INTERGENERATIONAL AND OCCUPATIONAL MOBILITY

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Abstract

This thesis is divided into three main chapters.

The first chapter provides an analysis of intergenerational mobility across countries, across cohorts and over the income distribution. It compares the patterns of intergenerational income mobility between fathers and sons in Germany, Italy, the United Kingdom and the United States. Among other findings, the analysis highlights that mobility is lowest for families at the extremes of the income distribution. Among university graduates, mobility is still lowest at the top. This calls for further research on the drivers of intergenerational mobility.

The second chapter investigates why intergenerational earnings mobility is lowest at the top and at the bottom, by exploring the role of social networks. The implications of a simple model are tested on data from the United Kingdom. The inverse U-shaped mobility patterns are explained in two steps. First, a range of findings is consistent with the hypothesis that family friends affect the offspring's educational and occupational choices. Second, the friend's job is correlated to the parent's job, in different ways at different income levels. Specifically, the richest and the poorest parents tend to have friends that are more similar to them than median parents.

The third chapter examines the effects of job polarization on individuals and households by assessing the roles of occupational mobility, changes in occupational wage premia, mating patterns across occupations and female labour supply. The paper uses the British Household Panel Survey to examine the UK over 1991-2008. The findings

suggest that most of the factors listed above have important roles. The period is characterised by pronounced movements in occupational premia and important roles for occupational mobility and assortative matching.

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Chapter 1

Introduction

Income inequality has increased since the 1970s in Europe and in the United States. This fact is well highlighted in the recent book of the French economist Thomas Piketty, "Capital in the 21st century" (2014). As explained by Solow (2014), the book underlines two main inequality trends.

The first is that the national income share of the top 10 percent has increased over time. The author mentions several factors that might contribute to this phenomenon. Examples are: changes in education, the decreasing role of trade unions, globalization and the competition from bottom earners in developing countries, and job polarization resulting from technological changes.

The second trend indicates that the top centile has risen even more than the top decile. This is partly associated to labour income, in particular when it comes to the rise in earnings of super-managers and CEOs. Partly, this is associated to the role of capital income and its inheritance. According to Piketty, the latter would explain the even larger increase of the top 0.1 percent.

In order to better understand the mechanisms underlying inequality, one should not stop at the cross-sectional level. Wealth inheritance is not the only mechanism through which family background can affect one's income. Other factors, such as ability, education opportunities, or job contacts, can be transmitted from parents to children. Intergenerational mobility may play an important role for inequality. Corak (2013) documents a positive relationship between higher inequality and lower intergenerational mobility, in several countries. This is the so-called Great Gatsby Curve.

This thesis is an attempt to shed some additional light on widening inequalities, at both intergenerational and intra-generational levels. It is divided into three main chapters.

The first chapter provides an analysis of intergenerational mobility across countries, across cohorts and over the income distribution. It compares the patterns of intergenerational income mobility between fathers and sons in Germany, Italy, the United Kingdom and the United States. It does so by using three different methods: Two-Sample Two-Stage Least Squares (TS2SLS), quantile regression and mobility matrices. The results from the TS2SLS indicate that the United Kingdom is, on average, the most mobile country, followed by Germany, Italy and the United States. In Italy and Germany the elasticity has increased across cohorts. The elasticity has risen in the UK as well, but at a lower rate. In the US, no such pattern emerges. At different income levels, quantile regressions do not provide strong evidence of a non-constant elasticity along the son's income distribution, except for Italy. The mobility matrices, instead, where the son's and the father's income quantiles are both considered, indicate lower intergenerational mobility at both top and bottom quantiles. In Italy and the US, individuals with fathers in top and bottom quintiles have a much higher chance of ending up in their same quintile. In Germany and in the UK this applies to fathers and sons in the top quintile.

The second chapter investigates why intergenerational earnings mobility is lowest at the extremes of the distribution, by exploring the role of social networks. The framework is based on the standard Becker-Tomes-Solon model (1979; 1986; 2004). It includes parental investment under uncertainty in both offspring's education and friends. The framework suggests that family friends influence the earning prospects of children, through education and on the labour market, by acting as job contacts. The inverse U-shaped mobility patterns are explained by the assumption that homophily in terms of income is stronger among individuals at the extremes. The implications of the model are tested using data from the British Household Panel Survey, the Annual Survey of Hours and Earnings and the New Earning Survey. First, the occupation of parental friends is significantly associated to the offspring's occupational income, conditional on parental characteristics. This implies that there may be a direct association between the parental friends' and the offspring's occupation. Second, individuals are more likely to have higher education if parental friends have a better job. This is consistent with the idea that education and networks are complements. In fact, parental investments in education are higher when their network is better as the returns to education are higher. Most importantly, the results confirm the hypothesis that homophily is not constant along the income distribution. Parents with a middle job have a more diverse network than parents with top or bottom jobs. As their children benefit from a more varied pool of job contacts, they have more chances to end up with a different kind of job than the one of their parents. This explains the shape of intergenerational mobility.

The third chapter focuses on issues linked to intra-generational inequality. Across much of the developed world, employment has declined in middle-wage routine occupations and increased in non-routine occupations at the top and bottom of the wage distribution. A large literature documents the consequences of job polarization in the United States (see, for example, Autor, Levy, and Murnane 2003; Autor and Dorn, 2013), in the United Kingdom (such as Goos and Manning, 2007; Salvatori, 2015) and in other European countries (see Goos, Manning, and Salomons, 2009). Their findings, based on cross-sectional or short longitudinal data, indicate that wage and employment polarization was mainly present in the 1990s in the US. In the UK, employment polarization characterized the labour market in the 1990s and 2000s, but wage polarization was largely absent. The paper examines these shifts and their effects on houselds in the UK, using British Household Panel Survey. It uses panel data to examine a period of pronounced polarization, over 1991-2008. Linking individuals to households, it assesses the roles of occupational mobility, changes in occupational wage premia, mating patterns across occupations and female labour supply. The paper estimates the occupational wage premia accounting for selection into occupations using panel fixed effects. The findings suggest that most of the factors listed above have important roles in explaining the effects of polarization on households. Most importantly, taking into account selection into occupation reveals large effects of polarization hidden by analyses of inequality using cross-sectional data. In particular, throughout the period, there were pronounced movements in occupational premia and important roles for occupational mobility and assortative matching. Taken as a whole, these results have implications for the effects of ongoing shifts in occupational and industrial structure on household welfare.

Chapter 2

Intergenerational mobility across countries and methods

2.1 Introduction

To what extent does our social and economic background affect our future? This question has received a lot of attention by social scientists.[1]

The theoretical foundation of the intergenerational literature is the seminal work of Becker and Tomes (1979; 1986). The model assumes that, in the presence of borrowing constraints, less-favoured families may be financially constrained. They may not be able to invest as much as they would like in their offspring's education, thus affecting their future income.[2] Solon (2004) augments this framework by explicitly accounting for public investments in human capital. His model predicts that the intergenerational elasticity (IGE, hereafter) is positively correlated with the inherited characteristics, the productivity of human capital investments and the returns to human capital. Instead,

[1]Economists have primarily focused on earnings or income, whereas sociologists have examined mobility between different class positions. Solon (1999), Black and Devereux (2011) and Björklund and Jäntti (2009) mainly review the economics literature. Blanden (2013) reviews studies from both economists and sociologists.

[2]With perfect capital markets, the parents choose the optimal level of investment in education for their children. In the absence of credit constraints, parental income would not directly affect the intergenerational relationship. This would mainly depend on the transmission of certain characteristics through inheritance, which the authors define as the "heritability of endowments".

the IGE decreases in the progressiveness of the public expenditure in education. Differences in these variables can explain different levels of intergenerational mobility across countries, over time, and along the income distribution.

This paper investigates the intergenerational transmission of labour income in four industrialised countries: Germany, Italy, the United Kingdom and the United States.[3] The aim is to provide comparable estimates of the patterns of intergenerational income mobility at three levels: across cohorts, at different income levels, and across countries.[4]

In order to reach this goal, I consider methodological issues, both in terms of sample and variable selection, and in terms of model specification.

This research contributes to the intergenerational literature in two ways. The first contribution is substantive. I believe that no cross-country article investigates the intergenerational mobility over time and at different income levels. Most studies in this area either focus on a specific aspect or on a given country. They refer to other research in order to complement their analysis. However, the empirical results are highly dependent on the sample selection and on the selected specification. This has been shown in the literature and this paper confirms it.[5] Therefore, the results of different papers

[3] Although the variable used in this paper is labour income, the terms "earnings" and "labour income" are used as synonyms. Additionally, unless differently specified, the term "income" refers to labour income.

[4] The appendix also presents a preliminary cross-country analysis of variation across regions.

[5] For example, Grawe (2004) illustrates that the use of two different surveys produce different estimates, for the same country and in the same period of time. The author estimates the IGE on two samples: the first sample is from the National Longitudinal Survey (NLS), the second from the Panel Study of Income Dynamics (PSID). The IGE for the former is significantly lower than that calculated on the latter. Grawe motivates this result by underlining the older age of both fathers and sons in PSID. The author also shows that the estimates based on the same dataset differ if computed on two different samples. For instance, the estimates on NLS of this study are around half of those of Zimmerman (1992) who

are not always easily comparable. Moreover, for Italy and Germany, to the best of my knowledge, no recent examination of the elasticity trend is available. I also believe that this is one of the first studies to include a subsample of East Germans.

The second contribution is methodological. I use the specification used by Solon and Lee (2009) in order to control for the life-cycle bias, and I adapt it to the different estimators. The authors suggest to augment the intergenerational equation with an interaction between the father's income and the son's age, normalised at forty. I also add an interaction between the father's income and his age. The estimates can then be interpreted for 40-year-old individuals. This facilitates their comparison of the findings across the four surveys. I use this specification also when computing the mobility matrices. To the best of my knowledge, this is one of the first studies based on income mobility matrices that include control variables.

The analysis is based on the following surveys: the German Socio-Economic Panel survey (GSOEP), the Italian Survey on Household Income and Wealth (SHIW), the British Household Panel Survey (and Understanding Society Survey, BHPS) and the American Panel Study of Income Dynamics (PSID). For each survey, there are two samples. The sample of sons consists of individuals between 30 to 59 years of age who are born in 1950 or after. Their fathers are born before 1950 and the paternal details refer to the period when the father was between 30 and 59. The second sample is the auxiliary one, with the "potential", or "fictitious", fathers. They are born before 1950 and aged between 30 and 59.

used the same survey. The author justifies this difference by highlighting the different sampling criteria: particularly, Zimmerman excludes from the analysis fathers and sons employed for less than thirty weeks per year and thirty hours per week.

In terms of methodology, the paper uses a set of Two-Sample Two-Stage estimators: Two-Sample Two-Stage Least Squares (TS2SLS), Two-Sample Two-Stage Quantile Regression (TS2SQR) and income mobility matrices.

In the four datasets, the respondents provide information about their father's characteristics during the son's teenage years. However, the paternal labour income is not available. I use the paternal socio-economic characteristics from the main sample and the labour income from an independent sample of "potential" fathers to predict it.

The Two-Sample Two-Stage Least Squares (TS2SLS) were first used by Arellano and Meghir (1992) and Angrist and Krueger (1992). Björklund and Jäntti (1997) are the first who applied it to intergenerational studies. Since then, they have been used extensively in the literature. Cross-country studies indicate Nordic countries, Canada and Germany have lower IGE than the Anglo-Saxon countries. The elasticity is lower in the UK than in the US.[6] The estimates presented in this paper for 40-year-old fathers and sons are in line with the literature. The IGE is 0.32 in the UK, 0.436 in Germany, 0.463 in Italy and 0.489 in the US. Not controlling for the different ages at which earnings are reported seems to underestimate the IGE in Germany. It overestimates it in the UK. This might explain the different ranking of countries in the previous studies.[7] The results also suggest that Germany, Italy and the United Kingdom experienced an increase in the IGE across cohorts, whereas no such trend emerges in the United States.

[6] Examples are Jantti et al. (2006) and Bratsberg et al. (2007).

[7] In fact, without the interaction between the father's and the son's age and the paternal income the IGE in Germany is 0.3. In the UK, it is 0.37.

As for the changes along the income distribution, the findings of this paper are in line with the few existing studies using quantile regression.[8] The TS2SQR highlight a U-shaped elasticity for the Italian sons. Instead, the estimates based on the three other surveys suggest that the IGE increases with the respondent's income quantile, but the estimates are not statistically different from the median.

In terms of mobility patterns, the existing literature is based on transition matrices. The studies reviewed by Solon (1999) and Black and Devereux (2011) highlight higher persistence at the extremes of the income distribution in Italy, Germany, UK and US.

I construct the mobility matrices with the probabilities resulting from a sequential (or generalised ordered) logit. The dependent variable is a categorical variable for the respondent's income quantiles.[9] Their advantage, with respect to the commonly used transition matrices, is that they can include control variables, such as individual and paternal characteristics. Moreover, the standard errors can be used for inference.

The mobility matrices indicate that the father's position in the income distribution affects his son's economic opportunities. In Italy and in the US, individuals with fathers in top and bottom quintiles have a higher chance of ending up in the same quintile. For example, in Italy the probability of being in the first (fifth) income quintile if the father is in the first (fifth) quintile is 13.5 (20) percentage points higher than if the father is in the third quintile. It is 21.5 (26) points higher than if the father is in the opposite quintile. In Germany and in the UK, this applies to fathers and sons in the top quintile. In Germany, a father in the fifth quintile increases the probability of the son of being

[8]Examples are Eide and Showalter (1999) for the US, Mocetti (2007) for Italy, Gregg et al. (2015) for the UK and Schnitzlein (2015) for Germany. These studies are discussed in the relevant section.

[9]I follow the example of two sociology studies, Logan (1983) and Breen (1994).

in the same quintile by 28 points with respect to a father in the first quintile. For the UK, it amounts to 18 percentage points. For all countries, the probabilities indicate that upward mobility (being in the fifth quintile if the father is in the first) is less likely than downward mobility. A series of further checks suggest that the findings cannot only be a mechanical result of the matrix construction.

The rest of the paper is organized as follows. Section 2.2 describes the datasets. Section 2.3 describes the methodology. Section 2.4 specifies the sample selection criteria. Section 2.5 outlines the results of the first stage regressions. Section 2.6 reports the results of the second stage estimations. Section 2.7 concludes.

2.2 Data

This research focuses on four countries: Germany, Italy, the United Kingdom and the United States.

For Germany, the selected survey is the German Socio-economic Panel (GSOEP), a longitudinal household based study which started in 1984 in the Federal Republic of Germany, to which Eastern German households were added from 1990. To compare GSOEP with the other surveys, the considered waves are those from the period 1991 to 2010 (2008 for the auxiliary sample). The survey is a rich source of data on families in Germany. The respondents can be matched with their parents, children, and/or spouses. More relevant for the purpose of this research is that the respondents are asked information about their parents. The information refers to the period when the respondents were 15 years old. The sample includes West and East Germans, provided that the sons have studied in West Germany. I use the attendance of a West German school as a way to ensure that the information about their fathers refers to a period when the fathers were in West Germany.[10]

The Italian Survey on Household Income and Wealth (SHIW) started in the 1960s. Over the years it has been extended to include several aspects of the economic and financial behaviour of around 8,000 households (24,000 individuals). Given its construction, it is not straightforward to follow individuals over time, as there is no unique individual identifier. Nonetheless, as long as they belong to the same household, individuals can be linked across waves by exploiting information about the identifier of the previous wave. Since 1987, the survey has been carried out every other year, which reduces the number of observations to a maximum of 10 per individual, from 1991 to 2010 (2008 for the auxiliary sample). Differently from the other surveys, the information about their fathers refer to when the latter were as old as the respondents at the time of the survey.

For the United Kingdom, the research combines British Household Panel Survey and Understanding Society Survey (BHPS, hereafter) to obtain observations about UK households from 1991 to 2010 (2008 for the auxiliary sample). BHPS began in 1991 with a representative sample of about 5,500 units and 10,300 individuals, to which households of Scotland, Wales and Northern Ireland were added subsequently. In 2009, the survey converged into Understanding Society Survey, where since the second wave

[10]The income of fathers living in East Germany before 1990 cannot be predicted using data referring to the post-1990 period. This is because of differences in the economy and in the labour market structure between the communist and post-communist era. The sample of East Germans is small: 453 people moved from West to East Germany after their studies. As a robustness check, I also consider a sample with West Germans only.

of this survey, the original BHPS sample has been inserted. The reference unit is the household, although all individuals of the original sample are followed throughout the years, even after joining a new household. Similarly to the other surveys, the respondents provide information about their parents that refer to the year when the respondents were 14 years old.[11]

For the United States, the selected dataset is the Panel Study of Income Dynamics (PSID). The study began in 1968 and interviewed a sample of over 18,000 individuals from 5,000 families. It was done annually until 1997 and then biannually. The survey collects details on individual's income, occupational position, education and other topics. Each individual is asked details about his or her parents, including occupation of the father when the respondent was 15 years of age.[12] For consistency with the other datasets, the considered years are from 1990 to 2009. Like for GSOEP and BHPS, the information about the respondent's parents refer to the teenage years of the respondents, precisely when they were 15 years old.

2.3 Methodology

Two-Sample Two-Stage Least Squares (TS2SLS) were first used to estimate female labour supply in Britain by Arellano and Meghir (1992). They were applied to intergenerational studies in Björklund and Jäntti (1997). Since then, an increasing number of

[11] Whereas only two intergenerational studies used BHPS (Ermisch and Francesconi, 2004; Nicoletti and Ermisch, 2007), this survey is more suitable than the yet more popular National Child Development Study (NCDS) and British Cohort Study (BCS). The reason is that the two surveys follow one cohort over time (the 1958 for NCDS and 1971 for BCS). It is not possible to examine the variation of IGE across cohorts.

[12] Other surveys have been used in intergenerational studies such as the National Longitudinal Surveys (NLS). These surveys, however, focus on specific cohorts. Consequently, they are less comparable to other datasets and face the same limitations mentioned for the British NCDS.

researchers have relied on this method, especially in order to overcome data limitations, occurring when fathers and sons are matched within a dataset.[13] This approach has two other advantages. First, a larger sample size allows more flexibility to set ex-ante criteria for sample and variable selection. In particular, it is easier to consider fathers and sons at a similar age, in order to reduce the life-cycle bias.[14] Second, TS2SLS may overcome the sample selection bias. The bias is common in matched data. It arises when sons and fathers are required to live in the same household for at least one wave to be included in the survey (Francesconi et al., 2006).

In brief, the first stage consists of dividing the respondents of each survey into two groups. The first, the auxiliary subsample, constitutes the fictitious fathers. The characteristics of these individuals are used to predict the paternal earnings of the individuals in the main sample, the sons, through the following equation:

$$y_f = \sum_{j=1}^{k} z_j \delta_j + v \tag{2.1}$$

where y_f is the vector containing the log of the father's labour incearningsome, z_j are personal characteristics such as age, education and occupation, δ_j are the related coefficients and v is a vector of white noise disturbances. The estimated coefficients,

[13] This technique is extensively explained in Arellano and Meghir (1992), Angrist and Krueger (1992) and Inoue and Solon (2010). Examples of its application in the field of intergenerational mobility are Mocetti (2007) and Piraino (2007) for Italy, Nicoletti and Ermisch (2007) for the UK and Grawe (2004) for the United States.

[14] Further details in Section 2.4.

$\hat{\delta}$, are then used in the second stage to predict paternal income in the main sample, $\hat{y}_f = \sum_{j=1}^{k} z_j \hat{\delta}_j$, where z_j are the same regressors of eq. 2.1.[15]

For the Two-Sample Two-Stage Least Squares, the model in the second stage is the following:

$$y_s = \beta_{TS}\,\hat{y}_f + \varepsilon \tag{2.2}$$

In this model, β_{TS} is the intergenerational elasticity (IGE) and indicates the fraction of income that is on average transmitted across generations. In general, β_{TS} ranges between zero (complete mobility) and one (complete immobility).

For consistency, z_j need to be identically and independently distributed (i.i.d.) in the two samples and independent of the error term, ε. If eq. 2.2 is correctly specified and with exogenous instruments, the estimator β_{TS} will converge in probability to the true parameter β. Similarly, the OLS estimator would also be consistent. These conditions are difficult to be satisfied. Indeed, the instruments used in the first stage, such as the parental education, are likely to have a direct effect on the son's income. With endogenous instruments, the estimated equation will be:

$$y_s = \lambda\, y_f + \sum_{j=1}^{k} z_j \gamma_j + \omega \tag{2.3}$$

where y_f is the true paternal income. In this case, the OLS estimator, β_{LS}, and the Two-Sample Two-Stage estimator, β_{TS}, will converge to:

[15] As mentioned in the previous section, z_j in the main sample refer to the paternal characteristics during the respondent's teenage years for BHPS, GSOEP, PSID. For SHIW, the questions refers to the period when the father is the same age as the respondent at the time of the survey.

$$p\lim(\beta_{LS}) = \frac{Cov(y_s, y_f)}{Var(y_f)} = \lambda + \sum_{j=1}^{k} \frac{Cov(y_f, z_j)}{Var(y_f)} \gamma_j \tag{2.4}$$
$$p\lim(\beta_{TS}) = \frac{Cov(y_s, P_z y_f)}{Var(P_z y_f)} = \lambda + \sum_{j=1}^{k} \frac{Cov(P_z y_f, z_j)}{Var(P_z y_f)} \gamma_j$$

where P_z is the projection matrix. Nicoletti and Ermisch (2007) show that, given that $Cov(y_f, z_j) = Cov(P_z y_f, z_j)$, the two estimators converge to the same probability limit if either $\gamma_j = 0$ or $Var(y_f) = Var(P_z y_f)$. The second condition is the same as imposing the ratio of the two variances to equal one. The ratio $\frac{Var(P_z y_f)}{Var(y_f)}$ represents the fraction of the variation in y_f that is attributed to the variation in z_j. This is the R^2 of the regression in the first stage (eq. 2.1). If γ_j is positive and y_f and z_j are positively correlated, β_{TS} is larger than or equal to β_{LS}, at least asymptotically.

Another statistic used in the intergenerational literature is the correlation coefficient:

$$\rho_{TS} = \beta_{TS} \sqrt{\frac{Var(P_z y_f)}{Var(y_s)}} \tag{2.5}$$

The correlation coefficient is the intergenerational elasticity weighted by the ratio between the standard deviation of the father's earnings and the standard deviation of the son's earnings. Jerrim et al. (2014) highlight the importance of considering the intergenerational correlation, especially with TS2SLS. The correlation, in fact, takes into account the lower variance of the father's predicted income, which is not controlled for by the value of the elasticity.

Nicoletti and Ermisch (2007) show that the OLS and the TS2SLS estimators of the correlation converge to the same probability limit if $Var(y_f) = Var(P_z y_f)$. If the the two variances are different from each other and $\gamma_j = 0$, ρ_{TS} is smaller than the correlation based on the OLS coefficient. If γ_j is non-zero for at least one instrument, the TS2SLS correlation can either underestimate or overestimate the OLS correlation.

The above discussion highlights that the rules used for the selection of the instruments with one sample apply to the two-sample setting. The instruments should be exogenous and non-weak. This implies that, first, the instruments should have the least correlation with the error term in the intergenerational equation. Second, the Adjusted R^2 of the first stage regression should be as close to 1 as possible.

Finally, as explained in Cameron and Trivedi (2005), in a two-step estimator the asymptotic distribution of the second-stage coefficient (the IGE in this case) depends on the distribution of the coefficient in the first stage (δ_j in eq. 2.1). The correct standard errors need to account for the randomness in the coefficients of the first stage. Therefore, I obtain the covariance matrix by simultaneously bootstrapping the first and the second stage. Following Cameron and Trivedi (2005), I use 999 bootstrap replications.[16]

2.4 Empirical strategy and sample selection

A main challenge in the estimation of intergenerational mobility is the difficulty of finding a suitable proxy for lifetime earnings. For example, Solon (1992), Zimmerman

[16] A comparison between Table 2.1 and Table A.9 shows that the standard errors are smaller if bootstrapped only in the second stage.

