var.: Education (in PIR-STD)				
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.17^{***}	-0.09^{***}	-0.03	-0.22^{***}	-0.16^{***}
	(0.02)	(0.03)	(0.03)	(0.05)	(0.06)
Female	0.09^{***}	0.07^{***}	0.07^{***}	0.06^{***}	0.06^{**}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Father in Out-of-work	-0.21^{***}	-0.20^{***}	-0.06	-0.09	-0.16
	(0.04)	(0.05)	(0.67)	(0.65)	(0.65)
Father in Middling	0.09^{***}	0.07^{**}	0.01	0.02	0.02
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Father in High-paying	0.71^{***}	0.50^{***}	0.31^{***}	0.21^{***}	0.20^{***}
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Father's education		0.14^{***}	0.13^{***}	0.09^{***}	0.09^{***}
		(0.01)	(0.01)	(0.01)	(0.01)
Mother's education		0.13^{***}	0.13^{***}	0.10^{***}	0.11^{***}
		(0.01)	(0.01)	(0.01)	(0.01)
Father's soc. class			0.13^{***}	0.10^{***}	0.09^{***}
			(0.01)	(0.02)	(0.02)
Number of siblings					-0.04^{***}
					(0.01)
Eldest child					0.08^{***}
					(0.03)
BCS cohort	-0.09^{**}	-0.11^{***}	-0.06	-0.16^{***}	-0.20^{***}
	(0.04)	(0.04)	(0.05)	(0.05)	(0.08)
Female × BCS	-0.01	0.01	-0.00	-0.02	-0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Father in Out. × BCS	-0.04	-0.11	-0.26	-0.23	-0.52
	(0.10)	(0.12)	(0.86)	(0.91)	(1.12)
Father in Mid. × BCS	0.02	0.01	-0.00	0.04	0.05
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
Father in High × BCS	-0.13^{***}	-0.05	-0.05	0.05	0.04
	(0.04)	(0.05)	(0.07)	(0.07)	(0.08)
Father's educ. × BCS		-0.06^{***}	-0.06^{***}	-0.03^{*}	-0.02
		(0.02)	(0.02)	(0.02)	(0.02)
Mother's educ. × BCS		-0.01	-0.00	-0.02	-0.03
		(0.02)	(0.02)	(0.02)	(0.02)
Father's soc. class × BCS			-0.05^{**}	-0.04^{*}	-0.04^{*}
			(0.02)	(0.02)	(0.03)
Number of siblings × BCS					0.04^{***}
					(0.02)
Eldest child × BCS					-0.03
					(0.04)
Parents' interest in education				Yes	Yes
Region FE				Yes	Yes
R^2	0.07	0.11	0.11	0.17	0.17
Adj. R^2	0.07	0.11	0.11	0.17	0.17
Num. obs.	20534	15342	14532	12329	10901

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Male in the NCDS58 cohort with father in low-paying occupation is the referent group. Father's occupation variables are dummy variables. Education variables and the father's social class variable 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. Estimate without standardized variables is reported in table C.3.

Table C.3: Determinants of the (non-standardized) child's education (according to father's occupation)

	Linear regression - Dep. var.: Education (in PIR)				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.60^{***}	0.42^{***}	0.44^{***}	0.45^{***}	0.46^{***}
	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)
Female	0.02^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{**}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Father in Out-of-work	-0.04^{***}	-0.04^{***}	-0.01	-0.02	-0.03
	(0.01)	(0.01)	(0.13)	(0.13)	(0.13)
Father in Middling	0.02^{***}	0.01^{**}	0.00	0.00	0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Father in High-paying	0.14^{***}	0.10^{***}	0.06^{***}	0.04^{***}	0.04^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Father's education		0.16^{***}	0.15^{***}	0.10^{***}	0.10^{***}
		(0.01)	(0.02)	(0.02)	(0.02)
Mother's education		0.12^{***}	0.12^{***}	0.10^{***}	0.10^{***}
		(0.01)	(0.01)	(0.01)	(0.01)
Father's soc. class			0.03^{***}	0.02^{***}	0.02^{***}
			(0.00)	(0.00)	(0.00)
Number of siblings					-0.01^{***}
					(0.00)
Eldest child					0.02^{***}
					(0.01)
BCS cohort	-0.02^{***}	0.05^{***}	0.05^{***}	0.02	0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Female × BCS	-0.00	0.00	-0.00	-0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Father in Out. × BCS	-0.01	-0.02	-0.05	-0.04	-0.10
	(0.02)	(0.02)	(0.17)	(0.18)	(0.22)
Father in Mid. × BCS	0.00	0.00	-0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Father in High × BCS	-0.02^{***}	-0.01	-0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Father's educ. × BCS		-0.09^{***}	-0.08^{***}	-0.05^{**}	-0.04^{**}
		(0.02)	(0.02)	(0.02)	(0.02)
Mother's educ. × BCS		-0.01	-0.01	-0.02	-0.03
		(0.02)	(0.02)	(0.02)	(0.02)
Father's soc. class × BCS			-0.01^{**}	-0.01^{*}	-0.01^{*}
			(0.00)	(0.00)	(0.00)
Number of siblings × BCS					0.01^{***}
					(0.00)
Eldest child × BCS					-0.01
					(0.01)
Parents' interest in education				Yes	Yes
Region FE				Yes	Yes
R^2	0.07	0.11	0.11	0.17	0.18
Adj. R^2	0.07	0.11	0.11	0.17	0.17
Num. obs.	20534	15342	14532	12329	10901