(1992) and Mazumder (2005a) demonstrate that the use of point estimates of income leads to biased results because of the impact of transitory shocks. Related to this, Haider and Solon (2006) underline that a bias does not only arise from measurement error in paternal earnings but also from error in the dependent variable. As the attenuation factor changes with age, and the outcome of the sons is usually observed at an earlier age than the age at which paternal earnings are considered, the elasticity might suffer from life-cycle bias, of which the direction depends on the age of the son.[17] The authors also suggest that this is less of a problem if the income of the sons is measured between their early thirties and their mid-forties.

I address this problem by selecting fathers and sons within a similar age range, as Figure 2.1 indicates.[18] The analysis is based on a panel of sons and potential fathers with positive annual labour income and who are between 30 and 59 years of age (hereafter, *ALL*).[19]

Males born after 1949 belong to the main sample if two criteria are met. First, the information provided about their real father must refer to the period when the latter are between 30 and 59 years of age. Second, their father is born before 1950.[20] Males

[17]A life-cycle bias appears when the slope of a regression of log earnings on the log of the present value of lifetime income is not the same for fathers and sons. Other applied literature, such as Grawe (2006), also investigates it.

[18]Women are excluded from the sample to simplify the interpretation of the results and the cross-country comparison. The main reason is that their career choices, and consequently their labour income, might be influenced by a higher number of factors. For example, women are more sensitive to issues related to selection into the labour market.

[19]The only exception is the wave from the British Understanding Society survey, where I derived this variable by multiplying the monthly income by twelve.

[20]The chosen cut-off years ensure a reasonable number of observations in both the main and the auxiliary samples for the 4 countries.

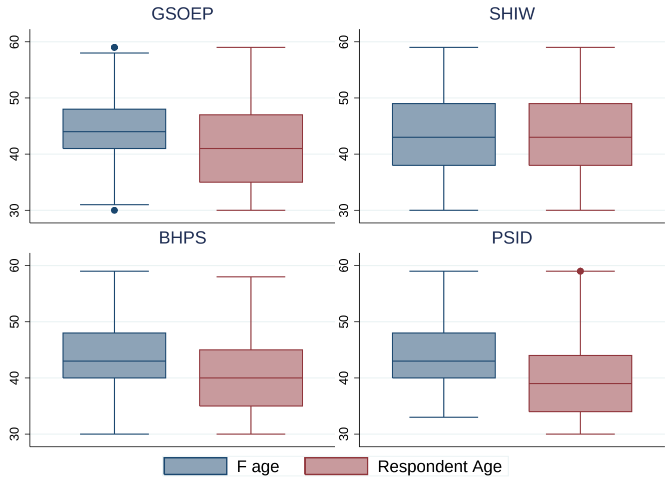

Figure 2.1: Mean and standard deviation of the ages of the respondent and of his father by country.

born before 1950 and with children in the household constitute the auxiliary sample of fictitious fathers.[21]

As robustness checks, five alternative subsamples are considered.

Three samples are based on additional criteria about age and number of wave, in line with the above mentioned literature on attenuation and life-cycle bias. The first adds age restrictions to *ALL* and considers only the respondents between 35 and 55 years of age (*A*55). The second sample includes only respondents and fictitious fathers with at least three-year averages of own earnings (*AV*3).[22] The third retains one observation per individual: when the age of the respondent (and of the fictitious father) is closer to 40 (*MIN*40).[23]

Finally, two additional sensitivity checks are reported in the appendix section A.6. Figure 2.2 reports the income distribution for employed and self employed individuals.

[21] For Italy, considering only individuals with non-missing information about their own children would reduce drastically the number of observations.

[22] As the appendix Tables in A.5 highlight, the average number of years is more than 4 in all datasets.

[23] The appendix section A.1 reports the summary statistics for ALL. The statistics and the estimations relative to the three alternative samples are in the appendix section A.5.

It highlights the presence of outlying observations and indicates some differences in the income distribution between employed and self-employed workers. To check whether the estimates are driven by outliers, I perform the analysis on two additional samples: a first sample without the top and bottom 1% earners, and a second without self-employed workers.

Across all samples, the main variable is the annual labour income.[24] Only respondents with positive income are included in this analysis. All income indicators are converted into constant US dollars, with the 2010 Consumer Price Index.

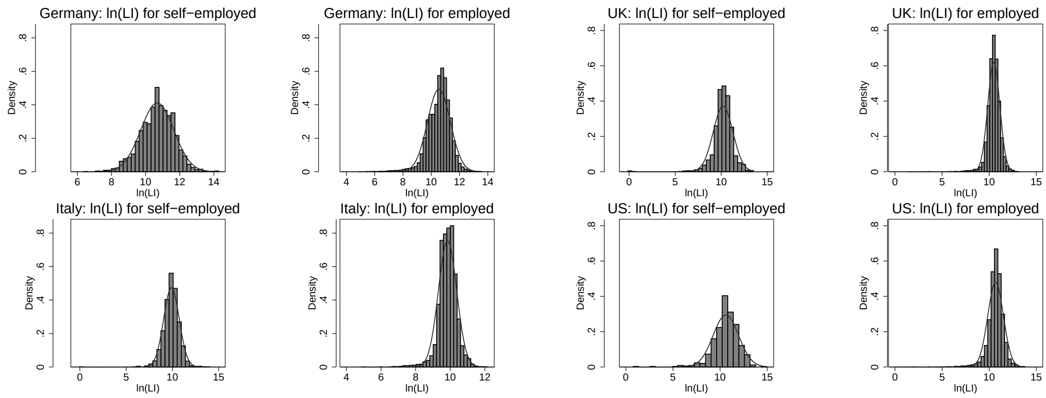

Figure 2.2: Distribution of ln(LI) by type of employment

2.5 First stage regressions

The selection of the instruments is a crucial stage for consistency. Despite disagreement over the relative contribution of each of the factors affecting earnings, a consensus seems to exist on the importance of variables such as age, education, experience in the labour market and gender (Mincer, 1974; Spence and Stiglitz, 1975; Heckman, 1985).

[24]The only exception is the wave from the British Understanding Society survey, where I derived this variable by multiplying the monthly income by twelve.

In the intergenerational literature, the instruments used vary from one study to another according to data availability. For example, Grawe (2004) uses only educational levels. Aaronson and Mazumder (2008) use the year and the state of birth. Björklund and Jäntti (1997) include eight occupational categories, one dummy variable for the fathers living in Stockholm and one if education is higher than the compulsory level. More recent studies, such as Mocetti (2007), Piraino (2007) and Nicoletti and Ermisch (2007) use a larger set of instruments.

This article only considers variables that are available in all four datasets.[25] The selected instruments provide information about occupation, education, geographical origin, date of birth and age, as indicated in eq. 2.6:

$$\begin{aligned} y_{fit} &= \lambda_0 + \lambda_1 age_{it} + \lambda_2 age_{it}^2 + \lambda_3 birth_i + \lambda_4 educ_{it} \\ &+ \lambda_5 race_{it} + \lambda_6 location_{it} + \sum_j \lambda_j job_{itj} + v_{it} \end{aligned} \tag{2.6}$$

The first three regressors are the age, the squared age and the year of birth. *educ* is a set of dummies for completed education. *race* indicates ethnicity. *location* is a categorical variable about the geographical position of the individual. Finally, *job* is a series of indicators providing information about the type of occupation, the sector and if the individual is employed or self-employed. The coefficients of this equation are used to predict the paternal income in the second stage. The prediction is based

[25] With some exceptions. For Italy, it is not possible to obtain information about racial origin. However, according to the latest report of the national institute for statistics (ISTAT), the percentage of non-Caucasian immigrants accounts for about 1.5% of the population, and 20% of these are children. For Germany, a precise indicator of the location of the father when the respondent was 15 years old is not available.

on information from the son about the father when the son was 14 or 15 years of age, except for SHIW.[26]

The surveys usually provide several indicators of the same socio-economic characteristic. For example, several variables provides information about occupation, based on different classifications.[27] I test alternative combinations of instruments to ensure a high adjusted R^2. The trade-off is between a suitable number of non-weak instruments and the comparability of results across countries. On the one hand, a reduced number of instruments may result in a larger bias. The checks reported in the appendix table A.7 seem to support this.[28] On the other hand, different values of adjusted R^2 across surveys may reduce the cross-country comparability. Taking this into account, the Aikake and the Bayesian Information Criteria, and the comparability of the regressors across surveys are the key criteria for the model selection. Ceteris paribus, for each country I selected the model with the highest Adjusted R^2 that is consistent with the average value in the other surveys. The results of the first stage regressions are reported in the appendix section A.1.[29]

2.6 Second stage regressions: model specifications and results

As mentioned in section 2.4, intergenerational estimates may suffer from attenuation and life-cycle bias. To reduce attenuation bias, some authors have favoured average

[26]Only in SHIW the information refers to the period when the father was as old as the current age of the respondent.

[27] The exception is Italy where the information about parental characteristics is limited.

[28]The table reports the different estimates of β_{TS} in eq. 2.2 on the same PSID sample, using different instruments in the first stage. The estimates vary from 0.868 to 0.556.

[29]As mentioned above, alternative models were tested. The results are not reported, but they are available upon request.

earnings (Solon, 1992), others have used educational attainment as an instrument for life-time earnings. Lee and Solon (2009), and Hertz (2007) suggest a way to account for the life-cycle bias. They augment the basic intergenerational regression with an interaction between the individual's age and the paternal income, and apply this model to study the intergenerational elasticity over time. The current research adapts to TS2SLS the specification proposed by Lee and Solon (2009).

The empirical specification for the second stage estimation of eq. 2.2 is eq. 2.7:

$$y_{sit} = \alpha_0 + \beta \hat{y}_{fi} + \alpha_1 birth_{si} + \alpha_2 (age_{fi} - 40) + \alpha_3 (age_{fi} - 40)\ \hat{y}_{fi} + \\ \sum_{k=1}^{p} \alpha_{4k} (age_{sit} - 40)^k + \sum_{k=1}^{p} \alpha_{5k} (age_{sit} - 40)^k\ \hat{y}_{fi} + \varepsilon_{it} \quad (2.7)$$

where f stands for father, s for son and p is the order of the polynomial for the respondent's age, and its interaction with the paternal income. *birth* is the year of birth, and $age - 40$ is the age normalised at 40.[30] The statistical significance of the coefficients and the results of the Ramsey Regression Equation Specification Error Test suggest that the introduction of a polynomial of order three better suits German data, whereas a polynomial of order one is more suitable for the three other datasets. With the interaction between the normalised age and the paternal income, β is estimated for a 40-year-old individual. For this reason, I also introduce the interaction between the father's age, normalised at 40, and his income. As a result, β reports the intergenerational

[30] The year of birth of the son explicitly accounts for the fact that individuals are not observed at the same age. If individuals were observed at the same age, selecting the year at which labour income is observed or the cohort would be the same.

elasticity for a 40-year-old respondent and a 40-year-old father, independently of the cross-country differences in the age of fathers and sons (Figure 2.1).

The interaction between the paternal age and the income, $(age_{fi} - 40)\ \hat{y}_{fi}$, renders the coefficients estimated on the German, British and American datasets consistent with those on the Italian data, where by construction the age of the son and the father is the same. When I estimate eq. 2.7 on SHIW, I substitute the paternal age and its interaction with the father's year of birth. In the other three datasets, the father's year of birth can be derived from $birth_{si}$ and age_{fi}.

The paternal year of birth is also a proxy for cultural changes over different generations of fathers. Table A.1 shows that, on average, the real fathers are born earlier than the fictitious ones. This is a way to control for the fact that the role of the characteristics used to predict paternal earnings may change over time (e.g. different returns to education).

2.6.1 The intergenerational elasticity: the baseline model

In this section I estimate the intergenerational elasticity, I compare it with other IGE studies and I assess the robustness of the results on different samples. For each survey and sample, Table 2.1 reports three estimators. The first section of the table shows β in eq. 2.7. The second section reports the correlation coefficients based on the βs. The third part indicates the intergenerational elasticities when α_3 and α_5 are equal to zero. This specification is useful to compare the results of this research with the existing literature.

The table reports the baseline results for the main sample (ALL) and for the alternative samples specified in section 2.4.[31]

Table 2.1: TS2SLS, OLS

	Germany		Italy		UK		US	
IGE estimates								
ALL (main sample)	0.437***	[0.057]	0.463***	[0.050]	0.317***	[0.058]	0.489***	[0.060]
Without extremes	0.450***	[0.055]	0.506***	[0.049]	0.318***	[0.056]	0.460***	[0.055]
Without self-employed	0.415***	[0.061]	0.501***	[0.068]	0.377***	[0.058]	0.515***	[0.060]
AV3	0.438***	[0.088]	0.387***	[0.082]	0.308***	[0.070]	0.504***	[0.070]
A55	0.430***	[0.074]	0.514***	[0.066]	0.358***	[0.073]	0.506***	[0.073]
MIN40	0.394***	[0.065]	0.565***	[0.067]	0.395***	[0.097]	0.520***	[0.074]
IGE estimates for $\alpha_3 = \alpha_5 = 0$								
ALL	0.300***	[0.040]	0.495***	[0.051]	0.379***	[0.055]	0.524***	[0.054]
AV3	0.291***	[0.056]	0.390***	[0.082]	0.372***	[0.080]	0.533***	[0.062]
A55	0.285***	[0.051]	0.596***	[0.069]	0.431***	[0.086]	0.488***	[0.066]
MIN40	0.399***	[0.053]	0.553***	[0.068]	0.397***	[0.063]	0.545***	[0.070]
ALL Correlation	0.250		0.299		0.192		0.236	
AV3 Correlation	0.326		0.628		0.294		0.331	
A55 Correlation	0.213		0.222		0.163		0.231	
MIN40 Correlation	0.213		0.285		0.170		0.312	
Obs ALL	21645		6940		14782		8448	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

Recent cross-country studies indicate that Nordic countries and Canada are characterised by a lower IGE than the Anglo-Saxon countries. Between the two, the United Kingdom is more mobile than the United States. Germany usually has a higher elasticity than Canada but lower than the United Kingdom and the United States (Blanden et al., 2005; Bratsberg et al., 2007; Jantti et al., 2006; Grawe, 2004).[32] The results presented here are in line with the existing literature. Italy and the United States are characterized by higher IGE than the United Kingdom and Germany. It is worth mentioning that without the interaction between the paternal income and the son's and

[31]The coefficients on the interaction terms are available in Table A.10 for the sample ALL and in the the appendix section A.5 for the other samples.

[32]Italy is not usually included in cross-country literature.

father's age, the IGE in the UK is higher than in Germany (0.38 versus 0.3) and consistent with the above mentioned studies. Notice also that although the lowest β is for the UK, it is positively correlated to the paternal age after 40. Table A.10 indicates that β increases by 0.016 in the main sample for each additional year (after 40), which is higher than the increase in the other countries. This may suggest that the age at which labour income is measured is more sensitive for some dataset, such as BHPS in this case. The findings further underline the importance of having similar ages, not only between fathers and sons, but also across surveys.

The results differ according to the selected sample. The estimates of the first section of the table suggest that the IGE is between 0.39 and 0.45 in Germany, and between 0.39 and 0.57 in Italy. It ranges between 0.32 and 0.4 in the UK, and between 0.46 and 0.52 in the US. For all countries except Germany, the elasticity is higher when only one-year observation per individual is considered. It is also higher when fathers and sons are between 35 and 55 years of age (A55). The results also suggest that considering only employed sons and fathers increase the IGE in all countries, but Germany (for more details, see the appendix section A.6.2). For all countries, except for the US, the coefficients increase when the top and bottom percentiles of the sons' and of the fathers' income distributions are excluded. This suggests that it may be worth exploring the elasticity at different quantiles. This may also result from the higher measurement error in the earnings in the extreme quantiles.

The findings of this paper suggest that the IGE in Germany is not very different from the IGE in the US. The results hold when only West Germans are considered. For example, when the top and bottom percentiles are excluded the elasticities amount to 0.45 and 0.46, respectively. This is in line with earlier studies, such as Couch and Dunn (1997) and Couch and Lillard (2004).[33] Similar conclusions emerge from Schnitzlein (2015), who also suggest that the low estimates of the previous literature are not robust to changes in sample. [34] More recent contributions, including the cross-countries studies mentioned above, instead, have questioned these findings. The absence of the interaction term may explain the lower estimates of the recent studies. Indeed,the introduction of the interaction terms between the parental income and the respondent's age raises the IGE from 0.3 to 0.437 in the main sample. Moreover, the polynomial of order three is statistically significant, which suggests the existence of non-linearities in the relationship between son's and father's earnings.[35]

In Italy, β is 0.495 without the interaction, which lies within the elasticities in Mocetti (2007) and Piraino (2007) (0.499 and 0.435, respectively). These two studies use TS2SLS and the same dataset.

In Britain, the intergenerational estimates differ across studies. Most researchers use either the National Child Development Study (Dearden et al., 1997), or the British Cohort Study, or both (Blanden et al., 2004). It is not straightforward to compare their results with those in Table 2.1. Both surveys are different from BHPS by construction,

[33] They find no significant differences between the IGE in the US (using PSID and NLS, respectively) and in Germany (with GSOEP).

[34] The author compares the intergenerational mobility in Germany and in the United States. The results of his baseline model indicate an elasticity ranging from 0.262 to 0.417 for West Germany and from 0.459 to 0.482 for the United States. He concludes that there are no relevant differences in the IGE in the two countries.

[35] In this research I include a small sample of 453 East Germans. The appendix Table A.8 indicates that the elasticity computed on the main sample (first column) is the same as when only West Germans are considered (the third column). Column two suggests that the IGE may be lower for those who went to East Germany after their studies, 0.233. This estimate, however, is not statistically significant. The appendix section A.2.1 further explores the existence of regional differences for the four countries.

since they follow one cohort of individuals over time. Ermisch and Francesconi (2004) are the first who use BHPS to estimate the IGE, 0.247, although they consider an occupational prestige score and not earnings.[36] Nicoletti and Ermisch (2007) use TS2SLS on a restricted sample of sons born between 1962 and 1972, aged between 31 and 45, who have co-resided with their father for at least one wave of the BHPS. Their IGE estimate is 0.365.

Table 2.1 identifies the United States as one of the countries with the highest level of intergenerational elasticity, from 0.460 to 0.520. This value is larger than 0.44, the elasticity obtained by Lee and Solon (2009), who use a similar specification and the same dataset. The authors, however, use Ordinary Least Squares and the respondents are younger (from 25 to 48 years old), whereas the income of their parents is measured at 40.[37] Additionally, they use family income. Within the TS2SLS literature, Björklund and Jäntti (1997) obtain a β of 0.516 on PSID using five-year averages of parental earnings, which is similar to 0.533, the IGE I obtain when earnings are measured as averages and without the interaction.

The second section of Table 2.1 reports the correlation coefficients. Overall, the correlation is higher when averages are considered. With this sample, the variance of the son's earnings is closer to that of the father's earnings. For the other samples, Tables A.2, A.1 and A.24 indicate that the difference between the variance of the son's and the father's incomes is larger. As a consequence, the second term in eq. 2.5 is smaller, thus

[36]Precisely, the Hope-Goldthorpe occupational prestige score, based on a survey in England and Wales where respondents had to provide information about social desirability of male occupations (Goldthorpe and Hope, 1974).

[37]Solon (1992), cited in Blanden (2009), estimates the IGE on PSID using least squares and instrumental variables. The latter are 20% larger than the former.

decreasing the correlation coefficient. The intergenerational correlation on the AV3 sample is at its highest in Italy (0.63), followed by the US (0.33), Germany (0.33) and the UK (0.29).[38] This exercise underlines the importance of considering both elasticity and correlation estimates.

To check whether the specification proposed by Lee and Solon (2009) improves the robustness of the estimates, I compare the coefficients of eq. 2.7 to the estimates obtained when α_3 and α_5 are equal to zero. The interaction between paternal income and age of the respondent introduced by Lee and Solon aims to reduce the life-cycle bias. To a certain extent, the variation of the estimates across the different samples is smaller with the interaction terms, especially for Germany. The difference, however, is limited. It may be due to the fact that, on average, the age of the son is similar to that of the father in all surveys and across the samples.

Finally, and as expected, the coefficients decrease, at least by half, when eq. 2.7 is augmented with dummies for the level of completed education (appendix Table A.11). Italy has the largest IGE in this case.

Overall, this section highlights the importance of the sample selection to compare the results of different studies. This does not only apply to cross-country comparisons but also to results on the same country. The findings suggest that even the ranking of countries may be sensitive to the selected specification and to the considered statistic.

To further investigate the transmission of paternal earnings, it might be useful to disaggregate the analysis. The next section investigates cross-country differences in

[38]For the following exercises, the correlations coefficients will not be reported. Although interesting, it is more useful to consider elasticities for an easier comparison with other studies.

the evolution of the IGE across cohorts. Sections 2.6.3 and 2.6.4 analyse if the transmissions change at different income quantiles.

2.6.2 The intergenerational elasticity over time

The goal of this exercise is to clarify the contrasting results in the literature about the mobility trend in the United States and United Kingdom, and to fill the gap in the literature for Italy and Germany. I modify eq. 2.7 in the following way:

$$y_{sit} = \hat{\alpha}_0 + \sum_{c=1950}^{1980} \beta_c D_c \hat{y}_{fi} + \hat{\alpha}_1 birth_{si} + \hat{\alpha}_2 (age_{fi} - 40) + \hat{\alpha}_3 (age_{fi} - 40)\, \hat{y}_{fi} + \sum_{k=1}^{p} \hat{\alpha}_{4k} (age_{sit} - 40)^k + \sum_{k=1}^{p} \hat{\alpha}_{5k} (age_{sit} - 40)^k\, \hat{y}_{fi} + \varepsilon_{it} \tag{2.8}$$

where $D_c\hat{y}_f$ is an interaction term between paternal income and cohort indicators and the other regressors are the same as in eq. 2.7. Figure 2.3 represents graphically the coefficients β_c for the main sample (*ALL*).[39]

The studies on the evolution of intergenerational mobility are not numerous and the existing ones in some cases provide contrasting evidence. For the United States, Aaronson and Mazumder (2008) apply TS2SLS on US Census data, with the state of birth and the cohort as instruments in the first stage. The authors consider individuals born between 1921 and 1975, from 25 to 54 years of age. Their findings indicate an increased mobility from 1950 to 1980. Instead, Lee and Solon (2009) and Hertz

[39] The coefficients and standard errors are reported in the appendix Tables A.13 and A.14. The main advantage of this sample is especially clear with this exercise, where it is possible to examine a greater number of cohorts: specifically, from 1950 to 1980 for Germany. For the United States, Italy and the United Kingdom there are not enough observations for the younger cohorts. Therefore, they have been grouped with cohort 1978.

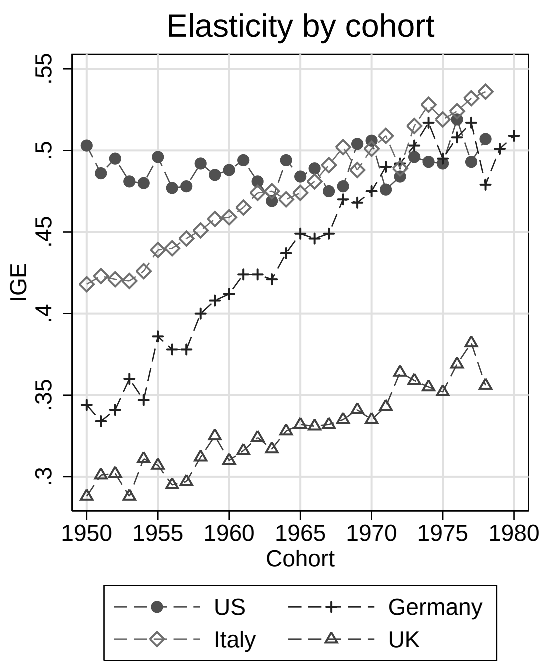

Figure 2.3: The trend of intergenerational elasticity by cohort and by country

(2007) provide evidence against the existence of a trend. Figure 2.3 indicates that the coefficients are very similar to each other and the Wald tests suggest that the differences are not statistically significant. Overall, the results on the alternative subsamples, in the appendix section A.5, confirm this conclusion.[40]

Figure 2.3 and Table A.13 suggest a reduction of mobility in the other three countries.