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Male in the NCDS58 cohort with father in low-paying occupation is the referent group. Education variables and the father's social class variable are defined in peer-inclusive ranking. Estimate with standardized variables is reported in table C.2.

D Logistic regressions

This appendix provides the regressions tables for the binomial and multinomial logistic regressions. Tables D.1 and D.2 present the coefficients from the probability of being in each occupation at first period for, respectively, the binomial and multinomial logistic regressions. Tables D.3 and D.4 present the coefficients from the probability of being in each occupation at age 42 for, respectively, the binomial and multinomial logistic regressions.

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

	Binomial logistic regression - Dependent variable: First period occupation							
	Out-of-work		Low-paying		Middling		High-paying	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	-1.96^{***}	-1.98^{***}	-1.87^{***}	-1.96^{***}	-0.02	-0.03	-1.12^{***}	-1.26^{***}
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)
BCS cohort	-0.38^{***}	-0.40^{***}	-0.13^{*}	-0.16^{**}	-0.39^{***}	-0.42^{***}	0.63^{***}	0.77^{***}
	(0.08)	(0.08)	(0.07)	(0.08)	(0.05)	(0.05)	(0.05)	(0.06)
Female	1.09^{***}	1.11^{***}	0.11	0.13^{*}	-0.66^{***}	-0.66^{***}	-0.14^{**}	-0.18^{***}
	(0.06)	(0.07)	(0.07)	(0.07)	(0.05)	(0.05)	(0.06)	(0.06)
Female × BCS	-0.06	-0.05	0.31^{***}	0.34^{***}	0.10	0.12	-0.10	-0.16^{**}
	(0.09)	(0.10)	(0.10)	(0.10)	(0.07)	(0.07)	(0.08)	(0.08)
Par. inc.	-0.05	-0.03	-0.08^{**}	-0.03	-0.07^{***}	-0.03	0.22^{***}	0.10^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
Par. inc. × BCS	-0.28^{***}	-0.25^{***}	-0.17^{***}	-0.12^{**}	-0.05	0.01	0.27^{***}	0.23^{***}
	(0.04)	(0.04)	(0.05)	(0.05)	(0.03)	(0.04)	(0.04)	(0.04)
Education		-0.17^{***}		-0.47^{***}		-0.27^{***}		0.83^{***}
		(0.03)		(0.04)		(0.03)		(0.03)
Education × BCS		-0.07		-0.05		-0.15^{***}		-0.03
		(0.05)		(0.05)		(0.04)		(0.04)
Pseudo R^2	0.05	0.06	0.01	0.04	0.02	0.04	0.04	0.14
Log Likelihood	-6579.43	-6539.62	-5969.79	-5788.83	-9364.01	-9174.56	-8552.59	-7693.88
Num. obs.	14556	14556	14556	14556	14556	14556	14556	14556

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.