In Italy, the coefficients increase from 0.418 to 0.536 for the individuals born in 1978 or after. They are different from each other at one percent level, although the confidence level decreases with two close cohorts.

A positive trend emerges in Germany as well, the coefficients ranging from 0.344 to 0.509. They are statistically different from each other, at all confidence levels.

[40]For the subsamples $AV3$ and $A55$,there are no statistically significant differences among β_c. Results based on MIN40 provide partial evidence towards a positive trend. Even in this case, however, the coefficients are not always statistically different from each other.

In the United Kingdom, the elasticity increases from 0.288 (1950 cohort) to 0.356 (1978 to 1980 cohort). The coefficients are statistically different from each other at one percent level of significance, except for later cohorts where the strength of the significance decreases. This trend is consistent with Blanden et al. (2004) and Blanden et al. (2007) who estimate the impact of family income on individuals born in 1958 (NCDS) and 1970 (BCS) and observe an increase in the IGE for the later cohort. Nicoletti and Ermisch (2007) conclude in favour of a statistically significant positive IGE trend but only for the individuals born after 1960. The authors, however, assess the trend by cohort groups and the results are sensitive to the categorisation.

It is interesting that the IGE is higher for the younger cohorts, at least in the three European countries. The expansion of educational opportunities and the number of graduates should positively affect mobility by decreasing the returns to education (Blanden, 2013). For Britain, Blanden et al. (2007) document a fall in the returns to education after age sixteen between the 1958 and 1970 cohorts. This is accompanied by a decrease in intergenerational mobility. The authors mention cognitive and non-cognitive skills, labour market attachment and the higher inequality of access to higher education as alternative variables that affect intergenerational mobility. The appendix Table A.14 suggests that when education is accounted for, the decrease in the elasticity is higher for earlier cohorts. A possible interpretation may be that factors other than education play a bigger role for the IGE of younger generations.[41]

[41] Another possible reason is that the used education dummies are not precise enough to capture the contribution of education to the labour income.

Germany is the country that experienced the highest increase in IGE, at least until the cohorts in the mid-seventies, followed by Italy and the United Kingdom. The IGE of cohorts born after 1965 is the same or larger in Italy than in the United States. Therefore, the coefficient for Italy in Table 2.1 results in part from the lower values of older cohorts. A similar comment applies to Germany. The elasticities are similar to those computed on PSID for those born after 1970, although the positive trend seems to flatten out after this period. The alternative samples confirm these findings, as the figures in the appendix section A.5 illustrate. This highlights that much more can be learnt when several dimensions of the same topic are analysed.

2.6.3 The intergenerational elasticity over the income distribution: two-sample two-stage quantile regression

The seminal model of Becker and Tomes, described in section 4.1, predicts higher IGE for poorer families. Less-favoured parents might be financially constrained and invest a lower amount in their children's human capital. This may imply that the IGE is not constant along the income distribution. To investigate this hypothesis along the son's earnings distribution, I estimate equation 2.2 at different quantiles. I use two-sample two-stage quantile regression, TS2SQR.[42] The estimated model follows eq. 2.9:

$$Q_{\alpha}(y_{sit} \mid \hat{y}_{fi}, X) = \hat{y}_{fi}\rho(\alpha) + X\delta(\alpha) + \varepsilon_{it}(\alpha) \tag{2.9}$$

[42] In the first stage, least squares estimates are used to predict paternal income, like for TS2SLS. In the second stage, the predicted income is used as a regressor in the quantile regression.

where $\rho(\alpha)$ indicates the IGE at the α quantile and X is the matrix of regressors of eq. 2.7. If applied to intergenerational studies, differing slopes indicate different sensitivity of different portions of the son's distribution to small changes in father's income.

As explained by Cameron and Trivedi (2005, p. 88), Koenker and Hallock (2001) and Koenker (2005, p. 5-25), the quantile regression measures the effect of the explanatory variables at a given quantile in the conditional distribution of the dependent variable. A main advantage of this methodology is its robustness to outliers. In addition, this approach does not make assumptions about the parametric distribution of the errors. This renders quantile regression particularly suitable for skewed and heteroscedastic data.

There are few studies relying on quantile regression and the results are mixed. Eide and Showalter (1999) are among the first researchers to use quantile regression in this field. They use conditional quantile regression on 612 matched pairs of fathers and sons from PSID and uncover higher coefficients at the bottom of the son's distribution (0.67 for the 10th percentile against 0.26 for the 90th percentile). The authors obtain similar results using the High School and Beyond dataset, with over 5,000 observations. By contrast, Schnitzlein (2015) finds higher IGE at the top of the offspring's distribution in the United States, as well as in Germany (on PSID and GSOEP), with conditional and unconditional quantile regressions. In Britain, Gregg et al. (2015) uncover the same pattern, or a J-shaped pattern when workless spells are included.[43] In Italy, Mocetti (2007) finds higher sensitivity at both extremes of the offspring's income distribution,

[43] They use unconditional quantile regression on the British Cohort Study

although the statistical significance of his estimates is only confirmed for the median and the quantiles above it.[44]

The results of this research are partially in line with the above literature. Figure 2.4 and Table A.15 in the appendix section A.4 indicate that in Italy the paternal income plays a greater role at both extremes of the offspring's marginal distribution. However, only the coefficients at the bottom are statistically different from the median. In the United States and in Germany, the estimates rise with the quantile but they are not statistically different from the median. In the United Kingdom, the association with the parental income increases until the median, but then it does not change significantly.[45]

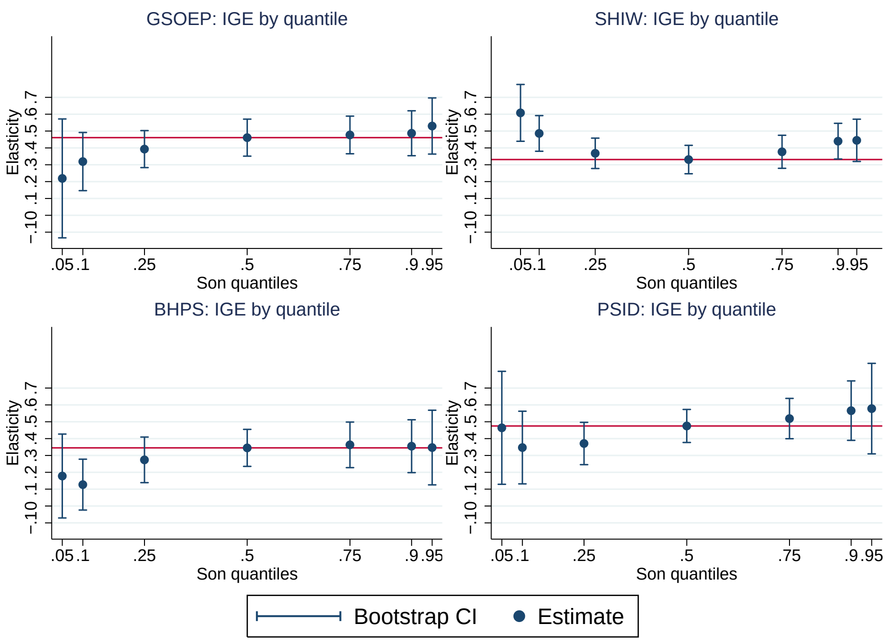

Figure 2.4: Two sample two stage quantile regression
Picture shows intergenerational elasticity by the son's income quantile. The CI are 95% CI. The red line indicates the median.

[44]Examples of studies for countries not included in this research are Corak and Heisz (1999), who uses non-parametric estimation techniques on Canadian men and Bratberg et al. (2007) for Norway who apply quantile regression to register data for Norwegians born in 1950, 1955, and 1960.

[45]Notice that the coefficients at the extreme quantiles are associated with larger confidence intervals. This suggests higher imprecision in the estimates and higher variability at the extremes.

The results of the TS2SQR provide little evidence in favour of the hypothesis that the IGE is not constant along the son's income distribution, except for Italy. This is not necessary the most suitable method to test the prediction of the model of Becker and Tomes. In fact, quantile regression does not directly account for the father's income distribution.

Alternative methods analyse the IGE at different levels of the fathers' income distribution. For example, Bratberg et al. (2007) compare Norway, Finland, Denmark (with register data), the Unites States (data from NLSY79) and Britain (NCDS). They explicitly account for non-linearities in the transmission of earnings through polynomials of different order according to the country. The authors estimate the elasticity at different percentiles of paternal earnings (10th, 50th, and 90th). For all countries, the estimates of the elasticity at the 10th percentile are much lower than at the 50th, in turn lower than at the 90th, although the difference is less striking in the Anglo-Saxon countries.[46] Alternatively, Björklund et al. (2012) use a non-linear regression by means of a spline function with pre-defined knots corresponding to paternal income percentiles. Their conclusions, based on a large sample of Swedish fathers and sons from register data, are consistent with Bratberg et al. (2007).

The next section discusses and implements another method that directly accounts for the income distribution of both fathers and sons.

[46]For Nordic countries, this shows that the elasticity in lower percentiles might be overestimated; it highlights as well that overall differences between Anglo-Saxon and Nordic countries might be overestimated by the linear model. Indeed, differences are smaller in the middle and at the top of the distribution than at the bottom.

2.6.4 Generalized ordered logit mobility matrices

Mobility matrices explicitly account for both the son's and the father's income distribution. Their other advantage with respect quantile regression is that they provide a more intuitive idea of mobility, including its direction.

The transition matrices report the relative frequencies (or probabilities) in each earning class, given the paternal income quantile and have been used in many studies.[47] These papers identify higher intergenerational persistence at the top and at the bottom of the income distribution (to a lower extent for Canada and the Scandinavian countries).

Although the information they provide is unique, other measures of mobility have been preferred. One reason is that it is not straightforward to introduce control variables. This is a main drawback for intergenerational income analyses, where the model needs to control for the fact that the income of the father and of the son are measured at different ages.

Sociologists use a similar approach. As they focus on occupational classes instead of income quantiles, they need to account for changes in the marginal distribution of occupational classes across generations. For this reason, their measure of relative mobility is based on the odds ratio. As indicated in Erikson and Goldthorpe (2002), it is a ratio of relative frequencies:

[47] Examples are in Dearden et al. (1997), Blanden et al. (2005) for studies on Britain; Corak and Heisz (1999), Mazumder (2005b) and Corak and Piraino (2010) for the United States and Canada; Checchi et al. (1999) and Piraino (2007) for Italy; Jantti et al. (2006) for Anglo-Saxon and Nordic countries.

$$OR = \frac{f_{ii}/f_{ij}}{f_{ji}/f_{jj}} \tag{2.10}$$

where i and j are two categories of the occupational classification. The ratio indicates the chance for an individual originated in class i to stay in class i (f_{ii}) rather than in class j (f_{ij}), relative to the same chance for an individual whose parent is in class j. In a limited number of studies, the odds ratio have also been recreated from a multinomial or a conditional logit.[48] For example, Breen and Goldthorpe (2001) have introduced education dummies in their conditional logit model. This approach has the advantage of introducing some control variables.

I build upon the work of the sociologists and construct a mobility matrix from a logistic model. It has two advantages with respect to the traditional transition matrices. It allows to control for the life-cycle bias, by adding independent variables. As there is a covariance matrix, it is also possible to do statistical inference on the persistence patterns. To the best of my knowledge, these variables have never been introduced in income transition matrices.[49]

I estimate a sequential, or generalised ordered, logit where the dependent variable is a categorical variable with as many categories as the number of income quantiles. The analysis is based on the generalized ordered logit because it is more efficient than models that do not account for data ordering (i.e. the multinomial logit). Although

[48] Goldthorpe (2007) cites Breen (1994), who builds upon Logan (1983) and uses a conditional logit.

[49] In a way, Jantti et al. (2006) correct for the ages of the fathers and the sons. To my understanding, however, this is done in the calculation of the paternal income.

more parsimonious, the ordered logit cannot be used as the the parallel odd assumption is violated.[50]

The model corresponds to a series of binary logistic regressions, with combined categories of the dependent variable:

$$P(y_i > m) = \frac{exp(\alpha_m + X_i\beta_m)}{1 + exp(\alpha_m + X_i\beta_m)}, \ \ m = 1, 2, .., M - 1 \tag{2.11}$$

where M is the number of income quantiles; X includes the parent's quantiles and the control variables of eq. 2.7; α_m are the $M - 1$ cut-off points. For this analysis, $M = 5, 10$.

After estimating the generalized ordered logit, I compute the predicted probabilities for each outcome for a 40-year-old son given the paternal income class. Then, I reproduce the mobility matrix. The advantage of computing the probabilities at a given age is that the results are more easily comparable across countries and with the other estimates of this research. The appendix Figure A.1 illustrates the matrix for the four countries.[51]

Despite differences in the magnitude of the probabilities, the matrices present some common characteristics. The comparison of the two extremes on the anti-diagonal suggests that upward mobility is less probable than downward mobility. In other words,

[50] According to this assumption, the coefficients of the covariates across a series of cumulative logits do not change according to the response variable outcome. The main difference between the two models is that the former estimates a series of coefficients (including one for the constant) for all the m points at which the dependent variable can be dichotomised, whereas the latter assumes that the threshold parameters do not depend on the regressors. The two models are described in Cameron and Trivedi (2005, p. 519-520), Williams (2006), Fu (1999).

[51] The appendix section A.4 reports the matrices with the bootstrap standard errors.

for all countries, it is more likely for those with the richest fathers to be in the lowest quintile than it is for those with the poorest fathers to be in the highest quintile. Indeed, the probability of being in the first quintile if the father is in the fifth quintile is less than 10% in the UK and in the US. It is less than 5% in Italy and in Germany. Overall, the individuals are more likely to be in the first quintile if their father is in the same quintile. Similarly, they have more chances of being in the fifth quintile if the father is in the fifth quintile.

Table 2.2: Probability differential for a 40-year-old son

	1st		2nd		3rd		4th		5th	
Germany										
1st	0.067***	(0.022)	0.091***	(0.025)	-0.001	(0.026)	-0.089***	(0.021)	-0.069***	(0.011)
2nd	0.028*	(0.016)	0.058***	(0.016)	-0.010	(0.019)	-0.036**	(0.017)	-0.040***	(0.012)
3rd	0	(.)	0	(.)	0	(.)	0	(.)	0	(.)
4th	-0.051***	(0.014)	-0.037***	(0.012)	-0.039**	(0.017)	0.033**	(0.016)	0.095***	(0.015)
5th	-0.093***	(0.015)	-0.079***	(0.015)	-0.087***	(0.021)	0.050**	(0.022)	0.209***	(0.025)
Italy										
1st	0.135***	(0.014)	0.044***	(0.015)	-0.032**	(0.015)	-0.083***	(0.014)	-0.064***	(0.011)
2nd	0.042***	(0.012)	0.032**	(0.014)	-0.007	(0.015)	-0.033**	(0.013)	-0.034***	(0.011)
3rd	0	(.)	0	(.)	0	(.)	0	(.)	0	(.)
4th	-0.059***	(0.011)	-0.030**	(0.013)	-0.008	(0.014)	0.031**	(0.014)	0.066***	(0.012)
5th	-0.080***	(0.011)	-0.076***	(0.013)	-0.069***	(0.014)	0.025*	(0.015)	0.199***	(0.016)
UK										
1st	0.039	(0.033)	0.094***	(0.030)	0.004	(0.025)	-0.063**	(0.027)	-0.074**	(0.030)
2nd	0.025	(0.028)	0.049**	(0.023)	0.021	(0.022)	-0.028	(0.023)	-0.067***	(0.025)
3rd	0	(.)	0	(.)	0	(.)	0	(.)	0	(.)
4th	-0.054**	(0.027)	-0.044**	(0.022)	0.003	(0.020)	0.034	(0.023)	0.060**	(0.028)
5th	-0.027	(0.032)	-0.051**	(0.023)	-0.037*	(0.021)	0.010	(0.024)	0.105***	(0.034)
US										
1st	0.129***	(0.031)	0.086***	(0.028)	-0.041	(0.029)	-0.091***	(0.028)	-0.083***	(0.023)
2nd	0.080***	(0.027)	0.063**	(0.026)	-0.079***	(0.027)	-0.052*	(0.028)	-0.012	(0.029)
3rd	0	(.)	0	(.)	0	(.)	0	(.)	0	(.)
4th	-0.019	(0.023)	-0.034	(0.026)	-0.102***	(0.026)	-0.020	(0.028)	0.175***	(0.034)
5th	-0.024	(0.024)	-0.073***	(0.022)	-0.120***	(0.027)	-0.015	(0.027)	0.231***	(0.035)

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Columns indicate quintiles of sons; rows of fathers. Bootstrap standard errors in parenthesis. The coefficients indicate changes in the probabilities of being in a given income quintile for a 40-year-old son according to the paternal quintile with respect to the same probability with the father in the third quintile

The role played by the paternal income quintile emerges more clearly from Table 2.2. The table reports the probability differential for being in quintile M if the father is in a given quintile with respect to the base probability. The base probability is the probability of being in quintile *M* if the father is in the third quintile.

For all countries, the probability differentials have the expected sign. Overall, sons with fathers in the first or second quintile are more likely to be in in the first and second quintile and less likely to be in the fourth or fifth quintile than sons with fathers in the third quintile. The opposite occurs for fathers in the fourth or fifth quintile.

Despite the overall probabilities, having a father in the top quantile has a similar effect in Germany, US and Italy. In fact, the probability of being in the fifth quintile increases by 21, 23 and 20 percentage points if the father is in the fifth quintile with respect to a father in the third quintile. In the UK, the probability differential is 11 percentage points. Moreover, for the four countries, the differential increases by an additional 7 points when comparing fathers in the first and fifth quantile.

At the other end of the distribution, fathers in the first quintile increase the sons' probability of being at the bottom by 13.5 and 13 percentage points in Italy and in the US with respect to fathers in the third quintile. In Germany, the percentage differential is smaller, 7 percentage points. In the UK, it is 4 points but it is not statistically significant.

The patterns identified by the matrices are reinforced, statistically, by the failure of the parallel line assumption for the ordered logit. Indeed, the statistical tests on the coefficients suggest that within a given son's income quantile, the coefficients at the cut-off points are statistically different from each other in several cases, and especially for higher paternal quintiles.

This exercise suggests that, for all countries, the paternal labour income plays a role in affecting the son's ranking in the income distribution, especially for those with very poor or very rich fathers.

2.6.4.1 Mobility matrices for graduates

To test the role of the investments in human capital and the predictions of the Becker and Tomes model , I compute the mobility matrix for a 40-year-old university graduate.[52]

The appendix Figure A.2 confirms that education plays a key role in promoting equality of opportunities. This figure suggests that, except for Italy, a graduate has less than 20% chance of ending up in the first quintile of the income distribution, regardless of the paternal quintile. In Italy, the probability is larger than 20% only if the father is in the first two quintiles. In both Italy and the US, however, a father in the first quintile increases the likelihood of being in that quintile by 5-6 percentage points, with respect to a father in the third quintile (see Table A.21). For a UK or a German graduate, the quintile of origin has no effect on the probability of being at the bottom. Moreover, in the UK and in the US an individual with a university degree has at least 20% probability of being in the fifth quintile. Notice that in the United Kingdom, for any graduate, the probability is larger than 35%. Despite this, however, having a father in the fifth quintile increases the chances of being in the fifth quintile by 9 percentage points with respect to having a father in the third quintile, and by 20 points if compared with a father in the first quintile. In the US, almost any graduate has more than 37% of being in the fourth or fifth quintile. Nonetheless, a US graduate with a father in the top two quintiles has a

[52]The appendix Table A.20 reports the matrices with the bootstrap standard errors. Table A.21 reports the probability differentials for a university graduate.

higher probability of being at the top by 25-26 points than a US graduate with a father at the bottom of the income distribution.

Overall, for all countries but Italy, education has increased the probabilities in the upper half of the matrix, above the main diagonal. For Italy, a university degree seems to have a lower impact on the mobility patterns. The fact that the fees are relatively low in Italy and that the returns to education are lower than in other countries might partially explain this. Another explanation might be the important role of contacts to find a job in Italy.[53]

2.6.4.2 Drawbacks of mobility matrices

A common criticism addressed to the transition matrices is that the extent of mobility may depend on how the matrix is constructed. For example, the lower mobility at the extremes of the distribution might only be a mechanical consequence of its design, particularly of the existence of floors and ceilings. They impede the individuals at the bottom to go further down and those at top to move further up. Overcoming this shortcoming is not straightforward if the goal is to maintain all the information provided by the mobility matrices.[54]

A way to check whether the results are driven from the matrix construction is suggested by Corak and Heisz (1999). If the higher persistence towards the extremes of

[53]It is not possible to rule a simpler explanation. That is, the education dummies in SHIW could be a poorer proxy than the education indicators used in the other surveys.

[54]For example, Black and Devereux (2011) mention Bhattacharya and Mazumder (2007) who propose an alternative measure. They use the probability that a son's percentile in the earnings distribution of sons exceeds the father's percentile in the earnings distribution of fathers. This measure, however, does not capture the extent of mobility, as it does not estimate by how much the son has exceeded the father. An alternative solution are mobility indices (Jantti et al., 2006), which take into account the different elements and diagonals of the matrix. However, they do not provide information about the direction of mobility.

the distribution was exclusively the result of a floor-ceiling effect, then only the top and bottom income quantiles would present significant spikes in the transition probabilities. Instead if that characteristic is common to the neighbouring classes, then something else is at work. The tables in the appendix section A.4 indicate that this is the case for the top and bottom elements in the British and American matrices. Instead, this occurs only at the bottom of the main diagonal on GSOEP and SHIW.

As a further check, I randomly assign income values to the fathers and sons. If the higher persistence is only caused by the fact that the individuals at the extremes of the leading diagonal cannot move further (up or down), higher probabilities should still characterise the extremes. Instead, the mobility matrices created on this new data show no sign of higher persistence at the extremes.[55]

Another possible objection is that the size of the quantile might affect the results. Fewer categories (for example, quartiles) might underestimate mobility with respect to more (for example, percentiles). If a finer disaggregation does not reduce the spikes significantly, then the higher persistence at the extremes cannot be explained solely by the matrix design. I estimate my model with deciles. The appendix Tables A.22 and A.23 report the resulting matrix. The increase in the number of categories does not reduce the persistence at the tails and it sometimes enhances it. For example, in Italy the probability of being in the bottom decile if the father is in the same decile is over 35%. The probability at the top is 15% (which is higher than with quintiles).

[55] The results are in the appendix section A.4.

2.7 Conclusions

This article provides a cross-comparison on the patterns of intergenerational mobility over time and along the income distribution. It is one of the first studies to analyse more than one dimension of intergenerational mobility in detail. It also computes the mobility matrices in a way that aims to control for the life-cycle bias.

The results indicate that the United Kingdom is the most mobile country. This is the only country for which the ranking is robust across any sample specification, and both in terms of elasticity and correlation coefficients. The ranking of the three other countries depends on the selected specification. Overall, however, the United States and Italy appear less mobile than Germany.

Another interesting result is that the elasticity increases across cohorts in Italy, Germany and the United Kingdom. Indeed, the elasticity for the younger cohorts is higher in Italy than in the United States. These patterns are robust across all sample specifications.

The investigation along the income distribution suggests that the paternal income matters to a different extent.

The quantile regressions provide evidence in favour of a U-shaped intergenerational elasticity in Italy. With the data from the other countries, the coefficients suggest an increasing elasticity at higher quantiles of the son's income distribution, but the median and the top quantiles are not statistically different.

The mobility matrices indicate lower levels of mobility for the sons whose fathers are at the top or at the bottom of the income distribution. Overall, it seems that the sons of richer fathers are more likely to be among the poorest than the sons of the poorest are of being among the wealthiest. In Italy and the US, individuals with fathers in top and bottom quintiles have a much larger chance of ending up in the same quintile. In Germany and in the UK this is true for fathers and sons in the top quintile. A series of controls supports the thesis that these results are not only a mechanical consequence of the matrix structure.