Table D.2: Probability of being in each occupation at first period (multinomial)

	Multinomial logistic regression - Dependent variable: First period occupation					
	(1)			(2)		
	Low	Mid	High	Low	Mid	High
Intercept	0.08	1.39^{***}	0.69^{***}	-0.00	1.38^{***}	0.53^{***}
	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
BCS cohort	0.23^{**}	0.13	0.77^{***}	0.22^{**}	0.12	0.89^{***}
	(0.10)	(0.08)	(0.09)	(0.10)	(0.08)	(0.09)
Female	-0.78^{***}	-1.26^{***}	-0.99^{***}	-0.76^{***}	-1.26^{***}	-1.02^{***}
	(0.09)	(0.07)	(0.08)	(0.09)	(0.07)	(0.08)
Female × BCS	0.26^{**}	0.01	-0.06	0.27^{**}	0.01	-0.12
	(0.12)	(0.10)	(0.11)	(0.12)	(0.10)	(0.11)
Par. inc.	-0.03	-0.00	0.21^{***}	-0.01	0.00	0.10^{***}
	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)
Par. inc. × BCS	0.09	0.21^{***}	0.40^{***}	0.10^{*}	0.22^{***}	0.36^{***}
	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
Education				-0.28^{***}	-0.02	0.77^{***}
				(0.05)	(0.04)	(0.04)
Education × BCS				0.03	-0.04	-0.05
				(0.07)	(0.05)	(0.06)
Num. obs.	14556	14556	14556	14556	14556	14556

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 child education in peer-inclusive ranking, both are standardized at the cohort level.

Table D.3: Probability of being in each occupation in the second period (binomial)

	Binomial logistic regression - Dependent variable: Second period occupation											
	Out-of-work			Low-paying			Middling			High-paying		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	-2.39^{***}	-2.45^{***}	-1.66^{***}	-1.97^{***}	-2.12^{***}	-1.94^{***}	-0.70^{***}	-0.75^{***}	-1.18^{***}	-0.16^{***}	-0.15^{***}	-0.50^{***}
	(0.06)	(0.06)	(0.09)	(0.05)	(0.06)	(0.09)	(0.04)	(0.04)	(0.08)	(0.04)	(0.04)	(0.08)
BCS cohort	-0.08	-0.08	0.20	-0.02	-0.03	0.14	-0.15^{***}	-0.16^{***}	-0.31^{**}	0.13^{***}	0.19^{***}	-0.06
	(0.09)	(0.09)	(0.13)	(0.07)	(0.08)	(0.13)	(0.05)	(0.05)	(0.12)	(0.05)	(0.05)	(0.11)
Female	0.98^{***}	1.02^{***}	0.81^{***}	0.89^{***}	0.97^{***}	0.90^{***}	-0.51^{***}	-0.50^{***}	-0.35^{***}	-0.61^{***}	-0.80^{***}	-0.80^{***}
	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)
Female × BCS	-0.03	-0.02	-0.02	-0.11	-0.10	-0.19^{*}	-0.15^{**}	-0.14^{*}	-0.15^{*}	0.21^{***}	0.26^{***}	0.34^{***}
	(0.11)	(0.11)	(0.11)	(0.09)	(0.09)	(0.10)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)
Par. inc.	-0.09^{***}	-0.05	-0.05	-0.08^{***}	-0.02	-0.00	-0.06^{**}	-0.01	0.00	0.17^{***}	0.06^{**}	0.04
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Par. inc. × BCS	-0.21^{***}	-0.18^{***}	-0.13^{***}	-0.18^{***}	-0.13^{***}	-0.08^{*}	-0.08^{**}	-0.04	-0.04	0.27^{***}	0.23^{***}	0.17^{***}
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Education		-0.36^{***}	-0.28^{***}		-0.62^{***}	-0.49^{***}		-0.46^{***}	-0.40^{***}		1.01^{***}	0.87^{***}
		(0.04)	(0.04)		(0.04)	(0.04)		(0.03)	(0.03)		(0.03)	(0.03)
Education × BCS		0.02	0.01		0.01	0.03		0.02	0.10^{**}		-0.19^{***}	-0.24^{***}
		(0.05)	(0.06)		(0.05)	(0.05)		(0.04)	(0.05)		(0.04)	(0.04)
Change with respect to the referent group as first period occupation (Out-of-work)												
Low-paying			-0.59^{***}			0.82^{***}			-0.18^{*}			-0.11
			(0.11)			(0.10)			(0.11)			(0.11)
Middling			-0.96^{***}			-0.32^{***}			0.99^{***}			0.07
			(0.09)			(0.09)			(0.08)			(0.08)
High-paying			-1.02^{***}			-0.79^{***}			-0.44^{***}			1.41^{***}
			(0.11)			(0.12)			(0.11)			(0.09)
Change between cohorts												
Low. × BCS			-0.50^{***}			0.10			0.29^{*}			0.02
			(0.15)			(0.13)			(0.15)			(0.15)
Mid. × BCS			-0.25^{*}			-0.23^{*}			0.42^{***}			0.03
			(0.13)			(0.12)			(0.12)			(0.12)
High. × BCS			-0.22			-0.05			0.19			0.07
			(0.15)			(0.15)			(0.15)			(0.12)
Pseudo R^2	0.04	0.05	0.09	0.03	0.08	0.13	0.02	0.05	0.12	0.03	0.15	0.21
Log Likelihood	-5646.72	-5559.07	-5374.23	-6775.16	-6454.73	-6119.99	-8155.80	-7911.74	-7342.98	-9558.17	-8377.14	-7825.20
Num. obs.	14556	14556	14556	14556	14556	14556	14556	14556	14556	14556	14556	14556