In terms of methodology, the findings confirm the importance of selecting relevant instruments in the first stage in order to reduce the bias. They also underline the importance of simultaneously estimating the first and second stage, in order not to underestimate the standard errors upon which the inference is based.

Moreover, the conclusions are sometimes dependent on the selected sample specification. The interactions between the respondent's and the father's age and the paternal income reduce the variability between the estimated coefficients and render the coefficients more easily comparable across samples. However, they do not ensure the same results when the sample selection criteria change. This further strengthens the relevance of this study and the possible challenges of cross-country and review articles that rely on other studies to complement their research.

For future research, it might be interesting to further explore why the impact of the paternal income changes according to the father's income level and why there are differences over time and across countries. Whereas higher persistence at the bottom is well explained by the existing theory that considers the role of private investments in education with the existence of credit constraints, other factors might explain the persistence at the top quantiles. The introduction of education suggests that its role in promoting intergenerational mobility seems to decrease across the cohorts. Additionally, conditioning on education does not eliminate the higher dependence on paternal income at the extreme quintiles of the transition matrices. This calls for further research, empirical and theoretical, on the drivers of intergenerational mobility.

Chapter 3

Intergenerational mobility over the income distribution: the role of social networks

3.1 Introduction

Why does one's economic background affect one's future prospects? According to the model of Becker and Tomes (1979, 1986) and Solon (2004), parents affect their offspring's future income through the transmitted ability and through investments in their education.[1]

The identified mechanisms are consistent with some of the stylized facts that emerge from the intergenerational literature, but there remain some puzzles.[2] Recent studies suggest that the intergenerational dependence is not constant along the income distribution, but it follows a U-shaped pattern.[3] In other words, they indicate that lower

[1]This is the reference framework for intergenerational studies. In this context, some families may be financially constrained and forced to invest a lower amount in their offspring's human capital.

[2]For example, different levels of public investments in education might explain some cross-country differences in intergenerational elasticity. As an example, the intergenerational elasticity in Scandinavian countries is lower than that in Anglo-Saxon countries. A review of intergenerational studies can be found in Solon (1999) and Black and Devereux (2011).

[3]Examples of studies on Anglo-Saxon and Mediterranean countries are Checchi et al. (1999), Corak and Heisz (1999), Jantti et al. (2006) and Blanden et al. (2005). The first chapter of my thesis confirms higher persistence at the extremes, at different levels, for Germany, Italy, United Kingdom and the United States. For Scandinavian countries, the literature, such as Björklund et al. (2012), detects lower mobility at the very top of the income distribution.

mobility characterizes families at the top and at the bottom of the income distribution. The Becker-Tomes-Solon model is consistent with the higher persistence at the bottom, where some families may be financially constrained. It fails to adequately explain the lower mobility at the top, where credit constraints are less of a problem.

This article contributes to the intergenerational literature by investigating an additional channel through which parents may affect their offspring's earnings: social networks. To address this issue, I first explore how social networks affect the patterns of intergenerational mobility in a simple model. I then examine these mechanisms in a new empirical analysis. The results suggest that accounting for social networks can contribute to interpreting the U-shaped intergenerational persistence pattern.

I begin my examination with a two-period two-generation model, where parents allocate their wealth between consumption, investments in their offspring's education and in new friends, who can act as job contacts.[4] I consider a society with perfect credit markets and where the offspring's future earnings are predicted with uncertainty. Each adult can be one of three types, according to the received level of education: top earner or highly skilled worker; median earner; bottom earner or unskilled worker. The key assumption is that it is less costly to invest in friendship with individuals who are more similar to oneself. For example, because people can meet new friends during their routine activities, at work or in their recreational time. Consequently, top earners invest more in friends at the top half of the earning distribution and bottom earners at the bottom half. Instead, median-earning parents have a more diversified network.[5] In this

[4]Notice that the term friend is used as a synonym of acquaintance, connection or contact.

[5]For median earning parents this would be the case if, for example, the cost in investing in high-earning friends is similar to that of investing in low-earning friends.

setting, the model predicts higher intergenerational mobility for median earners and for those born in median-earning families. It also highlights two transmission mechanisms. Family job contacts affect the offspring's labour market outcomes directly, through the job search, and indirectly by affecting the returns to education. It also suggests that parental job contacts are an effective driver of intergenerational transmission, especially at the beginning of the child's working career.

I test the model's assumptions and implications using the British Household Panel Survey (BHPS), the Annual Survey of Hours and Earnings (ASHE) and the New Earning Survey (NES, for observations before 1997).[6]

The predictions of the models are supported by the data. This is especially true for the sons at the top of the income distribution, where mobility is lower. The data also support the main assumption. Not only people tend to associate with similar others, but the association is stronger for individuals at the extremes of the income distribution. Afterwards, I investigate the role of family connections. The findings are consistent with theoretical model. If parents' friends have a better job, the chance that the child has a degree increases, after controlling for other factors, such as parental occupation. Maternal friends seem to have a higher impact than paternal friends. Finally, I augment the intergenerational equation of occupational income with friends' incomes. The goal is to check if there exists an association with friends' incomes that is not accounted for by the parental occupations. The estimations suggest that sons' incomes are statistically

[6] The BHPS is a longitudinal survey of British households that started in 1991 and ended in 2008. To my knowledge, BHPS is the only survey where it is possible to have information about the occupation of the respondents, of their parents, of their own friends and of the parental friends. ASHE is a comprehensive source of earnings information in the United Kingdom and is available from 1997. The NES is the predecessor of ASHE and provides data from 1970 to 1996.

associated to the paternal friends' incomes. Daughters' occupational income is correlated to the incomes of both paternal and maternal friends, even though the association is stronger with those of their mother's friends.

There is some evidence about the relationship between intergenerational mobility and job contacts. To the best of my knowledge, however, this is the first study that provides a framework accounting for the U-shaped intergenerational persistence. Zhong (2013) uses the model of Becker and Tomes to show that individuals born into wealthy families are more educated and get better jobs. The focus of Zhong's paper is different, as he investigates the implications of increased public spending in education in an overeducated society, and considers only the top of the income distribution.

This is also the first empirical article that manages to reconstruct an enlarged network, with precise information about child's occupation, as well as their father, mother and their friends. Related applied studies are Corak and Piraino (2010) and **?**, which look at the transmissions of employers from fathers to sons in Denmark and Canada. Another example is the study of Plug et al. (2015), which uses data on Wisconsin to compare same-sex high-school friends of their parents with the respondents' earning scores. Other studies account for the role of friends' employment status (but not occupation) on the probability of finding a job (Cappellari and Tatsiramos, 2015; Pellizzari, 2010).

The article proceeds as follows. Section 3.2 describes the theoretical model. Section 3.2.4 analyses its implications on the intergenerational elasticity. Section 3.3 performs the empirical analysis. Finally, the last section concludes.

3.2 Theoretical framework

Consider the following model, where agents live for two periods, childhood and adulthood. Each household is composed of two main actors: a parent or a unitary couple of parents, and a child. The parents (generation t) work and are responsible of the household's investment decisions, where they live with their child (of generation $t+1$). As a part of the household, the child benefits from these investments. The adults die at the end of the period. The cycle repeats itself with the child that at $t+1$ becomes an adult, works and makes investments for the household.

Similarly to Becker and Tomes (1979, 1986), each household's utility depends on its current consumption (z_{it}), and on the offspring's expected economic success as an adult.[7] Economically successful adults have a job that matches their education for the whole period (which is their working life). The economic success is represented by the present value of the expected wage, w_{it+1}.[8]

$$U(z_{it}, w_{it+1}) = u\left(z_{it}, \alpha \frac{E\left[w_{it+1}\right]}{1+r}\right) \tag{3.1}$$

where $0 < \alpha \leq 1$ is a weighting factor and could be interpreted as the degree of altruism.

[7]Becker and Tomes (1986) show that the main implications do not change if the offspring's consumption is considered instead.

[8]Notice that in Becker and Tomes there is no uncertainty about the child's future wage. Additional details are provided in section 3.2.2

At t, the parent works and receives a wage w_{it}. Adults are defined by their job: a top earner is a worker in a highly skilled job (type H); a median earner performs medium-skilled tasks (type M); finally, a bottom earner works in a low-skilled position (type L).

At the beginning of t, the household allocates its resources between current consumption (z_{it}), investments in new contacts or friends ($I_{it} - R_{it}$), and in the offspring's skilled education (x_{it}) :

$$z_{it} + I_{it}\left(s_{it}^{H}, s_{it}^{M}, s_{it}^{L}\right) - R_t(s_{it}^{H}, s_{it}^{M}, s_{it}^{L}) + x_{it}\left(e_{it}, g_{it}\right) = w_{it} \tag{3.2}$$

where e_{it} are the years of education; g_{it} is the public investment in human capital; s_{it}^{l} ($l = L$, M, H) is the number of new connections of type H, M and L; R_t are the instantaneous returns on the investment.[9] The components of eq. 3.2 are explained here below.

3.2.1 Contacts

Parents invest in highly skilled, medium-skilled and unskilled contacts. Ceteris paribus, it is cheaper to invest in connections that are similar to oneself. This is because it is easier to meet similar people during one's everyday routine, whereas meeting individuals of the opposite type would require non-routine activities.[10] For a top earner (bottom earner), an additional highly skilled (unskilled) friend is less expensive than a median-earning connection that is in turn less expensive than an unskilled (a highly

[9] In order to avoid additional notation, assume that there are no savings.
[10] For example, a low earner might register at a golf club in order to meet a top earner.

skilled) contact. A medium-skilled worker lies halfway between the other two types. I assume that their cost of investing in highly skilled and in unskilled contacts is the same. Moreover, it is less expensive for them to invest in an unskilled (a highly skilled) link than for a highly skilled (an unskilled) worker.

The total cost of the investment in friends, I_{it}, increases with the cost and quantity of connections. There are increasing marginal costs. This is due, for example, to the fact that people have to diversify their activities to keep meeting new contacts of the same type.

Connections generate some returns R_t from the moment they are made. These include all those services that result in direct monetary gains, for example child or elderly care, but also smaller services, such as a lift to the airport. Different types of friends can also provide skill-related services (i.e. helping with removals, repairing a leak in the kitchen or helping with income tax returns), which encourages the household to have friends of all types. I assume that the monetary value of these services is constant across types of household. In other words, the value of a service does not systematically change with the type of household receiving it.

In a society where jobs are found through formal and informal methods, friends may also be helpful as job contacts (not included in R_t).[11] Their role may be particularly important when there are frictions on the labour market.[12] In other words, family

[11]Goyal (2007, ch.6) reviews the mechanisms. Firstly, the contacts pass information about vacancies (Calvó-Armengol and Zenou, 2005). Secondly, firms use referrals as a way to overcome the challenge of the unobservable ability (Montgomery, 1992).

[12]Some empirical evidence supports the hypothesis that job contacts play a greater role at top- and bottom-level positions (Kramarz and Skans, 2014; Brown et al., 2012; Ioannides and Loury, 2004; Boxman et al., 1991). This would further strengthen the predictions of the model but it is not a necessary condition. I discuss how the predictions change with this assumption with reference to Figure 3.1.

connections can affect the offspring's economic status. This has a direct impact on the expected economic success in the utility function.

At the beginning of t, however, parents do not know with certainty whether the offspring will be successful.[13] Therefore, the expected economic success in the utility function is represented by the wage that matches the offspring's education multiplied by the offspring's likelihood of being in that type of job for his or her whole working life (π^l , where $l = L,M,H$).[14] In brief, π^l lies between 0 and 1 and increases, among other things, with the number of relevant job contacts.[15] Family friends may potentially contribute to improving the match between the job seeker and the vacancy, which might reduce the time spent in unemployment. For example, a friend working in a given company can provide the offspring with inside information about vacancies in that company (for example about the future boss or about the job interview). As the required information is quite specific, however, friends can only help in the search of jobs that are similar to theirs.

Ceteris paribus, π^l augments with each contact's "effectiveness". The effectiveness depends on the probability that contacts acquire information about vacancies and on the probability that they act on this information on behalf of the offspring. The stronger the position occupied by a given friend in the parental network, the higher the probability. On the one hand, it is true that, in terms of Granovetter (1973), the amount and variety

[13]Considering that the offspring starts a job at the beginning of $t+1$, assume that they apply for jobs at the end of t. A way to interpret it is to consider that the individuals took all the steps at the end of childhood to secure themselves a job before leaving the household of origin.

[14]One could also interpret it as the span of the adult life in which the parents expect their offspring to have a job that matches exactly the received education.

[15]Further details on its composition are provided in Appendices B.1.1 and B.1.3.

of information that weak ties might provide is potentially higher.[16] On the other hand, all other things being equal, individuals who have information about a job opening may prefer to pass it first to their strong ties.[17]

3.2.2 Offspring's education and expected wage

Similarly to Becker and Tomes, wage is a function of human capital, H_{it+1}, and of market luck u_{t+1}.[18] Eq. 3.3 models this relationship:

$$w^{l}_{it+1} = \gamma H^{l}_{it+1} + u_{t+1} \text{ for } l = L, M, H \tag{3.3}$$

where γ are the returns to human capital.[19] Human capital is made up of two components: education, e_{it}, and endowments, B_{it+1}.

The private investments in education increase with the amount of education and decrease with the amount of public funding. The investments vary with i as children are heterogeneous. If parents invest in education, they choose between two levels of non-compulsory education. The three types of jobs require three different education levels, hence three human capital levels :

[16]Specifically, Granovetter (1973) underlines the higher effectiveness of weak ties in finding a job because of the lower likelihood of having common contacts than with strong ties. According to his view, weak ties are less transitive and behave as bridges that connect subgroups of the social network (Goyal 2007, p. 127).

[17]Consistently with this perspective, Boorman (1975) indicates that the reasons why individuals invest in strong ties is because they fear weak ties might be pre-empted by other weak contacts.

[18]The second term could also be interpreted as the minimum revenue one obtains when not working.

[19]They are a function of the level of technology and of the ratio between human and non-human capital in an economy.

$$H_{it+1}^{l} = \phi^{l}(e_{it}, B_{it+1}) \text{ where } l = \begin{cases} H & \text{if } e_{it} \geq e_H \text{ , i.e. higher education} \\ M & \text{if } e_0 < e_{it} < e_H \text{, i.e. some non-compulsory education} \\ L & \text{if } e_{it} = e_0, \text{ i.e. compulsory education} \end{cases} \tag{3.4}$$

The second component, the endowments B_{it+1}, are characteristics that are not learnt at school, such as ability or social values. They follow a Markov process:

$$B_{it+1} = \alpha_{t+1} + hB_{it} + \upsilon_{it+1} \tag{3.5}$$

where α_{t+1} represents the influence of society and it is constant across households. B_{it} are the endowments of the previous generation and h is their "degree of inheritability" (eq. 3.5).

By incorporating π^{l} in eqs. 3.3 and 3.4, I obtain the offspring's expected wage:

$$E_t\left[w_{it+1}\right] = \gamma\left[\pi^{H}\phi^{H}(.)\,\mathbf{1}_{e_H} + \pi^{M}\phi^{M}(.)\,(1-\mathbf{1}_{e_H})\right]\mathbf{1}_e + \gamma\pi^{L}\phi^{L}(.)\,(1-\mathbf{1}_e) + u_{t+1} \tag{3.6}$$

where $\mathbf{1}_e$ and $\mathbf{1}_{e_H}$ are indicator functions. $\mathbf{1}_e = 1$ with private investments in human capital ($e_{it} > e_0$); $\mathbf{1}_{e_H} = 1$ if $e_{it} \geq e_H$.

3.2.3 Optimization and First Order Conditions (FOCs)

With perfect credit markets, investment and consumption decisions are separable. Therefore, the household selects the amount of education and of friends that maximizes its returns. This occurs at the point where the marginal costs are equal to the present value of the returns.

Eqs. 3.7, 3.8 and 3.9 represent the FOCs for the parental investment in highly skilled, medium-skilled and unskilled contacts (s_{it}^{H}, s_{it}^{M} and s_{it}^{L}, respectively):

$$I_H = R_t + \frac{\gamma \pi_H^H \phi^H(.)}{1+r}\mathbf{1}_e\mathbf{1}_{e_H} \tag{3.7}$$

$$I_L = R_t + \frac{\gamma \pi_L^L \phi^L(.)}{1+r}(1-\mathbf{1}_e) \tag{3.8}$$

$$I_M = R_t + \frac{\gamma \pi_M^M \phi^M(.)}{1+r}\mathbf{1}_e(1-\mathbf{1}_{e_H}) \tag{3.9}$$

where I_l indicates how the total investment changes with an extra l (for $l = H, M, L$) connection.[20] Ceteris paribus, the left-hand side of eq. 3.7 is lower for a top earner. The same applies to eq. 3.8 for a bottom earner, and to the left-hand side of eq. 3.9 for a medium-skilled parent.

In terms of education, parents decide to invest in their offspring's human capital (eq. 3.10) if its returns are at least equal to the costs:

$$x(.) = \frac{\gamma}{1+r}\left[\pi^H \phi^H(.)\mathbf{1}_{e_H} + \pi^M \phi^M(.)(1-\mathbf{1}_{e_H}) - \pi^L \phi^L(.)\right] \tag{3.10}$$

Following the same rule, parents select a high or a medium level of non-compulsory education, as indicated in eq. 3.11:

$$x_{e_H}(.) = \frac{\gamma}{1+r}\left[\pi^H \phi^H(.) - \pi^M \phi^M(.)\right] \tag{3.11}$$

[20]In terms of notation, when H, M or L are at the bottom right of a variable, it indicates a partial derivative of that variable with respect to s_{it}^{H}, s_{it}^{M}, or s_{it}^{L}.

Figures 3.1 and B.1 illustrate the implications of the FOCs.

Implication n. 1: Ceteris paribus, H, M and L households react strategically to the impact of s^l_{it} on π^l (where $l = L, M, H$).

Ceteris paribus, all households have more highly skilled friends if they invest in higher education than if they do not (for all households s^H_e in panel b is larger than s^H in panel a of Figure 3.1).[21] They invest more in medium-skilled contacts if they provide their offspring with a lower level of non-compulsory education (panel c and d). Finally, they invest more in unskilled friends if they do not invest in education at all (panel e and f). The difference increases with the sensitivity of π^l to an additional friend.

Under certain circumstances, the returns to the investment in social networks would not depend on the offspring's expected success (that is $\gamma\pi^l_l\phi^l(.) = 0$ in eqs. 3.7, 3.8 and 3.9).[22] It can be shown that this occurs if the household can predict the offspring's lifetime wage with certainty or if π^l does not depend on social contacts.

Implication n. 2: Ceteris paribus, H, M and L households invests more in friends of their own type.

For example, compare the investments in highly skilled contacts in panels a and b. The amount of new H connections is larger for H households than for M and L households, regardless of the investment in higher education ($s^{H\ of\ H}$ without education and $s_e^{H\ of\ H}$ with higher education). For those who invest in the offspring's higher education,

[21] In panel a the R locus indicates the returns to highly skilled friends, if the household does not invest in higher education. If the household invests in the offspring's higher education, the returns are higher and the locus becomes steeper (the blue line, $\frac{R+\gamma\pi^H_H\phi^H(.)}{1+r}$). As the likelihood that highly educated children get a highly skilled job for their whole adult life increases with the number of highly skilled job contacts ($\pi^H_H > 0$), their parent is better off by investing in highly skilled friends.

[22] In those cases the optimal investment in friends would be the amount of panel a.

the difference increases with the steepness of the $R+\frac{\gamma}{1+r}\pi_H^H\phi^H(.)$ locus. That is, it augments with the returns to education and with the marginal contribution of friends to the probability of finding a job of type H.[23] Notice that the network of a medium-skilled household is on average more diversified. Ceteris paribus, a medium-skilled household would invest more in L friends than a H household and more in H friends than an unskilled household. Therefore, on average, households of type H have more friends in the top half of the income distribution, those of type L in the bottom half, and those of type M have a similar amount of H and L friends.

Implication n. 3: Individuals born in L (H) households have the lowest π^H (π^L) and the highest π^L (π^H). π^M is higher in M households, but not by much.

Following Implication n. 2, parents invest more in friends similar to them. By construction, π^l increases in the amount of job contacts of the relevant type. It follows that π^H is larger for a highly educated individual with highly skilled parents (panel b). Similarly, π^L is higher for an offspring born into an unskilled family (panel f). Panel d shows that the advantage in π^M for the offspring of medium-skilled parents is lower because the optimal investment in friends of type M is more similar across households. Moreover, as the network is more diversified, the offspring born in a median-earning household is more likely to get a highly skilled (unskilled) job if highly educated (unskilled) than the highly educated (non-educated) offspring of unskilled (highly skilled) parents.

It may be worth highlighting that these differences would be amplified if we considered that social networks play a larger role for highly skilled (such as CEOs) and

[23] With $\gamma\pi_H^H\phi^H(.)=0$, the number of friends is only determined by differing marginal costs.

low-skilled jobs, as suggested by some studies mentioned in section 3.2. The dashed pink lines in Figure 3.1 indicate that an additional job contact would increase the returns by more than in the standard case (steeper line in panels a and e). Moreover, the contribution of the social networks to π^l would be higher (the intercept is lower for the pink line in panels b and f). At the same level of education, people born in H or L household would be more likely to end up with the same job as their parents than in the standard case.

Implication n. 4: The higher the parental wage, the higher the chance of investing in higher education, ceteris paribus

Eqs. 3.10 and 3.11 indicate that households invest in non-compulsory education up to the point where the returns to education are equal to the costs. Ceteris paribus, they invest more in education if the child is more able.[24]

Notice also that the returns to non-compulsory education increase with π^H and π^M and decrease with π^L. Following Implication n. 3, all other things being equal, less able children are more likely to get some education if born in wealthy families. They are also more likely to obtain higher education than children of medium-skill parents. Low-skilled parents are less likely to invest in non-compulsory education than other types of households. The returns to education of children of medium-skilled parents are more similar to each other. Therefore, their investment will be more reactive to smaller changes in other variables (such as ability and costs of education).[25]

[24]This would reduce the cost of education and increase its returns.
[25]The appendix Figure B.1 illustrates the implications for education.

It is easy to show that if job search only occurred through referrals, the parental network would entirely determine the offspring's job. Instead, with only formal search, parents would affect their children's future income only through the inherited endowments, such as ability. Similarly, the returns to the investments in education would not depend on social networks. The following section contributes to clarifying these ideas by commenting on the intergenerational elasticity coefficients in these two extreme cases.

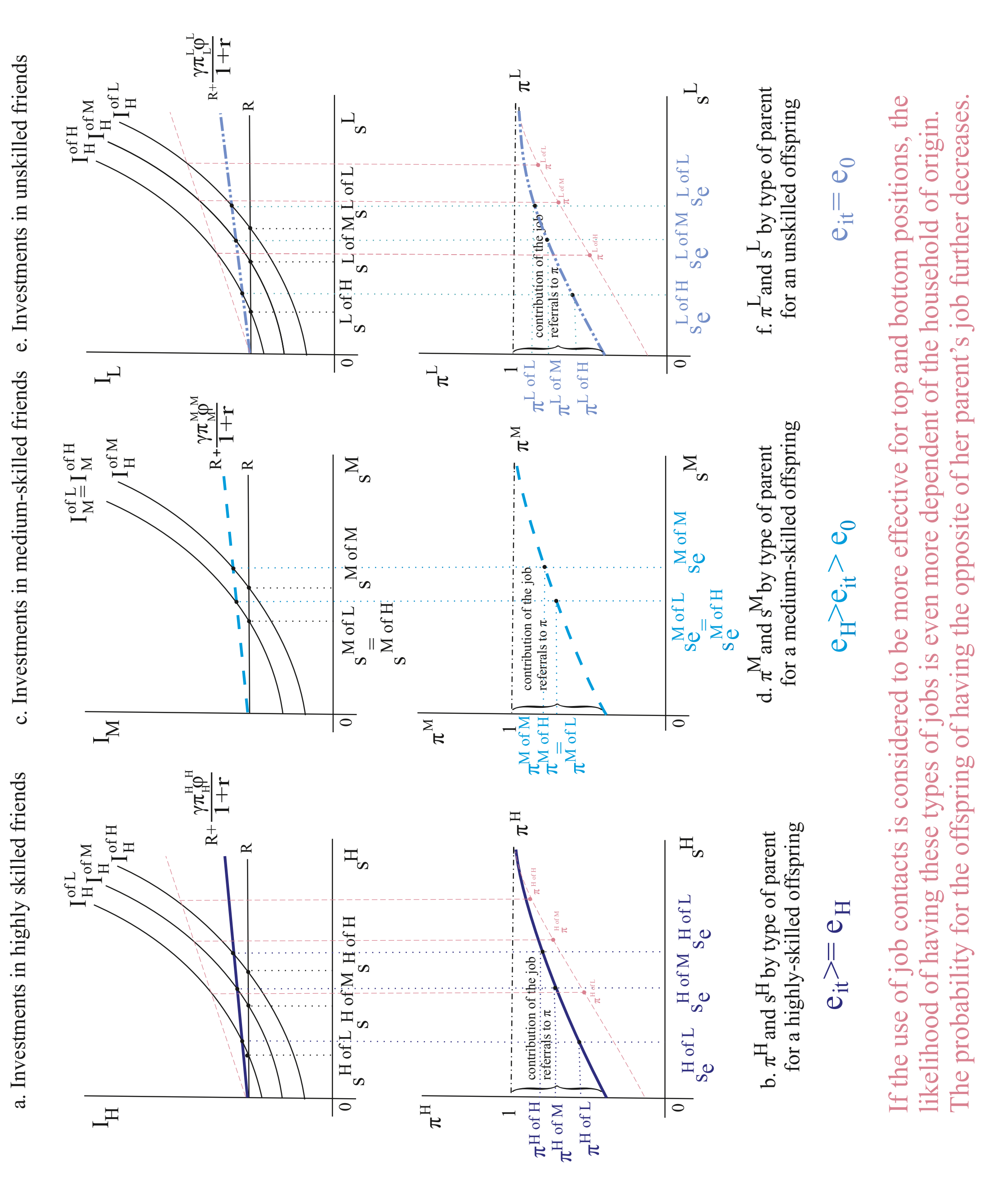

Figure 3.1: Parental investments in new friends and π by offspring's education level and type of parent

3.2.4 Implications for the intergenerational mobility

The type of capital markets and the methods used to find a job may affect intergenerational mobility. The appendix section B.1.3 uses the above model to derive and compare the intergenerational elasticity (IGE) for four different cases: with and without job contacts, with and without credit constraints. This section provides a summary of the results.[26]

With perfect capital markets, the parental income directly affects the offspring's income only when job contacts play a role in the job search.[27]

In the first case, with only formal search, parents affect the intergenerational elasticity only through the inherited characteristics. The IGE, in eq. B.19, increases with the returns to education, whereas it decreases with the progressiveness of public investments in education. The IGE could be negative if the degree of inheritability of the endowments is smaller than the progressivity of the public investment. This is because when the family income doesn't affect the child's educational level, higher returns to education can promote equality of opportunities and reduce intergenerational inequality. When the two terms are equal, the mobility across generations is perfect.

The second case is when job search only occurs through job contacts. In addition to the variables mentioned above, the IGE, eq. B.24, also increases in the effectiveness of the connections in helping with the job search. The intuition is that the more effective

[26]The steps of the derivation, including a description of the main assumptions, and detailed comments about the results are illustrated in the appendix section B.1.3.

[27]Notice that the conclusion would be different if households in t could predict the wage of the offspring in $t+1$ with certainty. This is the framework used by Becker and Tomes (1979, 1986) and Solon (2004). Case 6 in the appendix section B.1.3 shows that the parental income has no direct effect in this case, independently of the type of job search.

the contact, the higher the parental influence (through their network). Moreover, the IGE is a positive function of the technology that links the type of friend to the type of household. Implication n. 2 in the previous section suggests that the strength of this association depends on the family type and on the type of the relevant friends. Ceteris paribus, this parameter is lower for medium-skilled parents because they have a more diversified network. It is also lower when the relevant friends are those with medium-skilled jobs, because they are in larger numbers in all households. This implies that the IGE is lower for medium-skilled parents and for children in medium-skilled jobs.

The second case can be extended.[28] We can assume that the offspring develop their own contacts, in addition to the family connections, and that both help in the job search. The relationship between the IGE in this setting and the IGE in case 2 depends on the relationship between family and own connections. The more different the offspring's friends are from the parental friends, the lower the IGE. This is because over time, the amount of own relevant friends increases and the role of family friends decreases. This suggests that the role of job contacts in the IGE may be larger at the beginning of the offspring's working career. This is consistent with some empirical evidence, such as Corak et al. (2010; 2011) and Bingley et al. (2011), who show that sons in Canada and in Denmark are more likely to work in the same company as their father when they are younger and their first job is considered.

Finally, the above framework is modified to consider the implications on the intergenerational elasticity when capital markets are imperfect. Eqs. B.38 and B.40 show that the IGE is larger with imperfect capital markets, all other things being equal. The

[28]The IGE discussed in this paragraph is in eq. B.32.

results also suggest that the contribution of the parental income to the IGE coefficient due to the existence of credit constraints is larger than the role played by inherited characteristics. It is also larger than the parental contribution through the job contacts.

The above exercise underlines that not only access to education but also to jobs is an important determinant of intergenerational mobility. If job contacts play an important role in the job search, the IGE is higher, independently of the type of credit markets.

The implications highlighted above are consistent with the literature on job networks and on intergenerational mobility, suggesting a positive association between the IGE and informal search in the empirical literature. For example, Pellizzari (2010) reports that the use of networks for job search is at its lowest in Finland (around 10%) and at its highest in Spain (over 40%). It is indeed well-known that in Scandinavian countries the IGE is very low compared to Mediterranean countries (Black and Devereux, 2011). As another example, the literature review in Ioannides and Loury (2004) indicates that the use of network changes with ethnicity. The article mentions that in the United States Afro-American job seekers rely more on job contacts than Caucasians. Indeed, Mazumder (2008) reports a higher IGE for this ethnic group. Moreover, the literature mentioned in section 3.2 also suggests that job contacts may be particularly effective in the selection of top-level managers or unskilled positions. This would further strengthen the differences highlighted in case 2, where the elasticity is lower for the offspring in medium-skilled positions.

This implies that differences in the use (and efficiency) of job contacts across countries, over time or at different levels of income (or education) might contribute to clarifying the differences in intergenerational elasticity that emerge from the applied literature.

3.3 Empirical application and data

The second part of this article tests whether the data support the above theory.

I use three complementary data sources. The first is the British Household Panel Survey (BHPS), a longitudinal survey of British households that started in 1991 and was run annually until 2008. Although household-based, BHPS is a multi-purpose study that follows the same representative sample of individuals over time, even after they leave the household of origin.

For the purposes of this analysis, BHPS contains data on education, region of residence, economic activity, occupation and demographic characteristics of the respondents and their parents. Moreover, this study also provides information about the sex, age and occupation of the respondent's best friends, for seven waves[29]. What makes this survey unique is the possibility to have data about the friends of selected individuals and of their parents. In fact, it is possible to match an individual with their father and mother if they have lived together at least for one wave. Therefore, I can reconstruct a larger social network that includes the offspring's and the parental friends.

[29] Data about the best friend's occupation are only available for the waves in 1992, 1994, 1998, 2000, 2004, 2006 and 2008.

The second dataset is the Annual Survey of Hours and Earnings (ASHE). It started in 1997 and it is the most comprehensive source of earnings information in the United Kingdom (UK). It provides information about the levels, distribution and make-up of earnings and hours for employed workers. ASHE is based on a 1% sample of employee jobs taken from Her Majesty's Revenue and Customs (HMRC) Pay As You Earn (PAYE) records. The information about employees is provided directly by the employer, who receives a questionnaire and completes it on the basis of payroll records.

The predecessor of ASHE, and the third data source, is the New Earnings Survey (NES), an annual survey of the earnings of employees in Great Britain from 1970 to 1996. The main difference with ASHE is that workers from Northern Ireland were not included in the sample.[30] Like ASHE, it is based on 1% of those in the PAYE Tax Scheme. Although the survey was originally published in printed format and available by subscription only, the Office of National Statistics provides scanned pages of the volumes upon request.

Data from NES-ASHE are not available at disaggregate level. However, they provide mean (for NES and ASHE) or median (only ASHE) gross earnings by year, occupation and gender and other selected variables. For the purpose of this analysis, the variable based on NES-ASHE are the mean weekly gross earnings for full-time employees by occupation and sex.

[30] There are some variations on the sample. For example, the main sample for NES is derived from the Register for February, whereas for ASHE it is based on the Registers for February and April.

3.3.1 Variable and sample selection

To investigate intergenerational issues, researchers compare the same economic outcome across generations. The main variable of this study are the mean weekly earnings by year and occupation (or occupational income).[31]

I derive the occupational income for the parents, the offspring and their friends by matching their occupation to the corresponding mean earnings from NES-ASHE. [32]

The choice of the key variable is determined by data availability, as individual earnings are not available for friends. Nonetheless, occupational income has some advantages with respect to individual income. In particular, it may help reducing two types of bias that affect the intergenerational coefficients.[33] First, the coefficients based on occupational-based measures are less sensitive to transitory shocks. This might reduce the attenuation bias. Second, the use of mean income might also contribute to reducing the life-cycle bias. For example, this is because sons and fathers (or mothers and daughters) will have the same occupational income if they have the same occupation in the same year.

[31] Whereas in the past, the choice of the variable appeared to depend on the discipline (economists tend to prefer income and sociologists occupations), recent studies suggest that economists are starting to reconsider the use of some occupation-related indicators, such as the occupational prestige. One of the main reasons is because data about the parental earnings are not always available in administrative data, on which some of the recent work is based.

[32] The appendix section B.2 explains in details the challenges for its derivation. The results are robust to different measures of occupational income. Two alternative measures may be derived from BHPS: the Hope-Goldthorpe score (HG score) and the monthly labour income by occupation and by sex. Moreover, with these measures it was possible to derive also the median values. Both measures were used in a previous version of this paper. The results based on mean and median indicators derived from the BHPS are consistent with the estimates based on NES-ASHE earnings. The appendix explains the reasons why I use mean earnings from NES-ASHE.

[33] Examples of reference studies on this topic are Solon (1992), Zimmerman (1992), Mazumder (2005a) and Haider and Solon (2006). This is also discussed in the first chapter of my thesis.

The sample consists in matched triplets of fathers, mothers and children. Obviously, the interpretation of the results for females (mothers and daughters) might be more problematic. This is because of the different issues affecting the career choices of women and, more in general, their selection into the labour market. It may still be interesting, however, to compare daughters and sons. For this reason, I include the daughters in the sample, as well the the mothers and the maternal friends.[34]

The reference sample consists in 1,153 observations for sons and 1,017 for daughters with non-missing information about both parents and the parental network. The sample is created by matching the children with their parents, through their unique personal identifier. It decreases to 861 and 761 to include the son's and daughter's own friend. The appendix Table B.4 indicates that the sons are on average 21 years old and are born in 1979. The daughters are 20 years old were born in 1980. Their friends are of similar age. Their parents and the parental best friends are older. They are between 48 and 50 years old.[35]

When possible, larger samples are considered and the results are reported in the main section. However, the same analysis is also performed on at least one of the reference samples to ensure consistency and comparability of results throughout the investigation. The characteristics of the alternative samples are indicated in the appendix Table B.3. For example, to investigate homophily, all respondents can be considered, independently of the possibility of matching them with their mother and father. The

[34]In an earlier version of this paper, I performed the same analysis only on fathers and sons. The sample was larger as the sons did not need to be matched with their mothers. Nonetheless, the results are consistent with the current analysis.

[35]The sample includes individuals from 16 years of age. This is mainly due to data requirements. However, for some specific exercises or as further robustness checks I impose some age restrictions. These are indicated in the relevant sections.

key condition is the availability of the their own friend's occupation. Thus, for this exercise, the sample consists in 48,407 observations. 53% of the respondents are female and they are on average 39 years old.

3.3.2 Model specifications and baseline results

As anticipated in the previous section, the coefficients may be biased if the age of the children differs from the age of the parents. This is especially a problem when the children are not between their early 30s and mid-40s (Haider and Solon, 2006).

The summary statistics, in Table B.4, highlight that age differences may be an important issue for this analysis. The respondents (and their friends) are much younger than their parents (and the parental friends). This depends on the sample selection criteria and on how BHPS is constructed. In fact, younger individuals usually live with their parents. Additionally, for parents to be included in the sample they have to be working (and so have their best friends). This further limits, upward, their age, and in turn the age of their children. Moreover, as the variables for the offspring and their parents are measured in the same year, their ages are necessarily different.

As mentioned above, occupational earnings may be useful in this case. To reduce the gap between the ages of the two generations, I adjust the intergenerational equation so that the coefficient is interpreted for a 30-year old child. I follow the specification adopted by Solon and Lee (2009).[36] The additional term is the interaction between the

[36]This is similar to the approach followed in the first chapter of my thesis. It reviews the literature on the attenuation and life-cycle biases and explains the advantages of the solution suggested by Solon and Lee (2009).

child's age, normalised at 30, and the older generation's occupational income:

$$y_{it} = \delta_0 + \beta y_{jit} + \delta_{1it}(age-30) + \delta_2 y_{jit}(age-30)_{it} + \delta_4(age-30)_{jit} + \delta_5 birth_i + \varepsilon_{it} \tag{3.12}$$

where i is the respondent and j are the father, the mother or both parents. y_j stands for the log of j's occupational income. $age-30$ indicates the respondent's normalised age. age_j refers to j's age, $birth$ is i's year of birth.[37] β is the intergenerational elasticity (IGE, hereafter) for a 30-year old respondent.[38]

Eq. 3.12 is the baseline specification for the analysis. As a first explorative exercise, I estimate this equation on individual monthly labour income. I then compare the intergenerational elasticity obtained on individual income with that computed on NES-ASHE mean earnings. Moreover, as a further check, eq. 3.12 is also estimated with two alternative occupational-related measures derived from BHPS, the Hope-Goldthorpe score (HG score) and the monthly labour income by occupation and by sex.[39]

The appendix Table B.5 reports the estimates of β and δ_2 for sons and daughters. The analysis is based on a common sample of individuals with working parents.[40] The last column of estimates eq. 3.12 on the reference sample.

The first section of the table reports the results for sons. The elasticity coefficients estimated on the individual monthly labour income (first column) are similar to those

[37]Solon and Lee (2009) interact the log of the paternal income with the square, the cube and the quartic of the individual age. However, these were dropped from the models in this section because they are not statistically significant. The same applies to higher powers of i's age.

[38]Thirty is chosen as a compromise between the average age of the respondents, twenty-two, and of their parents, fifty. It is nonetheless possible to predict β at any other age by using δ_2.

[39]Additional details on these variables are provided in the appendix section B.2.

[40] It is a subsample of sample 2 in Table B.3. The lower number of observations is due to the fact that I include only the observations for which all the relevant income measures are available.

based on the occupational income (NES-ASHE earnings in the second column, occupational income predicted on the BHPS in the third column). They are also similar to the estimated intergenerational elasticity on the main sample (sixth column).

The IGE between fathers and sons ranges between 0.2 and 0.33 for a 30-year-old son. This implies that for a 40-year-old son, β would range between 0.3 and over 0.5. The estimates are consistent with the predictions of the literature for the United Kingdom, between 0.3 and 0.45.[41]

For daughters, the IGE with respect to the father is on average higher than for the sons. The estimates of β, however, are less consistent across the different specifications.[42] It is interesting to notice that the IGE computed on the actual income, 0.26, is similar to the estimate based on the Hope-Goldthorpe score, 0.25. The IGE based on the predicted income, is larger and ranges from 0.33 to 0.53. A possible explanation might be that female earnings are more sensitive to shocks than male earnings. As a result, the downward bias when β is computed on actual income is larger for daughters than for sons.

Finally, it is interesting to notice that the maternal income elasticity is close to zero in magnitude and not statistically significant. This does not change when the maternal income is the only intergenerational regressor in the model (last column of the appendix Table B.7). Whereas one might expect a smaller correlation between sons and mothers, the small correlation between daughters and mothers is unexpected. There may be serval explanations. One possible explanation might be the difficulty of capturing the true

[41]The first chapter of my thesis provides a survey of the recent literature.

[42]For the reasons explained in the relative appendix, the estimates for the variables predicted for females and based on BHPS (third and fifth columns) might not be reliable.

occupational income for females. However, this should affect both mothers and daughters in the same way. Additionally, as the following sections show, the data suggest a positive correlation between the individuals and the maternal friend, a female in 95% of the cases. Another possible explanation might be that if the mothers have a higher income, the parental income is higher and the children might postpone their productive work while waiting for better job opportunities. For example, they might choose lower paid position that are better in terms of long-term career advancement. This might be relevant as the individuals, and especially daughters, are particularly young. If that was the case, we would expect a higher elasticity for older children. An alternative reason might be that the maternal income is less relevant when the father is in the household, which is the case with this sample, by construction. The appendix Table B.8 tests these hypotheses. The table indicates that the IGE is positive for both daughters and sons when the father is not in the household. The value is 0.244. This is not explainable by different age profiles as the average ages of sons and daughters are the same as in the reference sample. When both parents are present, however, age seems to matter, at least for sons. It would be interesting to further investigate this issue and the mechanisms behind these results. The small sample size, however, prevents further checks.[43]

3.3.3 Transmissions of occupational income

The theoretical framework predicts that the intergenerational transmission of earnings is higher for children interested in jobs at the extremes of the income distribution. It

[43] Finally, as an additional check, Table B.6 shows the beta coefficients estimated on the average family income. It is calculated on the basis of the maternal and the paternal occupational income. The patterns are similar to the case above. The estimates are more consistent across different measures for sons than for daughters.

also predicts that, regardless of the offspring's job, the role played by family friends is greater for parents with top- or bottom-paying occupations, where the network is less diversified. The following sections test these implications. We find that the IGE differs at different quantiles of the offspring's marginal income distribution. We also find higher intergenerational persistence at the extreme quintiles of the joint distribution. The differences are not large and not always statistically significant. While looking at these results we should keep in mind the limitations of the sample. Specifically, the child's young age and the difference between the parental and the child' age, which may further increase the regression to the mean.[44] Nonetheless, the overall conclusions from the following sub-sections are in line with the findings of sections 2.6.3 and 2.6.4 in the first chapter of the thesis, based on different a sample and methodology.

3.3.3.1 At different quantiles of the offspring's distribution

To investigate the first implication, I calculate the elasticities at different quantiles of the offspring's distribution. I estimate eq. 3.13, where $Q_{\alpha}(y_{oit} \mid y_{ji}, X)$ is the α quantile of the offspring's income:

$$Q_{\alpha}(y_{oit} \mid y_{ji}, X) = y_{ji}\rho(\alpha) + X\delta(\alpha) + \varepsilon_{it}(\alpha) \tag{3.13}$$

for $o =$ sons, daughters and $j =$ parents. The matrix X includes the offspring's and parental age, the interaction between j's income and o's age normalised at 30, o's year of birth and economic activity. The average family's occupational income is computed

[44] Indeed, the occupational income is a good indicator of earnings provided that the individual does not change his or her occupation. This is a strong assumption for 20-year olds.

as the average occupational income between the mother and the father, where at least one parent works.

Figure 3.2 reports the coefficients and the standard errors for a 30-year-old offspring.[45] The results support, at least partially, the theoretical implications. The magnitude of the coefficients at different quantiles is different, even though the differences are not always statistically significant. In particular, for the sons, the coefficients corresponding to the top quantiles are statistically higher than the median. For the daughters, a J-shaped pattern emerges when considering the percentiles between the thirtieth and the eightieth.

Figure 3.2: Conditional quantile regression
Picture shows intergenerational elasticities of occupational income between the offspring and their parents along the offspring income distribution

3.3.3.2 Mobility matrices

In order to investigate the association between the offspring's and the parents' jobs, I also estimate the probability of the offspring to be in the same position in the marginal

[45]This exercise was performed on a larger sample of 4,186 observations of sons and 3,570 for the daughters. Individuals in this sample are matched with both parents and at least one parent works. Similar conclusions apply to the reference samples of sons and daughters, although the coefficients are not always statistically significant. Although not reported, these results are available upon request.

distribution as their parents, following the methodology explained in section 2.6.4. Specifically, after classifying the offspring and the parents into income quintiles, I estimate a sequential logit where the dependent variable is the child's income quintile:

$$P(y_i > m) = \frac{exp(\alpha_m + X_i\beta_m)}{1 + exp(\alpha_m + X_i\beta_m)}, \quad m = 1, 2, .., M-1$$

where $M = 5$ offspring's quintile and X includes the parental quintile and the control variables of eq. 3.13.

Table 3.1 reports the results. The coefficients in the table represent the difference in probability of being in a given quintile conditional on the parental quintile, with respect to the case with parents in the third quintile, the base category. For example, the probability to be in the first quintile for sons with parents in the first quintile is 6.9 percentage points higher than for sons with parents in the third quintile. Instead, the probability differential is close to zero for parents in the other quintiles. The findings suggest that the individuals can move along the income distribution quite freely, up to the fourth quintile. The paternal income does not seem to matter for the probability of being in the second to the fourth quintile. Although there are some differences in the magnitude of the coefficients, most of them are not statistically significant. To a certain extent, this also applies to the first quintile, where the parents' ranking only matters for parents in the bottom quintiles. Instead, the probability to be at the top depends on the parental quintile. For example, sons with parents at top are more likely by 6.5 percentage points to be at the top with respect to sons with parents in the third quintile, and by 13 points more than with parents at the bottom. A similar situation happens for daughters.[46]

Table 3.1: Children and parents: probability differential of transition

	1st		2nd		3rd		4th		5th	
Sons										
1st	0.069***	(0.020)	0.034	(0.023)	-0.017	(0.022)	-0.035	(0.025)	-0.052**	(0.021)
2nd	0.007	(0.016)	0.021	(0.021)	0.038*	(0.023)	-0.027	(0.026)	-0.039*	(0.021)
3rd	0		0		0		0		0	
4th	0.008	(0.022)	0.006	(0.021)	-0.026	(0.020)	-0.028	(0.023)	0.039**	(0.019)
5th	0.003	(0.025)	0.014	(0.026)	-0.055**	(0.023)	-0.057**	(0.024)	0.065***	(0.025)
Daughters										
1st	0.024	(0.022)	-0.023	(0.020)	0.035	(0.023)	-0.018	(0.023)	-0.018	(0.025)
2nd	0.040**	(0.020)	0.010	(0.022)	-0.020	(0.022)	-0.011	(0.022)	-0.020	(0.021)
3rd	0		0		0		0		0	
4th	-0.027	(0.021)	-0.009	(0.022)	0.007	(0.024)	-0.016	(0.021)	0.045**	(0.022)
5th	-0.029	(0.023)	-0.045**	(0.022)	-0.012	(0.028)	-0.003	(0.022)	0.088***	(0.023)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Bootstrap standard errors in parenthesis

3.3.4 The respondents and their network

According to the theoretical framework in Section 3.2, individuals prefer friends that are similar to them (homophily). This is especially the case for individuals at the top or at the bottom of the income distribution.

In the applied sociological and economic literature there are several studies supporting homophily, along different dimensions.[47]

Evidence in favour of homophily emerges from this study as well. This section explores this issue with 48,407 observations of respondents from 16 to 65 years old.[48] This larger sample consists in working males and females with working best friends.

[46] As a further check, I performed the same exercise on fathers and mothers separately. When only fathers are considered, the picture is very similar to that presented in this section. The mother's ranking in her distribution, instead, does not seem to affect the ranking of her child. The only exception is a higher chance of being in the extreme top and bottom quintiles if the mother is in those quintiles as well.