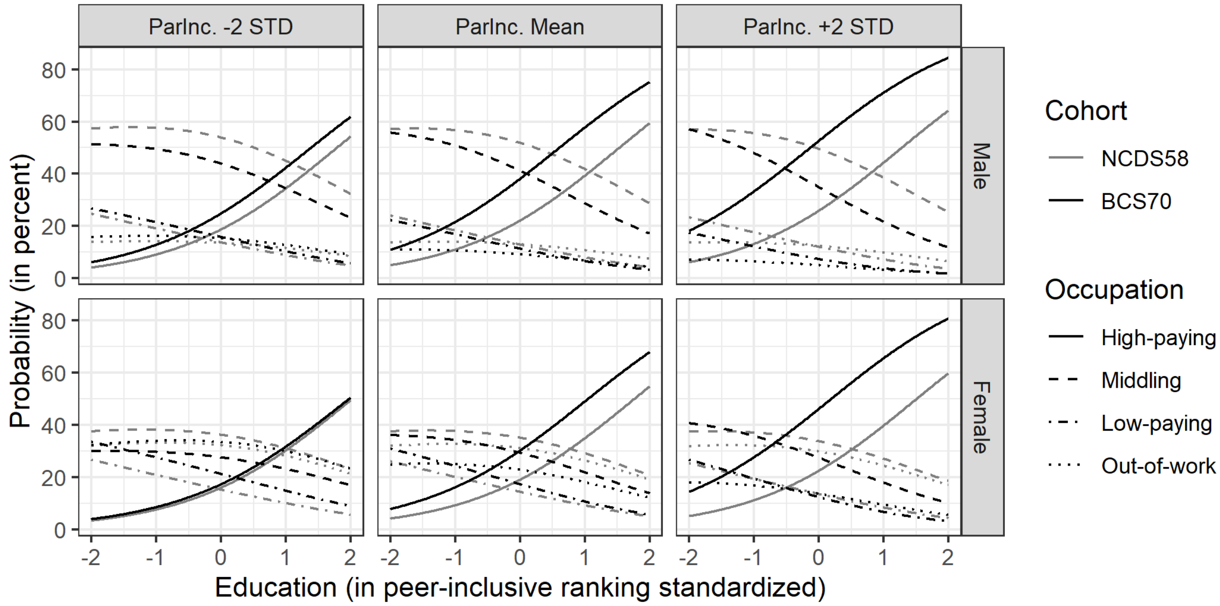
Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. Male in the NCDS58 cohort in out-of-work occupation in first period is the referent group. Parental income in logarithm and child education in peer-inclusive ranking, both are standardized at the cohort level.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

Table D.4: Probability of being in each occupation in the second period (multinomial)