[47] Some dimensions are race, ethnicity, education. McPherson et al. (2001) provide an overview of those studies after classifying them by theme.

[48] The summary statistics are provided in Table B.4.

All respondents are included, independently of the possibility of being matched with their father or mother. For consistency with the analysis, the appendix section B.3.2 reports the same exercise for the parental network on the reference sample. The results confirm that the considerations of this section are robust to changes in the number of observations and apply to our sample of parents as well.

The appendix section B.3.2 compares the demographic and socio-economic characteristics of the respondents and of their three closest friends. First, the graphs suggest that, in general, the closest friends are of similar age and live nearby. Second, the respondents have known most of them for more than 10 years. Third, the results suggest that friends also have a similar employment status. For example, the probability of having an unemployed friend is higher for unemployed respondents. In general, the similarities are stronger with best friends. They become weaker with the third closest friend.

Although homophily has been widely documented, to the best of my knowledge few (or no) studies document whether it changes along the income distribution.[49]

To investigate whether the association changes at different income levels, I analyse an income mobility matrix. I derive the matrix from a sequential logit model, as explained in section 3.3.3. The matrix reports the predicted probabilities for the best friend to be in a given income decile, conditional on the respondent's income decile.[50]

[49] The appendix Table B.11 reports the correlation coefficients between the occupational income of the respondents, their parents and their best friends. On average, the coefficient indicates a weak to moderate linear association with the occupational income of one's social network.

[50] The respondents and their friends are ranked into deciles according to their position in the income distribution. The ranking is done separately for males and females.

If people tend to associate with similar others, the highest probabilities are on the main diagonal of the matrix and the lowest on the anti-diagonal. Additionally, if medium-skilled individuals have a more diversified network, the extreme elements of the main diagonal are expected to be higher than the middle elements. The results confirm both expectations, for males and females.

The left panel in Figures 3.3 and 3.4 indicate that the probabilities on the main diagonal are higher than on the off-diagonal, even more so when compared to the minor diagonal.

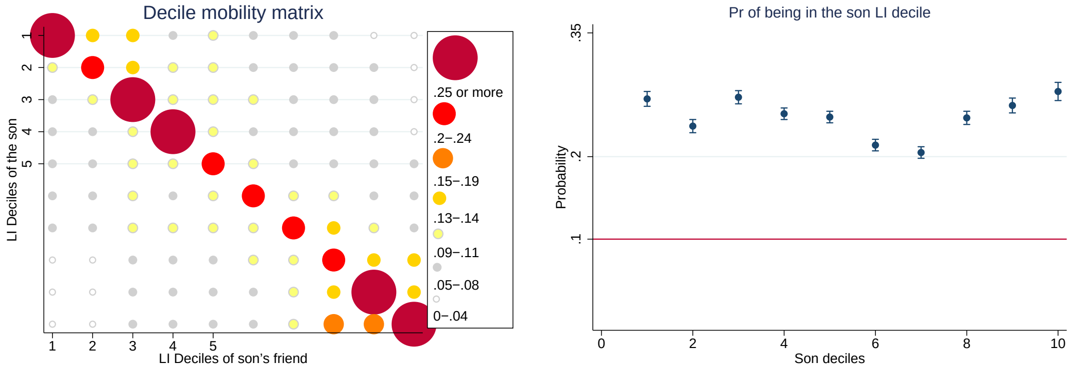

Figure 3.3: Logit mobility matrix for males and friends
Logit mobility matrix (left); Probability of being on the main diagonal of the matrix with standard errors. The horizontal line at 0.1 indicates perfect mobility (right)

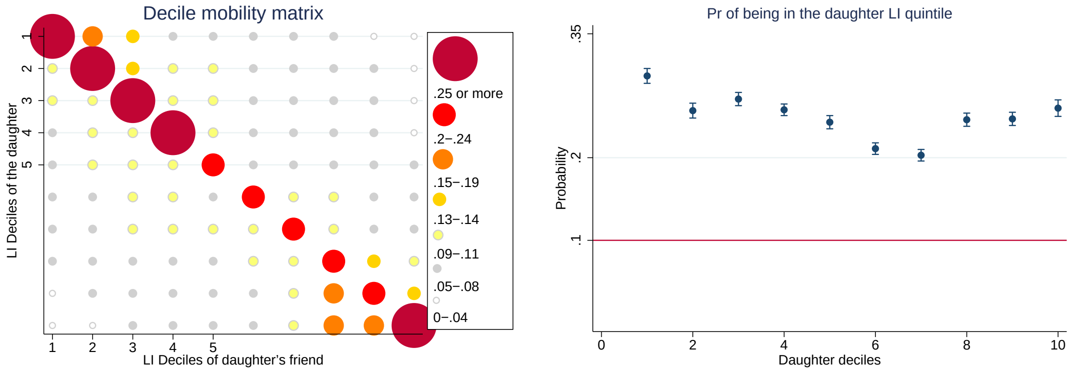

Figure 3.4: Logit mobility matrix for females and friends
Logit mobility matrix (left); Probability of being on the main diagonal of the matrix with standard errors. The horizontal line at 0.1 indicates perfect mobility (right)

For example, if a male (female) respondent is in the tenth decile, the probability for the friend of being in the same decile is 30 (27)%, whereas the probability of being in the first decile is 3 (2.8)%. Additionally, the probabilities of assortative matching are higher at the top and at the bottom than at the middle (24%).

The right panel of the figures illustrates the probabilities on the main diagonal with the bootstrap standard errors. It shows that the probabilities on the main diagonal are statistically larger than 10%, the case with no assortative matching.

It is worth noticing that when the same exercise is performed on randomly allocated quantiles, almost all the elements of the matrix are not statistically different from 0.10, or 10%. This supports the idea that these findings are not only the mechanical consequence of the matrix structure, nor of the existence of floors and ceilings.

As a further check, Table B.12 reports an alternative representation of respondents and their friends. The individuals are divided into ten income categories, where the width of each category is one tenth of the difference between the maximum and the minimum value of each marginal distribution.[51] The joint income distribution is skewed to the right, indicating a smaller amount of individuals in the top deciles. Nonetheless, the resulting transition matrix is in line with the comments about Figures 3.3 and 3.4.

3.3.5 Social networks and education

According to Becker and Tomes (1979, 1986), the parental income directly affects the offspring's income, through their education, when the financial markets are not perfect.

[51] Like before, it is done separately for males and females.

This paper argues that individuals born in richer households are likely to be more educated than others regardless of the type of credit markets, because family connections may help them find a better job, thus increasing their returns to education.

This section examines whether the probability of completing a given education level is associated with the occupation of the parental friends, after controlling for the occupational income of the parents. I estimate an ordered logit, where the dependent variable is a categorical variable for completed education (up to primary education, secondary education, further education, higher education).[52]

$$P(y_i > l) = \frac{exp(\alpha_j + X_i\beta)}{1 + exp(\alpha_j + X_i\beta)}, \quad l = 1,2,3 \tag{3.14}$$

for j=father, mother, and friends, and where X_i is a matrix of covariates. The matrix includes the offspring's economic activity, year of birth, age and sex, j's ages, the friends' economic activity and sex.[53]

This exercise is performed on a subsample of individuals who are at least 22 years old.[54] The summary statistics in the appendix Table B.13 indicate that 40% of the 905 respondents are female. They are on average 25 years old and 24% of them has at least a degree. Table 3.2 reports the predicted probabilities of completing a given level of education for an employed individual and the marginal effects.[55]

[52]The dependent variable is ordered and the parallel odd assumption is not violated.

[53]The model is estimated on sons and daughters to have a larger sample. The probabilities are predicted for daughters and sons separately. As a robustness check, I estimated the ordered logit on two separate subsamples. Although the statistical significance of the coefficients is reduced, the resulting probabilities are in line with the results reported in Table 3.2.

[54]I selected this age because it is the age at which at least the first degree is completed. An older age would allow for completing higher education levels but would further reduce the sample size. The summary statistics are available in the appendix section B.3.3.

[55]The odds ratios are reported in the appendix section B.3.3.

Table 3.2: Marginal effects of the probabilities of completing education

	Primary		Low secondary		High sec. or vocational		Degree or more	
Sons								
Probabilities	0.068***	(0.014)	0.384***	(0.031)	0.369***	(0.025)	0.178***	(0.022)
Marginal effects								
ln F LI	-0.046***	(0.017)	-0.157***	(0.050)	0.074**	(0.030)	0.128***	(0.041)
ln M LI	-0.027	(0.016)	-0.091*	(0.054)	0.043	(0.028)	0.074*	(0.044)
ln F friend LI	-0.011	(0.014)	-0.037	(0.047)	0.017	(0.022)	0.030	(0.038)
ln M friend LI	-0.057***	(0.018)	-0.195***	(0.044)	0.092***	(0.030)	0.159***	(0.039)
Female F friend	0.027*	(0.015)	0.091**	(0.050)	-0.043*	(0.026)	-0.074*	(0.040)
Female M friend	0.022*	(0.012)	0.102**	(0.050)	-0.013	(0.015)	-0.111***	(0.055)
Daughters								
Probabilities	0.041***	(0.009)	0.285***	(0.032)	0.404***	(0.024)	0.271***	(0.031)
Marginal effects								
ln F LI	-0.030***	(0.011)	-0.148***	(0.048)	0.013	(0.021)	0.165***	(0.052)
ln M LI	-0.017	(0.011)	-0.085*	(0.051)	0.007	(0.013)	0.095*	(0.056)
ln F friend LI	-0.007	(0.009)	-0.035	(0.044)	0.003	(0.006)	0.039	(0.049)
ln M friend LI	-0.037***	(0.012)	-0.184***	(0.042)	0.016	(0.026)	0.205***	(0.050)
Female F friend	0.017*	(0.010)	0.086*	(0.047)	-0.007	(0.013)	-0.096*	(0.051)
Female M friend	-0.015	(0.012)	-0.072	(0.060)	0.006	(0.011)	0.080	(0.066)
Observations	905		905		905		905	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Bootstrap SE in parenthesis. F stands for father, M for mother. LI for occupational income.

The results suggest that the friend's occupation is correlated with the respondent's education, even after controlling for the parental jobs. For example, at the mean of the other variables, one-unit log increase of the maternal friend's occupational income increases the probability of being a university graduate by 0.159 percentage point for sons and by 0.205 points for daughters. This implies, for example, that the probability of having a degree for daughters increases from 27% to 47% if the maternal friend's income changes from the fifth to the ninetieth percentile.[56]

The occupational income of the paternal friend is not statistically significant. However, the probability of graduating is lower if the paternal friend is a female. Particularly, the magnitude of the effect is the same (in the opposite direction) as that of one-unit log increase in the maternal income.

[56]The difference between the first and the ninety-ninth percentile is 1.33 unit log.

The occupational incomes of the parents and of their network play a greater role for low (primary or lower secondary) or high (university degree) educational outcomes, whereas their impact seems smaller in the probability of obtaining a higher secondary or vocational certificate. This is in line with the theoretical model, according to which, the type of job of the parents and of their friends is less determinant when parents decide to invest in a moderate level of non-compulsory education.

Although it is not possible to test in a more direct way the mechanisms through which the family friends influence the offspring's outcomes, the results indicate a possible role of family friends in the child's education. The significant association cannot be explained by homophily, which would directly connect the father (or the mother) to his (her) best friend, but not to the respondent. Also, the significance cannot be attributed only to the fact that it could be a proxy for the parental occupation, as these variables are included in the model.

3.3.6 The use of job contacts and intergenerational elasticities

The literature reviewed in the previous sections indicates that the use of family friends in the job search may be higher for younger individuals (Ioannides and Loury, 2004), and they will also be more likely to use help from their parents (Corak and Piraino, 2010).[57]

[57] A possible explanation may be that the work experience one develops over time reduces the need to use informal search methods.

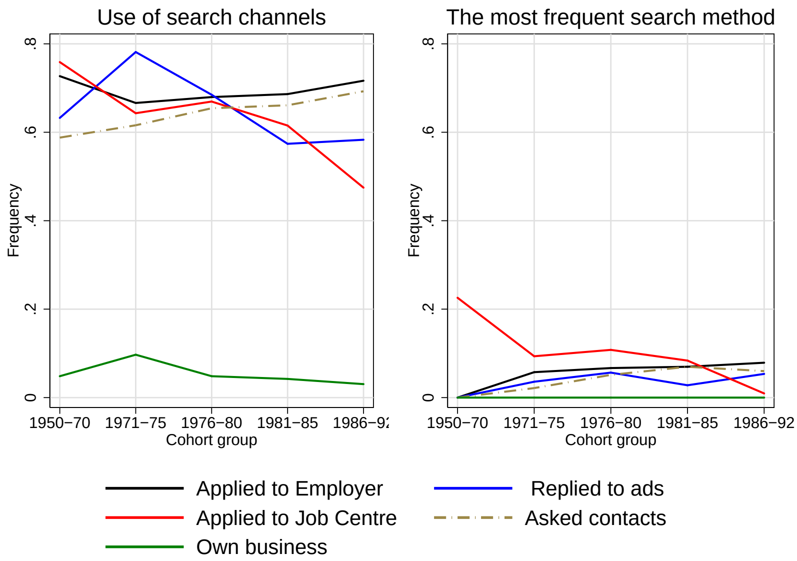

Figure 3.5: Methods of job search by birth cohort group

Figure 3.5 is consistent with these findings. It illustrates the average use of the different channels by cohort group on a reduced sample.[58] On average, a respondent is looking for a job 17% of the time around the time of the survey (with a minimum of 7% and a maximum of over 66%). The left panel indicates that those actively searching for a job usually select more than one search method. For example, respondents from younger cohorts went to an employment agency or replied directly to vacancy ads with a frequency of 40% and 50%. They asked their friends or contacts 70% of the time, and they contacted directly the employer in over 70% of the cases.

The right panel of the figure illustrates the search method that is strictly preferred by a given cohort group. For example, for 15% of the youngest respondents asking to job contacts has been the most used method. For over 10% of them the most frequent

[58] 284 individuals have been unemployed and looked for a job at least once in the 4 weeks before any BHPS interview (the average percentage is higher for younger cohorts). These respondents are asked about their search methods. To construct the figure, each method is weighted by the number of times the individual is looking for a job and by the number of waves the respondent appears in the survey. The patterns are the same if the figure is created by age group.

method has been replying to ads, whereas none of them strictly prefers going to the Job Centre or starting their own business. The remaining percentage are those who have used two or more methods the same number of times. Although the differences are limited, both panels seem to highlight some age differences. Specifically, the direct application to the employer as well as the use of job contacts seems to be more popular among younger cohorts. Instead, visiting an employment agency is more common for older cohorts.

3.3.6.1 Intergenerational and intra-generational elasticities

If one of the channels of intergenerational mobility is help provided by the parental network in the job search, the occupation of the respondent should be correlated with the job of the parental friends. To test this hypothesis, I augment eq. 3.12 to include the occupational income of the parents' and of the offspring's friends:

$$\begin{aligned} y_{it} &= \tilde{\delta}_0 + \sum_j \tilde{\beta}_j y_{jit} + \tilde{\delta}_1 Norm.age_{it} + \sum_j \tilde{\delta}_{j2} Norm.age_{it}\, y_{jit} \\ &\quad + \sum_j \tilde{\delta}_{j3} Norm.age_{jit} + \tilde{\delta}_4 birth_i + \sum_j \tilde{\delta}_{j5} female_{ji} + \varepsilon_{it} \end{aligned} \tag{3.15}$$

where i is the offspring, j is the father, the mother, and the best friends and *Norm.age* is the normalized age. Specifically, the intergenerational coefficients ($\tilde{\beta}_j$ for the father, the mother, and the parental friends) are for a 30-year-old respondent. The intra-generational coefficient (for j = own friend) is at the mean age (around 22 years).[59]

[59] As mentioned above, 30 is a compromise between the age of the adults (parents and their friends) and the age of the offspring. However, the offspring's best friends are on average as old as them. This

In order to account for the differences between female and male friends, a dummy variable indicates a female friend ($female$). The other covariates are the same as in eq. 3.12.

Table 3.3 reports the estimation results of eq. 3.15. It presents two sets of results, for sons and daughters. The first column estimate eq. 3.15 for j = the father and the paternal friend. The second column only considers the mother and her friend. In column three, both parents with their friends are included. Finally, in the fourth column, the offspring's own friend is also included. In the fourth column, the intra-generational elasticity is positive and statistically significant. For sons, the magnitude is statistically larger with male friends.

Overall, the results suggest that the occupational income of the child is positively associated to that of the parental friends. The magnitude of the coefficients and their statistical significance, however, depend on the sex of the offspring and of the friend. In general, sons have a stronger relationship with the paternal friends and daughters with the maternal one. Homophily or peer effects might explain the positive association between the occupation of the respondents with their own friends. As for the family friends, homophily would occur with parents and not with children. Moreover, the income of parents is included in the model. As a result, the association between the income of the family friends and offspring may be explained by something else than an indirect association through the parental income. A possibility might be the help

is why the age is normalized at the mean. Notice that the coefficient would not change by omitting the interaction between normalized age and the own friend's occupational income. I decided to keep it for consistency with the others: it is in fact possible to predict $\tilde{\beta}_j$ at different ages by adding $\tilde{\delta}_{j2}$ (obviously multiplied by the difference between the old and new age). As an example the appendix Table B.15, reports the results of the last column of Table 3.3 at different values of normalized age for the subsample of sons.

provided on the labour market (especially when education is controlled for). That might also be consistent with the fact that, at least to some extent and mainly for sons, the sex of the friend matters.[60] Another exaplanation may be that family friends can influence one's achievement by being role models. Both explanations would be consistent with an inverse U-shaped intergenerational mobility. Unfortunately, however, at this stage it is not possible to explore the mechanisms further.

The results are robust to the inclusion of dummies for own and parental education, and region of residence (appendix Table B.16).

These findings are also consistent with the estimates based on models that consider the occupation of parents, friends and parental friends separately (see the appendix Table B.17).[61]

3.4 Conclusions

This paper investigates an additional channel for the intergenerational transmission of earnings. The new channel is family friends.

In the standard model à la Becker and Tomes, parents can anticipate the future earnings of their children with certainty. Therefore, the parental income determines

[60] An alternative explanation might be that individuals of the same sex are more likely to have similar earnings. However, this does not explain why the daughter's income, who experience a higher association with the maternal friend, is not statistically associated to the mother's income.

[61] The goal is to check whether the results mentioned above change when fewer variables are included in the model and on a larger sample size. The first three columns of the table estimate $\tilde{\beta}_j$, when only the paternal, the maternal and the own friend are respectively included. They are based on the reference samples. Columns 4 to 6 repeat the same exercise but without imposing a common sample, which allows for a larger number of observations. The only worth-mentioning difference is that, on a larger sample, the job of the maternal friend is not only positively associated to the daughters but also to the sons (see column 5 of Table B.17).

Table 3.3: Intergenerational elasticities

	(1)		(2)		(3)		(4)	
Sons								
F ln LI	0.250***	(0.097)			0.298***	(0.113)	0.275**	(0.116)
M ln LI			0.055	(0.088)	-0.080	(0.107)	-0.072	(0.104)
F friend ln LI	0.143**	(0.069)			0.183**	(0.075)	0.182**	(0.079)
Female F friend ln LI	-0.075	(0.077)			-0.064	(0.075)	-0.035	(0.085)
M friend ln LI			0.170	(0.127)	0.104	(0.126)	0.196	(0.120)
Female M friend ln LI			-0.161	(0.102)	-0.150	(0.108)	-0.156	(0.100)
Friend LI							0.295***	(0.048)
Female friend ln LI							-0.136*	(0.069)
Observations	1153		1153		1153		861	
Daughters								
F ln LI	0.298**	(0.118)			0.344***	(0.117)	0.221	(0.137)
M ln LI			-0.121	(0.108)	-0.253**	(0.117)	-0.263*	(0.142)
F friend ln LI	0.345***	(0.128)			0.290**	(0.125)	0.172	(0.129)
Female F friend ln LI	0.069	(0.078)			0.075	(0.083)	-0.002	(0.082)
M friend ln LI			0.488***	(0.143)	0.349**	(0.140)	0.293*	(0.169)
Female M friend ln LI			-0.038	(0.102)	-0.023	(0.096)	-0.051	(0.110)
Friend LI							0.189***	(0.054)
Female friend ln LI							0.027	(0.072)
Observations	1017		1017		1017		761	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father, M for mother, LI for labour income. Controls include ages and respondent's year of birth. For a 30-y-o. Friend LI for a 22-y-o respondent

the offspring's income only when capital markets are imperfect. When families are not credit-constrained, parents affect their children's income only though the inherited endowments, such as ability.

When parents cannot predict their children's future earnings with certainty, because the expected earnings depend also on labour market conditions, the parental income matters even with perfect capital markets. I consider three types of parents with top-, median- or bottom- paying jobs. Parents invest in their children's human capital and in friends. Different levels of human capital investments are a necessary, although not sufficient, condition to obtain different types of job.

A way to improve the chances of obtaining a job is through the help of family friends, as job contacts. I assume, however, that they are only useful if the children are looking for a job similar to the one of the friend. I also assume that it is less costly for parents to invest in friends that are similar to them and that marginal costs are increasing. Consequently, top-earning (bottom-earning) parents will have more top-earning (bottom-earning) friends. More generally, they will have more friends in the top (bottom) half of the income distribution. Median earners will have a more diversified network, if for example we assume that their cost of investing in high- and low-earning contacts is similar.

This implies that, with the same level of human capital, children of top-earning (bottom-earning) parents will be more likely to find a top (bottom) job. Children of median earners will be more likely to find a median job but the difference in probability is smaller. Moreover, they will also be more likely to find a top (bottom) job than the children of bottom (top) earners. This results in lower mobility for families at the extremes of the income distribution. The help on the labour market is the first mechanism through which family friends can affect intergenerational mobility.

Additionally, if the returns to education change according to the type of friends, parents may be more or less inclined to invest in higher levels of human capital according to the amount of their top- or median- earning friends. This is the second mechanism.

The use of friends as job contacts and the predictions of the above model are consistent with the U-shaped intergenerational persistence highlighted in the empirical literature. In this framework, differences in the use of job contacts across countries and different ethnic groups might also explain the different in intergenerational persistence. The results would be further reinforced if we assumed, as showed by some studies on social networks, that job contacts are more effective for jobs at the extremes of the earnings distribution.

I use the British Household Panel Survey, the New Earnings Survey and the Annual Survey of Hours and Earnings to test the implications of the model, its assumptions and the identified mechanisms. Data suggest that lower intergenerational mobility characterizes the top of the income distribution. This is in line with the existing literature in terms of quantile regressions (such as Gregg et al., 2015) and mobility matrices (such as the first chapter of my thesis) for the UK.

Family connections are associated with sons' and daughters' education and are correlated with their occupational income, after controlling for parental income. Most importantly, parents at the top and the bottom of the earnings distribution have less diverse networks, closer to their own occupation.

There are some differences according to the gender. For example, sons' occupational income is not associated with the maternal friend. Moreover, for daughters it seems that the parental income is not as important to determine their position in the income distribution. The only exception is for daughters with parents in the top quintile. In that case, their probability of being in the same quintile of their parents is higher. Additionally, the maternal friend appears to have an higher impact on the offspring's education probabilities than the paternal friend.

The results of the empirical analysis are consistent with the mechanisms of the model, where family friends play a role in affecting the offspring's economic outcome. For simplicity, I have only considered their role as job contacts. In a more general way, however, parental friends can influence the offspring by inspiring them, as role models. This may be particularly relevant for this analysis, which considers best friends. In fact, best friends may not be the most effective job contacts. According Granovetter (1973), weak ties might be more effective to help with job search than strong ties.

Another point to take into consideration is that the UK may provide a conservative estimate of the role of networks on intergenerational mobility. In this country, in fact, social networks are less frequently used in job search than in other parts of the world. For future research, it will be interesting to test the same predictions for countries where the use of job contacts is more widespread, such as in Spain and Italy.