	Multinomial logistic regression - Dependent variable: Second period occupation								
	(1)			(2)			(3)		
	Low	Mid	High	Low	Mid	High	Low	Mid	High
Intercept	0.38^{***}	1.37^{***}	1.69^{***}	0.28^{***}	1.38^{***}	1.69^{***}	-0.19^{*}	0.45^{***}	0.81^{***}
	(0.08)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.11)	(0.11)	(0.10)
BCS cohort	0.06	−0.02	0.14	0.06	−0.03	0.18^{*}	−0.01	-0.38^{**}	−0.16
	(0.11)	(0.09)	(0.09)	(0.11)	(0.10)	(0.10)	(0.16)	(0.16)	(0.14)
Female	−0.12	-1.22^{***}	-1.23^{***}	−0.08	-1.22^{***}	-1.43^{***}	0.03	-0.95^{***}	-1.25^{***}
	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.09)	(0.10)	(0.09)	(0.09)
Female × BCS	−0.06	−0.12	0.16	−0.07	−0.11	0.22^{*}	−0.14	−0.12	0.27^{**}
	(0.13)	(0.12)	(0.11)	(0.13)	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)
Par. inc.	0.01	0.04	0.19^{***}	0.03	0.04	0.08^{**}	0.04	0.05	0.07^{*}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Par. inc. × BCS	0.04	0.13^{**}	0.34^{***}	0.05	0.14^{**}	0.31^{***}	0.04	0.09	0.22^{***}
	(0.06)	(0.05)	(0.05)	(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	−0.03	-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^{**}	0.62^{***}	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.	14556	14556	14556	14556	14556	14556	14556	14556	14556

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.

Figure E.1: Probability of being in each occupation at first period, according to child education



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 child education, expressed in peer-inclusive ranking standardized, at several points of the parental income distribution (at -2 std., at the mean and at +2 std.). Probabilities are computed for males and females in both cohorts according to the multinomial logistic regression reported in columns (2) of the table D.2 in the appendix.

E Additional material

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

Figure E.1 shows the probability of being in each occupation at first period according to child education, evaluated at several points of the parental income distribution. Figure E.2 provides the change in 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. Figures E.3 provides the change in probability of being in each occupation in the second period conditional on first-period occupation at several points of the child education distribution for females only. Table 7 presents the change in intra-generational mobility across cohorts for females only.

Figure E.2: 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.) and at the mean of the child education distribution. Probabilities are computed for females in both cohorts according to the multinomial logistic regression reported in columns (3) of the table D.4 in the appendix.

Figure E.3: Change in probability to be in each occupation in the second period according to the first-period occupation and child education (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 child education distribution (at +1 std., at the mean and at +1 std.) and at the mean of the parental income distribution. Probabilities are computed for females in both cohorts according to the multinomial logistic regression reported in columns (3) of the table D.4 in the appendix.

F Robustness checks

F.1 Squared parental income

This appendix provides a robustness check on the role of squared parental income. Tables F.1 and F.2 show the coefficients of the binomial logistic regressions for the probability of being in each occupation in first and second periods, without and with squared parental income.

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

	Binomial logistic regression - Dependent variable: First period occupation							
	(1)				(2)			
	Out	Low	Mid	High	Out	Low	Mid	High
Intercept	-1.96^{***}	-1.87^{***}	-0.02	-1.12^{***}	-1.94^{***}	-1.87^{***}	-0.01	-1.14^{***}
	(0.05)	(0.05)	(0.04)	(0.04)	(0.06)	(0.06)	(0.04)	(0.04)
BCS cohort	-0.38^{***}	-0.14^{*}	-0.39^{***}	0.65^{***}	-0.48^{***}	-0.17^{**}	-0.33^{***}	0.70^{***}
	(0.08)	(0.07)	(0.05)	(0.05)	(0.08)	(0.08)	(0.05)	(0.06)
Female	1.10^{***}	0.11	-0.66^{***}	-0.15^{***}	1.10^{***}	0.11	-0.66^{***}	-0.15^{***}
	(0.06)	(0.07)	(0.05)	(0.06)	(0.06)	(0.07)	(0.05)	(0.06)
Female × BCS	-0.06	0.31^{***}	0.09	-0.09	-0.06	0.31^{***}	0.09	-0.09
	(0.09)	(0.10)	(0.07)	(0.08)	(0.09)	(0.10)	(0.07)	(0.08)
Par. inc.	-0.09^{***}	-0.12^{***}	-0.08^{***}	0.27^{***}	-0.09^{***}	-0.12^{***}	-0.08^{***}	0.26^{***}
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Par. inc. × BCS	-0.27^{***}	-0.19^{***}	-0.09^{***}	0.22^{***}	-0.32^{***}	-0.21^{***}	-0.02	0.29^{***}
	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)
Par. inc.^{2}					-0.03	0.00	-0.01	0.02
					(0.02)	(0.02)	(0.02)	(0.02)
Par. inc.^{2} × BCS					0.10^{***}	0.03	-0.06^{***}	-0.06^{**}
					(0.03)	(0.03)	(0.02)	(0.02)
Pseudo R^2	0.05	0.01	0.02	0.05	0.05	0.01	0.03	0.05
Log Likelihood	-6577.81	-5960.65	-9348.72	-8511.39	-6571.70	-5959.59	-9337.65	-8507.40
Num. obs.	14556	14556	14556	14556	14556	14556	14556	14556

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

	Binomial logistic regression - Dependent variable: Second period occupation							
	(1)				(2)			
	Out	Low	Mid	High	Out	Low	Mid	High
Intercept	-1.60^{***}	-1.77^{***}	-1.08^{***}	-0.51^{***}	-1.65^{***}	-1.73^{***}	-1.03^{***}	-0.54^{***}
	(0.09)	(0.08)	(0.08)	(0.07)	(0.09)	(0.09)	(0.08)	(0.07)
BCS cohort	0.23^{*}	0.14	-0.32^{***}	-0.16	0.18	0.13	-0.30^{**}	-0.10
	(0.12)	(0.12)	(0.12)	(0.10)	(0.13)	(0.12)	(0.12)	(0.11)
Female	0.80^{***}	0.85^{***}	-0.39^{***}	-0.67^{***}	0.80^{***}	0.85^{***}	-0.38^{***}	-0.67^{***}
	(0.08)	(0.07)	(0.06)	(0.06)	(0.08)	(0.07)	(0.06)	(0.06)
Female × BCS	-0.05	-0.21^{**}	-0.16^{*}	0.31^{***}	-0.04	-0.21^{**}	-0.17^{**}	0.32^{***}
	(0.11)	(0.10)	(0.08)	(0.08)	(0.11)	(0.10)	(0.08)	(0.08)
Par. inc.	-0.08^{**}	-0.09^{***}	-0.08^{***}	0.19^{***}	-0.10^{***}	-0.08^{**}	-0.07^{**}	0.17^{***}
	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Par. inc. × BCS	-0.12^{**}	-0.10^{**}	-0.05	0.12^{***}	-0.18^{***}	-0.09^{*}	-0.01	0.16^{***}
	(0.05)	(0.05)	(0.04)	(0.04)	(0.06)	(0.05)	(0.05)	(0.04)
Par. inc.^{2}					0.06^{***}	-0.04^{*}	-0.05^{***}	0.03^{*}
					(0.02)	(0.02)	(0.02)	(0.02)
Par. inc.^{2} × BCS					0.04	0.02	-0.00	-0.05^{**}
					(0.03)	(0.03)	(0.03)	(0.02)
Change with respect to the referent group as first period occupation (Out-of-work)								
Low-paying	-0.53^{***}	0.87^{***}	-0.10	-0.33^{***}	-0.53^{***}	0.87^{***}	-0.10	-0.34^{***}
	(0.11)	(0.09)	(0.10)	(0.10)	(0.11)	(0.09)	(0.10)	(0.10)
Middling	-0.97^{***}	-0.36^{***}	0.97^{***}	-0.03	-0.97^{***}	-0.36^{***}	0.97^{***}	-0.03
	(0.09)	(0.08)	(0.08)	(0.07)	(0.09)	(0.08)	(0.08)	(0.08)
High-paying	-1.22^{***}	-1.13^{***}	-0.69^{***}	1.73^{***}	-1.23^{***}	-1.13^{***}	-0.69^{***}	1.73^{***}
	(0.11)	(0.11)	(0.10)	(0.08)	(0.11)	(0.11)	(0.10)	(0.08)
Change between cohorts								
Low. × BCS	-0.51^{***}	0.08	0.25	0.12	-0.51^{***}	0.07	0.24	0.12
	(0.15)	(0.13)	(0.15)	(0.14)	(0.15)	(0.13)	(0.15)	(0.14)
Mid. × BCS	-0.25^{*}	-0.19	0.44^{***}	0.08	-0.23^{*}	-0.20	0.42^{***}	0.07
	(0.13)	(0.12)	(0.12)	(0.11)	(0.13)	(0.12)	(0.12)	(0.11)
High. × BCS	-0.21	0.02	0.28^{*}	0.02	-0.19	0.01	0.27^{*}	0.02
	(0.14)	(0.15)	(0.14)	(0.11)	(0.15)	(0.15)	(0.14)	(0.11)
Pseudo R^2	0.08	0.10	0.10	0.14	0.08	0.10	0.10	0.14
Log Likelihood	-5431.29	-6278.71	-7452.61	-8472.61	-5420.46	-6276.13	-7445.31	-8470.13
Num. obs.	14556	14556	14556	14556	14556	14556	14556	14556

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.