As expected, intergenerational elasticities between the individuals and their fathers are larger than those between individuals and parental friends. This is because there are additional transmission mechanisms. Besides those already mentioned above, parents transmit their genetic characteristics to the offspring. Additionally, the income associated with the parental jobs can be correlated to different levels of credit constraints.

Unexpectedly, the maternal income has no statistically significant association with the earnings of her children, not even with daughters. Some tests performed in the analysis seem to indicate that when both parents are in the household, the mother's income does not matter. However, it is not possible to draw definite conclusions. For future research, it may be interesting to further investigate the reasons behind this result. It would also be interesting to further explore differences between sons and daughters.

One limitation of this analysis is the sample. By construction, the children are young and on average they are 30 years younger than their parents. This can lead to biased coefficients of intergenerational elasticity.

Additionally, the sample size is small. A larger sample would allow testing other implications of the theoretical framework. For example, the consequences for intergenerational mobility of the evolution of the social networks over time.

Chapter 4

Job polarization and household income

4.1 Introduction

As in the US, the UK labour market has seen a large shift in occupational structure over at least the last 25 years. This shift has seen employment decline in middle-earning occupations, and grow in occupations at the tails of the wage distribution. This shift, termed job polarization, has generated a large literature, focussing on explanations for its cause.[1] Despite this, few papers in the literature have examined the consequences of polarization for workers and households themselves.[2] We contribute to the literature, therefore, by examining how polarization has affected earnings, working patterns and income, tracking households over time using panel data from the British Household Panel Survey over 1991-2008. Our sample covers a period when polarization was particularly pronounced.

[1] See the extensive literature review below.

[2] An exception is Cortes (2016), which examines the evolution of male earnings, and which we discuss below.

There are several channels through which job polarization can impact income at the household level. First, if a worker finds himself in a declining occupation then, presumably, he is in greater danger of losing his job. Even if the worker can find a new job, he will suffer from the loss of job-tenure and, perhaps, occupation-tenure effects (Kambourov and Manovskii, 2009). Then, job risks are doubled if the worker's spouse is also in a declining occupation, or ameliorated if the spouse is in a growing occupation. Meanwhile, of course, shifts in the demand for occupations constantly change income through general equilibrium effects on occupational premia. On the other hand, the household is potentially insured to these factors by the flexibility of spousal labour supply and the added worker effect. Assessing the relevance of these channels is important because the welfare consequences of occupational shifts depends crucially on what happens to workers in declining occupations, and how their households can cope.

Accordingly, we base our analysis around a decomposition of income growth into several components. These components capture effects from the following factors: changes in occupational wage premia in the (male) head's initial occupation, changes to head earnings arising from occupational mobility, changes in spousal earnings, and changes to other income, potentially reflecting changes to the tax and transfer system.[3] We can also partially decompose spousal effects into components coming from mating patterns across occupations and from labour supply responses. We estimate the occupational premia using wage equations that take into account selection across occupations using a fixed effects estimator, which is consistent with a simple Roy model. As such,

[3] In this paper we focus on the first three components. We leave changes to the tax and transfer system to future work.

our analysis builds on that in Cortes (2016), who assesses the impact of job polarization in the US using panel data, but focusses on men only.[4]

In the spirit of Acemoglu and Autor (2011), we segment workers into four categories, based on the main task content of their occupation. Specifically, these four categories are based on dichotomies into cognitive vs non-cognitive and routine vs non-routine. We then allocate workers to these task cells using their occupation, classified according to the 1990 Standard Occupational Classification (SOC90). The sizes of the task groupings show strong changes over the period 1991-2008, which differ by men and women. Employment for men was high in manual routine jobs (such as factory work) at the beginning of the sample, but declined strongly. Similarly, employment for women was high in cognitive routine jobs (such as secretarial work), but also declined strongly. Meanwhile, for both sexes, employment in cognitive non-routine jobs (such as professional services) has grown strongly. By the end of the period, cognitive non-routine, professional, jobs take up by far the largest fraction of employment for both men and women.

Our findings are as follows. We first find, somewhat surprisingly, that workers in the declining manual routine occupation suffered no loss in income compared to those in the fastest-growing professional occupation. In particular, we categorize households according to the task of the male head. We orient the analysis around males in order to reduce the problem of selection into the labour market. We then track these households over the following 10 years, conditioning on age, but not conditioning on any future

[4]Cortes (2016) also examines females briefly, but does not consider the impact of polarization on households as a whole.

outcomes. We find that mean income growth of the manual routine (factory) households is nearly identical to those in the cognitive non-routine (professional) households, with a tight 95% confidence interval. This result is robust to conditioning on other initial characteristics, such as education.

Why have the households in declining occupations done so comparatively well? We answer this by pursuing the decomposition discussed above. Our decomposition is attractive because it does not rely on both males and females being present in the household; we can assess the evolution of household incomes for single males on a par with males in couples. As such, our decomposition does not suffer from the issues of selection which are faced by related analyses (such as Blundell et al., 2016, discussed below).

We find that the apparently flat profiles mask large changes in the structure and dynamics of wages and earnings. First, wspousehen selection into occupations is taken into account, the price on professional (cognitive) jobs shows a large divergence from routine jobs, for both men and women. In fact over the period of the BHPS, the underlying price of professional jobs rose by around 15% compared to manual routine and cognitive routine jobs. Alongside this, for women, occupational prices grew fastest for jobs at the bottom of the wage distribution, in manual non-routine routine work. These findings have several noteworthy implications.

First, the divergence between prices of professional jobs and routine jobs implies a strong sorting over time based on unobserved quality. This result is implied by the fact that the wage difference disappears when we ignore selection issues and estimate by OLS. In short, the evidence implies that the average quality of workers in professional jobs has gone down substantially over time, which has caused the flat structure in average wages.

Second, and on a related note, this finding provides fresh evidence of polarization explained by demand-side factors. The literature discussed below has hypothesized that job polarization seen across the developed world has been generated by factors such as technological change that is biased against workers in routine occupations, and trade factors. However, the evidence from wages is mixed and often inconsistent with this view, because average wages in many countries are flat across occupations.[5] Our findings, however, provide fresh evidence of polarization in wages: evidence that supports an increased demand for workers in professional occupations. At the same time, the results also provide evidence of strong demand for low-wage manual non-routine workers, at least for females.

Third, and more in line with the focus of the current study, these results have implications for the effects of occupational mobility. Our decomposition implies that, on average, workers in routine occupations switched to higher-paying occupations. Therefore, although they suffered from declines in occupational prices, they overall gained from the ability to switch occupations. In short, these workers on average gained from the expansion of the professional occupational sector, and so did not suffer in this respect from polarization. This finding contrasts with the findings of Salvatori (2015) which implies that the decline in middling (routine) occupations was caused by workers downgrading to lower occupations. On the other hand, our findings are consistent

[5] See, for example for the UK, Blundell and Etheridge, 2010; Brewer and Wren-Lewis, 2016.

with evidence for the UK in Carrillo-Tudela, Hobijn, She, and Visschers (2016), who use a short, high-frequency panel from the Labour Force Survey, and find that workers on average gain from occupational switches.

In terms of the other channels discussed above we have the following findings. We document noticeable mating patterns across occupations. In particular men working in manual occupations are much more likely to be married to women in manual occupations. Overall, we document that men working in declining occupations were generally married to women working in declining occupations, even conditioning on regional factors. Therefore, the limited effects of polarization in terms of household income is despite this correlation across couples. In terms of labour supply, we find little response of female labour supply to switches in male occupation, implying that the insurance value of female labour supply is less important in explaining the effects of polarization. This is despite the fact that we see large labour supply changes in general for women in response to shifts in their own occupational premia. These results are consistent with estimates of elasticities of labour supply for women in response to their own wage, and to shocks to the husband.[6]

These results contribute to our understanding of polarization in a number of ways. Primarily, they imply that individuals in routine occupations did not experience occupational downgrading in the UK. This finding corresponds well to findings using panel data from the US in Cortes (2016) and contrasts with implications from cross-sectional data such as Salvatori (2015). Second, as discussed, we provide additional evidence on the evolution of occupational premia in the UK using the panel data estimates. These

[6] See Blundell, Graber, and Mogstad (2015) and Blundell, Pistaferri, and Saporta-Eksten (2016).

estimates contribute to our understanding of polarization. Finally, to the best of our knowledge we are the first paper to document mating patterns across occupations, and to discuss how these influence the effect of polarization at the household level.[7]

spouse

The rest of the paper is organized as follows. Section 4.1.1 reviews the relevant literature. Section 4.2 describes the data and shows the evolution of occupations and earnings in the repeated cross-section. Section 4.3 describes the model of earnings and the decomposition of household income, used to frame the results. Before showing the results of the decomposition section 4.4 shows the evolution of incomes, which forms the basis of the decomposition. Section 4.5 then describes the main results. The final section concludes.

4.1.1 Literature Review

Our paper is related to several literatures in labour economics. A large literature focuses on the consequences of job polarization on wages and employment. These are well documented in the United States [8], in the United Kingdom[9] and in other European countries.[10] Their findings, based on cross-sectional or short longitudinal data, indicate that wages and employment in routine jobs grew less than those in high and low earning occupations (Autor and Dorn, 2013; Salvatori, 2015), with differences across countries. Employment and wage polarization characterized the US labour market in

[7]Several papers, such as Abramitzky, Delavande, and Vasconcelos (2011), explore matching on occupations, but in very different settings.

[8]see, for example Autor, Levy, and Murnane 2003; Autor, Katz, and Kearney, 2008; Autor and Dorn, 2013

[9]see Goos and Manning, 2007; Salvatori, 2015

[10]see Goos, Manning, and Salomons (2009); Goos, Manning, and Salomons, 2014

the 1990s. In the UK, employment polarization persisted in the 2000s, but wage polarization was largely absent. Similarly, other European countries, such as Germany, experienced employment polarization only, without wage polarization. These studies underline as well some differences across the type of routine jobs. For example, the decline in employment was particularly high in some manual routine occupations (craft occupations, and in plant and machine operatives), as indicated by Salvatori (2015) for the UK and Acemoglu and Autor (2011) for the US. However, in the US the employment shifted from middling to bottom occupations. Instead, the UK experienced a growth in top occupations. As for wages, those of some cognitive occupations in the US and in the UK, such as clerks and secretaries, were not affected as much as the one of the other routine occupations.

A somewhat distinct, but equally large and influential, literature investigates the occupational mobility of workers using longitudinal data. For example, Groes, Kircher, and Manovskii (2015) use Danish administrative data to compare the job switches and the changes in wages of male workers. They find that within the same occupation, high and low earners are more likely to leave their occupation than medium earners. The only exceptions are occupations with steeply rising or declining productivity. In the first case, low earners tend to leave. In the second case, high earners have a higher chance to do so. The authors suggest that these findings are consistent with a model of vertical sorting under absolute advantage and learning about workers' abilities.

In a related paper, Kambourov and Manovskii (2008) argue that occupational mobility is related to wage inequality. They find that the percentage of workers switching occupations in the United States increased over time, from 16% per year in the 1970s to 21% per year in the 1990s. They develop a general equilibrium model with occupation-specific human capital and where the level of experience is heterogeneous. According to their results, mobility might account for over 90% of the increase in wage inequality between the 1970s and the 1990s.

The authors further investigate the role of human capital in an empirical paper. Kambourov and Manovskii (2009) use the Retrospective Occupation-Industry Data Files released as part of the Panel Study of Income Dynamics (PSID) to estimate the returns to employer, industry and occupational tenure for the period 1968-1993. They restrict the sample to employed white males between 18 and 64 years old. They control for overall labour market experience and other variables, such as union membership and education. They also take into account employer, job, occupation and individual specific effects. When the three variables are included in the same regression, employer and industry tenure have a quantitative small effect on wages. Instead, occupational tenure has a larger impact. For example, wages increase by 12%–20% with 5 years of occupational tenure. This result holds when occupation is considered at 3-digit level. At 1-digit level, the returns to industry tenure become statistically significant, even though they are still only half as those to occupational tenure. Moreover, the occupational returns with occupation at 1- or at 2-digit level are smaller than at 3-digit level. This leads the authors to highlight the determinant role of the occupation-specific human capital.

As discussed, our paper is most closely related to Cortes (2016). He exploits the longitudinal dimension of the Panel Survey on Income Dynamics (PSID) to investigate employment switches and wage growth of routine and non-routine male workers in the US. His findings are consistent with the other studies on job polarization. The workers in routine occupations perform worse than those in non-routine jobs. Indeed, the wage premium of the former appears to have fallen from 1976 to 2005, whereas it has increased for the latter. This also applies to those who switched from a routine to a non-routine job, at least in the long run (ten years).

The research mentioned above focuses on employment and wage changes of individual workers. Our paper also relates to research on the transmission of individual-level inequality to the family, both in terms of income and consumption.

Several studies investigate the role of marriage as a risk sharing mechanism, exploring how labour supply reacts to a spousal shock. Hyslop (2001) uses a life cycle model to explore the relationship between the couple's labour supply and their contribution to earnings inequality. His analysis is based on the PSID from 1979 to 1985. First, he finds a positive correlation between the husbands' and wives' earnings and wages. The correlation is higher for wages than for earnings, implying that hours are not independent of wages and that the positive correlation is attributed to permanent factors. The results also suggest that there is no intertemporal cross-substitution between the changes in one spouse's wages and the changes in the other's hours. Second, as for inequality, the study shows that the labour supply elasticities explain over 20% of the rise in family inequality and 50% of the rise in inequality of married women. They do not appear to contribute to the rise in male inequality.

Recently, Blundell et al. (2016) examine the association between wage and consumption inequality to understand how wage shocks affect consumption and labour supply. They use a life cycle model in which husband and wife make unitary decisions about household consumption and their individual labour supply. They consider three potential sources of smoothing: self-insurance through credit markets, adjustments in the family labour supply, and access to external sources of insurance. They use PSID and the Consumer Expenditure Survey to estimate the contribution of each mechanism. Their results suggest that the first two types of insurance explain most of the smoothing, with differences over the life-cycle. For younger couples, labour supply responses play a greater role for consumption decisions. Instead, for couples older than 50 some of the insurance is taken up by saving.

Our paper also relates to those on assortative mating. A recent example is Eika et al. (2014), who assess the pattern of educational assortative mating in Norway and in the US, and its contribution to inequality. They use administrative data for Norway and the Current Population Survey for the US, from 1980 to 2007. They find evidence of assortative mating in both countries. Over time, assortative mating among high-educated individuals has decreased, whereas it has increased for low-educated. According to the authors, this also explains why it does not seem to be associated to the evolution of household inequality over time. The effect of its increase for low skilled couples is offset by its decline among college graduates.

In summary, despite the numerous studies about job and wage polarization, most research is based on cross-sectional or short longitudinal surveys (such as the Labour

Force Survey). The limitation of this type of surveys is that they do not allow for a deeper investigation on the occupational transitions and wage changes. The literature on occupational mobility, which focuses on occupational patterns, does not directly take into account the polarization of wages and employment. To the best of our knowledge, Cortes (2016) is the first study to use panel data to investigate job polarization. Additionally, as far as we know, the existing research in this area considers individual workers. The large related literature on family labour supply accounts for shocks to wages but does not explicitly investigates if workers with different occupations react in different ways.

4.2 Data

4.2.1 British Household Panel Survey

We base our analysis on the British Household Panel Survey (BHPS). The Survey began in 1991 with a representative sample of about 5,500 units and 10,300 individuals, drawn from 250 areas of Great Britain. We use the baseline survey and ignore the later booster samples of low-income households and from Scotland, Wales and Northern Ireland. It is a longitudinal and household-based multi-purpose study. The longitudinal dimension allows us to investigate the patterns of job polarization and its impact on household income over almost twenty years, from 1991 to 2008. The survey follows all the adult members of a given household over time, even after joining a new household. This provides direct information for the heads of the household and their spouse.

The present study focuses on the original BHPS sample, from 1991 to 2008. Although some of the individuals surveyed in BHPS are now part of the Understanding Society Survey, we chose not to merge the two Surveys for three main reasons. First, excluding later waves allows us to investigate the consequences of polarization without the issues raised by the Great Recession after 2008. Second, we avoid additional attrition. As indicated by Lynn et al. (2012), only 79% of the sample in the BHPS participated to the second wave of Understanding society, in 2011. Third, we can construct a consistent measure of occupation (discussed below) over the whole period. The occupation of the members of the original BHPS sample is available in terms of the 1990 Standard Occupational Classification (SOC90), even after the introduction of the 2000 Standard Occupational Classification.[11] It is important to be able to have the occupations expressed in terms of one unified classification because there is no perfect correspondence between the two classifications.[12]

[11]Only for 3 respondents, 4 observations in total, the information about the SOC90 is missing. Originally, 5 individuals had some waves where the information about their occupation was missing. For 2 of these individuals, it was possible to impute the missing task and occupation in terms of SOC90. For the other 3 individuals, instead, it is not feasible as it is not possible to establish a pattern.

[12]This is well illustrated in the technical report of the Office for National Statistics (Beerten et al., 2001). The report is based the Labour Force Survey (LFS) for the summer quarter of 2000. This LFS is dual coded to both the 1990 and the 2000 SOC to clarify the impact of the revision in the SOC. According to that report, only 70% of the occupations are in the same major groups using the summer 2000 Labour Force Survey Data. When considering the task content of each occupation, only 61% of the 2000 occupations can be unambiguously attributed a task following the 1990 classification. For 30% of the cases, there are two concurrent tasks. Three tasks correspond to the same 2000 occupational code in 8% of the occupations. Finally, around 1% of 2000 occupational codes could be expressed equally in terms of all four tasks of the SOC90. Obviously, the risk would be to observe a change in the task content of the occupation which is only due to the change in the used classification.

4.2.2 Variable Definitions and Sample Selection

The main variable for this analysis is the job task. Following Acemoglu and Autor (2011), we use the occupation major groups of the 1990 Standard Occupation Classification (SOC) as a proxy of the task content of each occupation. We construct four broader groups by merging the nine occupational categories of the 1990 SOC rather than imputing task data to these categories.[13] We follow the same categorisation that Acemoglu and Autor (2011) apply to US data. Note that this approach implicitly assumes that the task content of each occupation is similar in the UK and in the US.[14]

Specifically, the four groups classify the occupations according to the type of their predominant task. The first includes all the cognitive non-routine occupations: these are, managers and administrators, professional occupations, associate professional and technical occupations. The second cluster is for the occupations involving manual and routine tasks, and comprises craft and related occupations, plant and machine operators. The third group includes the jobs who are predominantly characterized by cognitive and routine tasks: clerical and secretarial occupations, and sales occupations. The fourth group consists in the occupations that involve mainly manual and non-routine tasks: personal and protective service occupations, and other occupations. For much of the analysis, we use an additional category including males and females without a job (unemployed or out of the labour force).

[13]Acemoglu and Autor (2011) compare the categorisation done using the occupational categories mentioned above and the classification obtained by attributing each occupation a task measure using the US Department of Labor's Dictionary of Occupational Titles (DOT). The authors conclude that the pattern of task intensity across the occupations for the two measures is comparable.

[14]Example of another UK study that uses the same methodology is Salvatori (2015).

We use the categorical variable with the five categories to investigate the employment patterns. In order to examine the effects of job polarization at the intensive margins and on wages, the relevant variables are the natural logarithms of worked hours, of earnings and of household income. For earnings, we use the usual monthly pay. This derived variable measures the wage or salary received by the employees in their current main job before tax and other deductions. As for the worked hours we take into account that the usual pay may include the compensation for overtime. We combine the usual working hours with the hours worked overtime in a normal week. As the number of normal worked hours is bounded at 97, we bound the variable at 97. We do this to ensure the comparability of the results with the employees who do not any overtime. Additionally, only 0.2% of the observations concerning employees reported a total number of hours larger than 97.[15] For the household income, we use an equivalised and deflated measure. The selected variable indicates the total net household income in the current week. Like for earnings, the variable is deflated at 2010 constant prices. It is equivalised using the modified OECD equivalence scale.[16]

We consider men and women in their prime age, between 25 and 64. The lower bound at 25 reduces the risk of including the changes between jobs of the labour market entrants who do casual or part-time jobs at the beginning of their career or while in education as occupational shifts. We set the upper bound at 64 as those working after this age are increasingly highly selected. Moreover, older workers might change from

[15]In the final sample, this affects 31 males for a total of 41 observations. 17 of them are in a cognitive non-routine job, 9 of them in a manual routine job. It affects 5 females, for a total of 13 observations. 4 of them are in a cognitive non-routine occupation.

[16]The scale is the following: 1 for the first adult, 0.5 for other individuals aged 14 or older, 0.3 for those younger than 14.

their job to a lighter occupation instead of officially retiring. Additionally, in order to be able to consider the dynamics, individuals are only included in the sample if they have provided information about their earnings in at least 5 waves. Moreover, if the individuals have a job, we only include them if they are employed. Finally, observations with missing values in the variables indicating the occupation or labour force status, the number of worked hours (if employed) and the completed level of education were excluded. As Table 4.1 indicates, the resulting sample consists in 2,363 males and 2,426 females, for a total of 28,406 and 30,835 observations, respectively. In 1,985 of these for males, and 4,436 for females, the individuals are unemployed or out of the labour force. The appendix section C reports the summary statistics on the main sample, by sex.

Table 4.1: Sample selection

	Males		Females	
Description	N	n	N	n
BHPS original sample	65,357	8,039	73,311	8,597
Aged between 25-64 y.o.	44,855	5,609	47,875	5,690
Non-missing education and occupation/LF status	44,603	5,562	47,677	5,657
Without self-employed	37,691	5,146	45,039	5,554
With information about worked hours (if employed)	36,797	5,113	44,255	5,536
Earnings for at least 5 waves	28,406	2,363	30,835	2,426

4.2.3 Trends in Employment and Earnings

Figure 4.1 plots the fraction of men and women in five different occupational groups over time. As mentioned above, we classify the occupations in four broader groups, according to the type of the predominant task that characterizes them. The groups are cognitive non-routine, cognitive routine, manual routine and manual non-routine occupations. The fifth group includes the individuals who are unemployed or out of the labour force.[17]

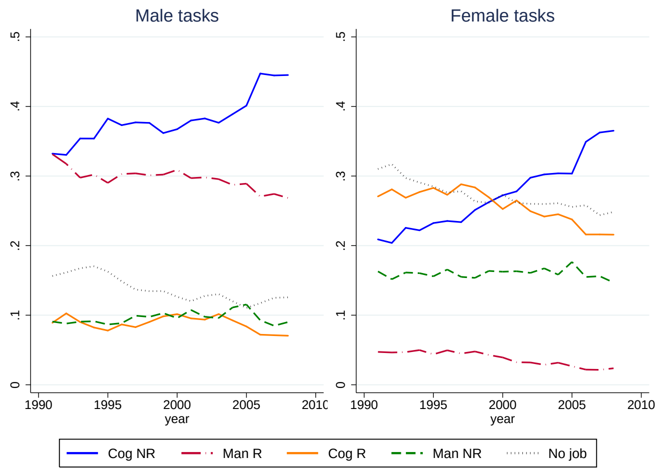

Figure 4.1: Employment patterns by occupational group
Picture is based on the sample of 25 to 64 y-o men (left panel) and women (right panel)

The left panel illustrates the distribution of occupational groups for the males in our sample. Males belong mainly to two categories of jobs. On average, cognitive non-routine and manual routine workers account for 68% of the individuals in this sample, over all years. The other two occupational groups include 9% of workers each. The men without a job represent 14% of the total sample.

As for the trend over time, the most striking feature is the large increase in the fraction of cognitive non-routine workers, largely offset by the decreases in the percentage of manual routine workers. In 1991, cognitive non-routine and manual routine workers represented each 33% of the the sample. The percentage increased to 45% in 2008 for cognitive non-routine employees, whereas it decreased to 27% for manual routine workers. These shift combine both composition effects as cohorts enter and leave the

[17]The figures in the appendix section C indicate that the patterns identified here below are robust across samples.

sample, and transitions within individuals. We document the transitions later in the analysis.