F.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 F.3 and F.4 show the coefficients of the binomial 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 D.1 and D.3.

Table F.3: Probability of being in each occupation in first period (First-period age robustness check)

	Binomial logistic regression - Dependent variable: First period occupation											
	Out-of-work			Low-paying			Middling			High-paying		
	(Base)	(23)	(26)	(Base)	(23)	(26)	(Base)	(23)	(26)	(Base)	(23)	(26)
Intercept	-1.98^{***}	-1.98^{***}	-2.31^{***}	-1.96^{***}	-1.96^{***}	-1.99^{***}	-0.03	-0.03	-0.09^{***}	-1.26^{***}	-1.26^{***}	-1.01^{***}
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)
BCS cohort	-0.40^{***}	0.28^{***}	-0.07	-0.16^{**}	-0.03	-0.13^{*}	-0.42^{***}	-0.29^{***}	-0.36^{***}	0.77^{***}	0.28^{***}	0.52^{***}
	(0.08)	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
Female	1.11^{***}	1.11^{***}	1.69^{***}	0.13^{*}	0.13^{*}	0.20^{***}	-0.66^{***}	-0.66^{***}	-0.91^{***}	-0.18^{***}	-0.18^{***}	-0.46^{***}
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
Female × BCS	-0.05	-0.59^{***}	-0.63^{***}	0.34^{***}	0.26^{***}	0.27^{***}	0.12	0.18^{***}	0.36^{***}	-0.16^{**}	0.07	0.12
	(0.10)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)
Par. inc.	-0.03	-0.03	-0.04	-0.03	-0.03	-0.06	-0.03	-0.03	-0.03	0.10^{***}	0.10^{***}	0.12^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Par. inc. × BCS	-0.25^{***}	-0.11^{***}	-0.23^{***}	-0.12^{**}	-0.12^{**}	-0.10^{**}	0.01	0.04	0.01	0.23^{***}	0.13^{***}	0.20^{***}
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Education	-0.17^{***}	-0.17^{***}	-0.34^{***}	-0.47^{***}	-0.47^{***}	-0.42^{***}	-0.27^{***}	-0.27^{***}	-0.30^{***}	0.83^{***}	0.83^{***}	0.92^{***}
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Education × BCS	-0.07	0.29^{***}	0.10^{**}	-0.05	0.06	-0.10^{*}	-0.15^{***}	-0.13^{***}	-0.13^{***}	-0.03	-0.25^{***}	-0.12^{***}
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Pseudo R^2	0.06	0.03	0.09	0.04	0.03	0.04	0.04	0.04	0.05	0.14	0.09	0.14
Log Likelihood	-6539.62	-7081.91	-6423.45	-5788.83	-5832.50	-5773.72	-9174.56	-9236.04	-8948.25	-7693.88	-7471.95	-7724.98
Num. obs.	14556	14372	14503	14556	14372	14503	14556	14372	14503	14556	14372	14503

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. Column (Base) corresponds to the baseline estimate from column (2) in D.1 with first-period occupation at the age of 23 (resp. 26) for the NCDS58 (resp. BCS70) cohort. Column (23) estimates the same regression with first-period occupation at the age of 23 for both cohorts, whereas column (26) corresponds to age 26.

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

	Binomial logistic regression - Dependent variable: Second period occupation											
	Out-of-work			Low-paying			Middling			High-paying		
	(Base)	(23)	(26)	(Base)	(23)	(26)	(Base)	(23)	(26)	(Base)	(23)	(26)
Intercept	-1.66^{***}	-1.66^{***}	-1.63^{***}	-1.94^{***}	-1.94^{***}	-1.80^{***}	-1.18^{***}	-1.18^{***}	-1.06^{***}	-0.50^{***}	-0.50^{***}	-0.70^{***}
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
BCS cohort	0.20	-0.08	0.17	0.14	-0.17	-0.01	-0.31^{**}	-0.36^{***}	-0.43^{***}	-0.06	0.42^{***}	0.14
	(0.13)	(0.12)	(0.13)	(0.13)	(0.12)	(0.13)	(0.12)	(0.11)	(0.12)	(0.11)	(0.10)	(0.11)
Female	0.81^{***}	0.81^{***}	0.73^{***}	0.90^{***}	0.90^{***}	0.81^{***}	-0.35^{***}	-0.35^{***}	-0.34^{***}	-0.80^{***}	-0.80^{***}	-0.69^{***}
	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Female × BCS	-0.02	0.09	0.06	-0.19^{*}	-0.09	-0.10	-0.15^{*}	-0.16^{*}	-0.16^{*}	0.34^{***}	0.24^{***}	0.23^{***}
	(0.11)	(0.11)	(0.11)	(0.10)	(0.10)	(0.10)	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)
Par. inc.	-0.05	-0.05	-0.05	-0.00	-0.00	0.01	0.00	0.00	0.01	0.04	0.04	0.02
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Par. inc. × BCS	-0.13^{***}	-0.17^{***}	-0.13^{***}	-0.08^{*}	-0.10^{**}	-0.09^{*}	-0.04	-0.05	-0.04	0.17^{***}	0.21^{***}	0.18^{***}
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Education	-0.28^{***}	-0.28^{***}	-0.28^{***}	-0.49^{***}	-0.49^{***}	-0.49^{***}	-0.40^{***}	-0.40^{***}	-0.35^{***}	0.87^{***}	0.87^{***}	0.83^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Education × BCS	0.01	-0.02	0.01	0.03	-0.05	0.02	0.10^{**}	0.06	0.06	-0.24^{***}	-0.15^{***}	-0.20^{***}
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
Change with respect to the referent group as first period occupation (Out-of-work)												
Low-paying	-0.59^{***}	-0.59^{***}	-0.66^{***}	0.82^{***}	0.82^{***}	0.80^{***}	-0.18^{*}	-0.18^{*}	-0.25^{**}	-0.11	-0.11	-0.03
	(0.11)	(0.11)	(0.11)	(0.10)	(0.10)	(0.09)	(0.11)	(0.11)	(0.10)	(0.11)	(0.11)	(0.11)
Middling	-0.96^{***}	-0.96^{***}	-0.97^{***}	-0.32^{***}	-0.32^{***}	-0.52^{***}	0.99^{***}	0.99^{***}	0.97^{***}	0.07	0.07	0.17^{**}
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
High-paying	-1.02^{***}	-1.02^{***}	-1.01^{***}	-0.79^{***}	-0.79^{***}	-0.92^{***}	-0.44^{***}	-0.44^{***}	-0.76^{***}	1.41^{***}	1.41^{***}	1.67^{***}
	(0.11)	(0.11)	(0.11)	(0.12)	(0.12)	(0.11)	(0.11)	(0.11)	(0.11)	(0.09)	(0.09)	(0.09)
Change between cohorts												
Low. × BCS	-0.50^{***}	-0.24	-0.43^{***}	0.10	0.14	0.11	0.29^{*}	0.34^{**}	0.35^{**}	0.02	-0.24^{*}	-0.06
	(0.15)	(0.15)	(0.15)	(0.13)	(0.13)	(0.13)	(0.15)	(0.15)	(0.15)	(0.15)	(0.14)	(0.15)
Mid. × BCS	-0.25^{*}	-0.03	-0.24^{*}	-0.23^{*}	0.08	-0.03	0.42^{***}	0.36^{***}	0.43^{***}	0.03	-0.36^{***}	-0.07
	(0.13)	(0.13)	(0.13)	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)
High. × BCS	-0.22	-0.10	-0.24	-0.05	0.38^{**}	0.08	0.19	0.32^{**}	0.51^{***}	0.07	-0.44^{***}	-0.19
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.12)	(0.12)	(0.12)
Pseudo R^2	0.09	0.08	0.09	0.13	0.11	0.13	0.12	0.11	0.12	0.21	0.20	0.22
Log Likelihood	-5374.23	-5307.35	-5347.10	-6119.99	-6114.29	-6070.89	-7342.98	-7322.64	-7261.69	-7825.20	-7832.08	-7722.34
Num. obs.	14556	14372	14503	14556	14372	14503	14556	14372	14503	14556	14372	14503

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 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. Column (Base) corresponds to the baseline estimate from column (3) in D.3 with first-period occupation at the age of 23 (resp. 26) for the NCDS58 (resp. BCS70). Column (23) estimates the same regression with first-period occupation at the age of 23 for both cohorts, whereas column (26) corresponds to age 26.