The right panel reports the distribution of occupations over time for females. On average, most females either have a cognitive occupation (53% of the sample) or do not have a job (27%). The fraction of those in manual routine occupations is 4%, whereas 16% work in a manual non-routine job. Consistently with the literature (Salvatori, 2015) and the pattern identified for men, the figure shows an increase in cognitive non-routine occupations and a decline in routine occupations.[18] In 1991, 27% of the females in the sample (over 40% of the female workers) were working in a cognitive routine occupation. This was the the largest category of employees until 1999. After 1999, the cognitive non-routine workers became the largest group. The percentage of women in this group increased from 21% to 37% over the period 1991-2008; by the end of the sample period it is 15 percentage points higher than the fraction of women in cognitive routine jobs.

Next, we consider their monthly earnings. After classifying the workers in occupational groups, for each of them we compute the average log earnings over time. Figure 4.2 plots the mean earnings for men (left panel) and women (right panel). The figure highlights that workers in cognitive non-routine occupations earn by far the most.

[18] Specifically, Salvatori, 2015 uses the LFS and the New Earnings Survey Panel Dataset (NESPD) to analyse the changes in employment shares between 1979 and 2012. The main results are robust to the three classifications he uses. The first is the decreases in employment shares of routine occupations with respect to non-routine ones. Compositional effects, or between-groups changes, are the main driver of the decrease. This decrease accounts for most of the reduction in the occupations in the middle of the income distribution. In this case, within-group changes seem to account for most of the contribution to the decline in middling occupations.

Manual routine workers earn the second highest. The samples for the other two occupations are fairly similar. Notice the difference in earnings across groups remains roughly constant over time, reflecting apparently flat occupational premia

The left panel of the figure indicates that males in manual routine occupations experience the second highest average earnings. In terms of earnings growth over the period 1991-2008, there are no striking differences between manual routine and cognitive non-routine jobs. The former increased by around 24%, whereas the latter by 21%. The number of observations in the other two categories is significantly smaller. Indeed, the line has bigger spikes. If we consider the period from 1991 to 2005, the earnings growth of cognitive routine jobs increased by 18%. Earnings of manual non-routine workers rose by 28%, more than those of the other occupations.

The right panel shows that a similar pattern emerges for women, where on average earnings grew more than for men. The routine occupations pay similar earnings and are higher than those of manual non-routine jobs. The most striking feature is that it is this last group, however, for which earnings grew the most, by 53% from 1991 to 2008. Earnings growth in manual routine and cognitive routine jobs is similar (35% and 31%, respectively). These percentages are in line with the growth of earnings in cognitive non-routine occupations, 34%.

The profiles shown are in line with the recent results from the literature on the UK. Salvatori (2015) reports the wage changes for three decades, in the 1980s, 1990s and in the 2000s using data from the LFS and the NESPD. The large employment losses experienced by clerical, crafts, and operatives occupations was not accompanied by a systematic lower performance in terms of wage growth. Instead, clerical occupations, for example, is the group with an overall largest growth, after the non-routine cognitive occupations. In a similar way, craft occupations performed as well as occupations characterized by an increase in their employment shares, such as service and sales occupations. Plant and machine operatives are the group with the overall lowest wage growth. However, this seems mainly driven by the low values in the first two decades. In the 2000s, their pattern is comparable to that of clerks and craft occupations.

Salvatori (2015) also shows that non-routine manual occupations, especially services, experienced an overall large wage growth over the three decades. Additionally, all the occupation within the category are characterised by the largest wage growth in the 2000s. Finally, the wages of non-routine cognitive occupations grew the most in the 1980s, but in the 2000s their growth decreased with respect to that of the other occupations.

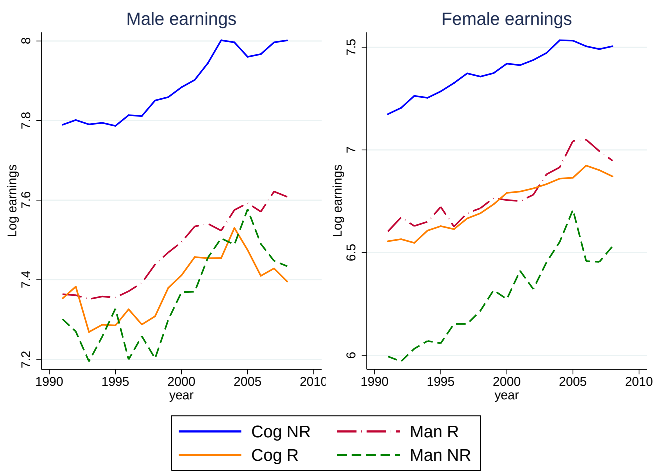

Figure 4.2: Mean log earnings over time by occupational group
Picture is based on the sample of 25 to 64 y-o men (left panel) and women (right panel)

4.3 Organizing Framework

We now present our organizing framework for examining the effects of polarization. Motivated by the discussion in Acemoglu and Autor (2011), Cortes (2016) and Böhm (2015), we assess the effects by analysing the growth over time in resources for those working in each task. Our framework therefore involves an accounting decomposition of growth in household income into growth in male earnings, female earnings and other income. We centre most of the discussion around male occupation rather than female occupation to reduce concerns about selection into the labour market. Nevertheless, we estimate many of the objects of interest for women alongside men.

Our framework also breaks down growth in male earnings into two important components. As discussed in the introduction, these components are movements in task prices, and effects of occupational mobility. Our framework therefore requires specifying a wage equation for males in terms of task prices. We therefore do this before examining the decomposition of household income.

4.3.1 Wage Equation and Occupational Prices

Observed log wage $\ln w_{it}$ at time t depends on the chosen occupation, on the worker's skills and on an idiosyncratic unobserved component that is constant across occupations, u_{it}:

$$\ln w_{it} = \sum_j D_{ijt} z_i a_j + \sum_j D_{ijt} \theta_{jt} + u_{it} \tag{4.1}$$

where D_{ijt} is an indicator for the occupation and takes value one if the the individual's occupation is j at time t and zero otherwise. Moreover, a_j are the returns to skills that are specific to each occupation and z_i captures the time-invariant component of skills. Finally, θ_{jt} captures the time-varying component of the occupational wage premium.

This framework follows that used in Cortes (2016), in turn based on the model of Jung and Mercenier (2012) and on Gibbons et al. (2005). The framework can be rooted in a model set in an economy with four occupations or occupational groups (cognitive non-routine, cognitive routine, manual routine and manual non-routine) and a continuum of workers with different skills, individuals select their occupation based on their comparative advantage. Specifically, as highlighted in Cortes (2016), with no frictions, the worker will choose the job with the highest wage. At any given time, sorting into occupations is based mainly on fixed differences in returns to occupations a_j and heterogeneity in z_i. The main driver of occupational mobility would be the change over time in the occupation wage premium θ_{jt}, the coefficient of interest. In short, as skill premia differ across occupations (as underlined by Gibbons et al., 2005), workers with different levels of ability self-select into different occupations.

Consistent estimation of θ_{jt} requires that the stochastic component u_{it} is not occupation-specific, and therefore does not drive selection into occupations. In our setting, this residual captures all other idiosyncratic components, both persistent and transitory. The error term, however, may include search frictions. These frictions may actually affect the occupational choice of the workers. In fact, workers may not be able to enter their desired occupation at t. In this case, the occupational choice will depend on the skills, on the premium and on the stochastic component u_{it}. For the consistency of the estimators, it is important that even though it affects the selection into an occupation, u_{it} is uncorrelated with the wage. Therefore, the identifying assumption is that selection into occupation in each period is random, conditioning on occupation fixed effects and the individual's skills. Because the regressors are orthogonal to u_{it}, the coefficients are estimated consistently.

For the actual estimation, we augment eq. 4.1 to account for another set of variables that may affect wages, such as a polynomial of order four for age, the region of residence, the marital status, the union membership and year dummies.[19] These controls are included in the matrix X of eq. 4.2:

$$\ln w_{it} = \sum_j D_{ijt}\gamma_{ij} + \sum_j D_{ijt}\theta_{jt} + \delta X_{it} + u_{it} \tag{4.2}$$

We estimate the equation with fixed effects at the occupation spell level for each individual. This captures the time invariant component, $\gamma_{ij} \equiv z_i a_j$, and demeans the wage within each occupation spell. The wage premium θ_{jt} is estimated by interacting dummies for occupational groups and years. The omitted occupation is the routine occupation: manual routine for men and cognitive routine for women. These are the two routine categories that employ the majority of workers for each gender. The year dummies control for changes over time that affect all workers regardless their occupation or skill level. The omitted year is the first year of the survey, 1991. Therefore, θ_{jt} is interpreted as the changes in the occupation wage premium over time, with respect to

[19] We also estimate this equation with alternative sets of control variables to verify the robustness of our results. These will be discussed in the subsection below.

the base year (1991) and with respect to the change experienced by the base occupation (manual routine for men and cognitive routine for women). The standard errors are clustered at the individual level.

As mentioned by Cortes, the identifying assumption rules out dynamic effects, like the fact that workers can adjust their expectations about their abilities over time. It is worth underlining, however, that Gibbons et al. (2005) find that the occupation wage premium seems unaffected by learning if the comparative advantage of a skill with respect to an occupation is taken into account.

Another issue that is not accounted for is that switching may be more costly for workers with higher occupational tenure. This may be particularly relevant because of the higher returns to the occupation-specific human capital as indicated in Kambourov and Manovskii (2009). In order to account for this, we augment eq. 4.2 with a term for occupation-specific tenure:

$$\ln w_{it} = \sum{}_j D_{ijt}\gamma_{ij} + \sum{}_j D_{ijt}\theta_{jt} + \sum{}_j D_{ijt}F_j Ten_{ijt} + \delta X_{it} + u_{it} \tag{4.3}$$

where Ten_{ijt} is the individual i's tenure in occupation j at time t and F_j are the returns to tenure in occupation j. In this framework, an individual occupation choice will not only depend on their skill and on the occupation wage premium but also on their tenure. Kambourov and Manovskii (2009) estimate a quadratic function of occupation tenure. The empirical estimation in Cortes (2016) suggests that returns to tenure are lower in routine than in non-routine occupations. As the author mentions, this does not account for the fall in the occupation wage premium in routine jobs. This fall is robust to different tenure profiles.

4.3.2 Decomposition of Household Income

With the wage model in hand, we decompose income changes in the following way. First note that if Y_{it} is total (net) household income, its proportional change, Δ^T, at lag T can be written as

$$\frac{\Delta^T Y_{it+T}}{Y_{it}} = \frac{1}{Y_{it}} \left(\Delta^T Y^m_{it+T} + \Delta^T Y^f_{it+T} + \Delta^T Y^o_{it+T} \right)$$

where Y^m_{it} is male earnings for household i, Y^f_{it} is female earnings, and Y^o_{it} is income from other household members and net transfers from the government. According to the framework discussed above, log male earnings can be written as

$$\ln Y^m_{it} = \gamma_{ij} + \theta_{jt} + \ln x_{it}$$

where x_{it} captures covariates, other than information on the occupation, alongside the earnings residual. In particular, x_{it} captures, for example, the returns to age, education and to region of residence.

We can decompose earnings further. Suppose the male in household i works in occupation j at time t and occupation l at time $t+T$,which might or might not equal j. Then we can define

$$\ln \hat{x}_{it+T}(t) \equiv \left(\gamma_{il} - \gamma_{ij}\right) + \left(\theta_{lt+T} - \theta_{jt+T}\right) + \ln x_{it+T}$$

Intuitively the variable $\hat{x}_{it+T}(t)$, captures earnings corrected for changes in occupation between periods $t+T$ and the base period t. In line with the discussion above, this might pick up growth in earnings purely down to ageing and, for example, changes in region of work. It can alternatively be calculated as $\hat{x}_{it+T}(t) \equiv Y^m_{it+T}/\left(\exp\left(\gamma_{ij}\right) \times \exp\left(\theta_{jt+T}\right)\right)$ i.e. the observed earnings divided by both the time-$t+T$ premium in the *initial* occupation, and the individual fixed effect in the original occupation. On the other hand, the component $\left(\gamma_{il}-\gamma_{ij}\right)+\left(\theta_{lt+T}-\theta_{jt+T}\right)$ captures the pure effects of occupational switching.

Pushing the decomposition further, and examining earnings in levels, we have

$$\Delta^T Y^m_{it+T} = \exp\left(\gamma_{ij}\right)\left(\exp\left(\theta_{jt+T}\right)\left(\hat{x}_{it+T}-x_{it}\right)+x_{it}\left(\exp\left(\theta_{jt+T}\right)-\exp\left(\theta_{jt}\right)\right)\right)$$

where $\exp\left(\theta_{jt+T}\right)\left(\hat{x}_{it+T}-x_{it}\right)$ captures the earnings effects purely from any changes in occupations, together with residual wage changes, while $x_{it}\left(\exp\left(\theta_{jt+T}\right)-\exp\left(\theta_{jt}\right)\right)$ captures the effects from changes in occupational premia in the initial occupation.

In terms of total household income we can then write

$$\frac{\Delta^T Y_{it+T}}{Y_{it}} = \frac{1}{Y_{it}}\left(\exp\left(\gamma_{ij}\right)\left(\underbrace{\exp\left(\theta_{jt+T}\right)\left(\hat{x}_{it+T}-x_{it}\right)}_{\text{occ. switching}}\right.\right.$$

$$\left.\left.+\underbrace{x_{it}\left(\exp\left(\theta_{jt+T}\right)-\exp\left(\theta_{jt}\right)\right)}_{\text{change in occ. premia}}\right) + \underbrace{\Delta^T Y^f_{it+T}}_{\text{spousal effects}} + \underbrace{\Delta^T Y^o_{it+T}}_{\text{other effects}}\right)$$

where the last terms capture spousal effects and changes to the tax and transfer system, alongside other effects. The spousal effects capture the effects of differential mating based on occupation together with potentially endogenous female labour supply effects, which we do not model. Finally note that by bringing the individual-specific occupation fixed effect $e^{\gamma_{ij}}$ to the front of the above expression, we can potentially examine heterogeneity of effects across the ability distribution *within* occupations; we could do this by ordering all workers in a given occupation by their estimated fixed effect γ_{ij} and then conditioning results accordingly. These heterogeneous effects are assessed in detail by Cortes (2016).

We can therefore decompose the growth in average household income according to the following set of regression functions:

$$\mathbb{E}\left[\Delta^T \ln Y_{it+T} | X_{it}, \gamma_{ij}\right] \approx \mathbb{E}\left[\frac{\Delta^T Y_{it+T}}{Y_{it}} | X_{it}, \gamma_{ij}\right]$$

which equals:

$$e^{\gamma_{ij}}\mathbb{E}\left[\frac{1}{Y_{it}} \underbrace{e^{\theta_{jt+T}}\left(\hat{x}_{it+T} - x_{it}\right)}_{\text{occ. switching}} | X_{it}, \gamma_{ij}\right] + e^{\gamma_{ij}}\mathbb{E}\left[\frac{1}{Y_{it}} \quad \underbrace{x_{it}\left(e^{\theta_{jt+T}} - e^{\theta_{jt}}\right)}_{\text{change in occ. premia}} \quad | X_{it}, \gamma_{ij}\right]$$
$$+\mathbb{E}\left[\frac{1}{Y_{it}} \quad \underbrace{\Delta^T Y^f_{it+T}}_{\text{spousal effects}} \quad | X_{it}, \gamma_{ij}\right] + \mathbb{E}\left[\frac{1}{Y_{it}} \quad \underbrace{\Delta^T Y^o_{t+T}}_{\text{other effects}} \quad | X_{it}, \gamma_{ij}\right]$$

Note that we expect changes to pure residuals (aside from education and age effects etc.) to average zero, and so the term $\mathbb{E}\left[\frac{1}{Y_{it}} e^{\theta_{jt+T}}\left(\hat{x}_{it+T} - x_{it}\right) | X_{it}, \gamma_{ij}\right]$ should mainly capture effects from occupational switching.

Moreover, to a certain extent we can decompose the spousal effects further. If Y_{it}^{f} is female earnings then it equals wages times hours. In this case

$$\begin{aligned}\Delta^T Y_{it+T}^{f} &= \Delta^T w_{it+T}^{f} h_{it+T}^{f} \\ &= w_{it+T}^{f} \underbrace{\Delta^T h_{it+T}^{f}}_{\text{labour supply}} + h_{it+T}^{f} \underbrace{\Delta^T w_{it+T}^{f}}_{\text{assort. matching}}\end{aligned}$$

The assortative matching effect is the average change in wages and captures the successes females have in the labour market conditional on initial male occupation. However, of course we only observe wages if hours are positive in both t and $t+T$. Therefore in fact we cannot decompose the spousal effect in general. We are, however, able to compute both the total effect, $\mathbb{E}\left[\frac{1}{Y_{it}}\Delta^T Y_{it+T}^{f}|X_{it},\gamma_{ij}\right]$, conditional on male observables and the pure labour supply effect, $\mathbb{E}\left[\frac{1}{Y_{it}}\Delta^T h_{it+T}^{f}|X_{it},\gamma_{ij}\right]$, also conditional on observables. We can then compare signs and magnitudes to examine any assortative matching effect. Note finally that these last expressions are in levels rather than logs. We can therefore compute them including zeros and even when a spouse is not present. These expressions therefore also pick up demographic factors from differential changes to the household for men in different occupations.

4.4 Wage, Earnings and Income Changes

4.4.1 Changes in household income by initial occupation of male heads

Our analysis is based around quantifying the average growth in income across (initial) occupations. As discussed we organize the households according to the occupation of males. Similarly to Cortes (2016), we estimate the following simple equation:

$$\Delta \ln y_{i(t+T,t)} = \beta task_{it} + \delta X_{it} + \varepsilon_{it} \; for \; T = 1, 2, ..10 \tag{4.4}$$

where $\Delta \ln y_{i(t+T,t)}$ is the change in $\ln y$ between t and $t+T$ for worker i. $task$ is the occupation at time t, split into the four groups. Manual routine is the base category for males. X is the matrix of controls, which includes the year, the region of residence, and the level of completed education. Moreover, we add a quartic term in age. The coefficient β reports the percentage difference in change in y between an individual in a given occupation and a routine worker, the base category.

The strength of looking at income compared to examining earnings alone is that we do not have to be concerned about selection into employment. Indeed, the income is available for all households, independently of the employment status of their members. As such, we perform this exercise on all men, married or not. The sample is therefore all men of the original BHPS sample who are between 25 and 64 years old and who are either employed or without a job, and with information about their earnings in at least 5 waves.[20]

Fig 4.3 reports the income growth differential between households with male heads in a given occupation with respect to manual routine households. The horizontal axis of the figure indicates the values of T, the number of years after the initial period, t. We estimate eq. 4.4 ten times, for each value of T, from 1 to 10. Each line plots the β coefficient in eq. 4.4 for a given occupational group for each of the 10 regressions. Each

[20] We exclude self-employed individuals.

regression is performed on pooled data, with standard errors clustered at the individual level. The left panel indicates that the average income growth in households where the husbands are in cognitive non-routine jobs at t is almost identical to families where the heads started as manual routine workers. This occurs despite the large shift in the share of employment in these two sectors. The right panel better highlights this result, by reporting the 95% confidence interval around this growth differential. The figure also shows that households with heads in manual non-routine have done the best. However, few men belong to this group or are cognitive routine workers, so we focus most of the following discussion on the distinction between manual routine and cognitive non-routine workers.

As a final point, we point out that the results are robust to the exclusion of the additional control variables, such as education, region of residence and marital status.

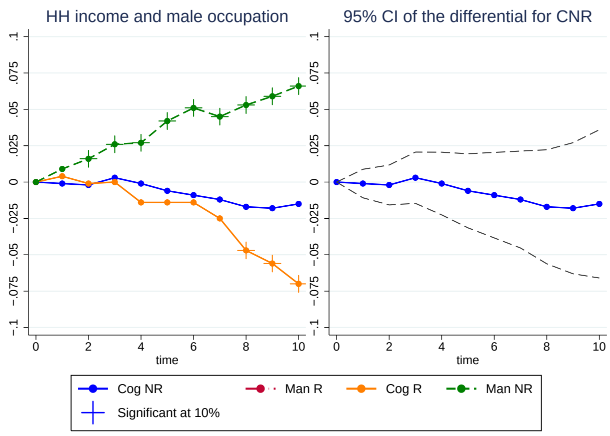

Figure 4.3: Changes in the household total net equivalised income by male initial occupation
Picture shows coefficients on future changes to income relative to manual routine workers after controlling for education, region of residence, marital statusWeOccupational wage premia restrict our sample to couples

4.4.2 Changes in earnings by initial occupation: Men

As discussed in section 4.3, we assess the growth in household income using a formal decomposition. Before doing this, in the next two subsections we examine the growth in males and female earnings and working patterns more descriptively. We re-estimate equation 4.4 on each subsample. First we consider males. Figure 4.4 illustrates the change differential in earnings and wages for males in a given occupation.

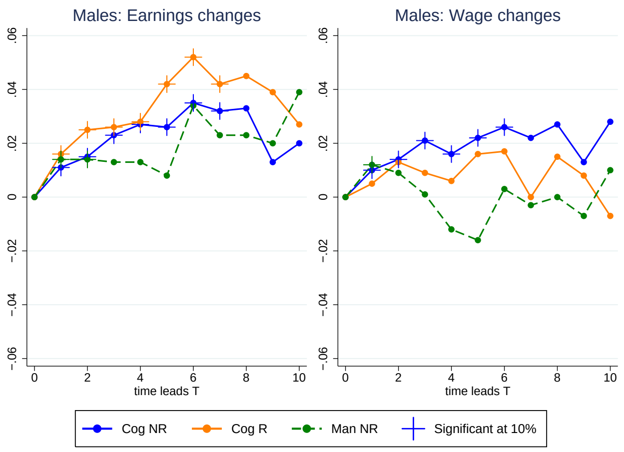

Figure 4.4: Changes in earnings and wages for men by initial occupation

Overall, the findings suggest small differences based on the initial occupation, at least in the long term. The top left panel indicates that, in the medium period, the earnings of those who started with a manual routine job in time t grow less than those in cognitive occupations. At $t+6$, the earnings change for cognitive non-routine workers is 3% above that of those initially in manual routine worker. Cognitive routine employees experience an earnings change that is 5% above the change for manual routine workers. For longer time horizons, however, the coefficients become statistically insignificant.

The right panel indicates that the change differential in wages is smaller in magnitude, reaching at most 2.8% after 10 years. This percentage refers to the differential between non-routine cognitive and routine manual workers. Just as for earnings, however, the wage changes between these two occupational groups are statistically different up to after 6 years. These findings are in contrast to those in Cortes (2016) for the US. He finds that the wages of workers who start in a routine occupation grow significantly less than those in non-routine jobs, over all time horizons. For example, they grow 11% less after 10 years and from 17% to 20% less after 20 years.

Notice, however, that the author only includes year dummies as control variables in eq. 4.4.[21] Differently from Cortes, we control for a set of variables. Among those variables, it may be worth highlighting the importance of age. All other things being equal, older workers might be more likely to be in higher-paying positions. If they already are in posts of higher responsibility at t, it may be more difficult for them to experience high wage increases. For example, the changes from t to $t+T$ might be lower than for individuals who received a promotion after time t. Another reason to control for age is because of its link with job tenure. The summary statistics suggest that, on average, manual occupations have the highest tenure.[22] This might partly explain why the differences are not statistically significant in the long-term. The longer job tenure characterizing male workers in manual routine occupations might offset the lower increase in wages with respect to non-routine cognitive workers. However, longer job

[21]With the same specification, the differences would be statistically significant in the long term in Britain as well (see Table C.2 in the appendix). For example, workers starting in a routine manual job would expect their real wages to grow on average 6.3% less over the subsequent 10 years than workers in non-routine cognitive occupations.

[22]It amounts to 7.5 (6.2) years for routine and 6.3 (6.3) years for non-routine male (female) employees. Men (women) in cognitive non-routine occupations have had their job for 5.3 (4.3) years. Those in cognitive routine occupations have worked there for 5 (4.7) years, on average.

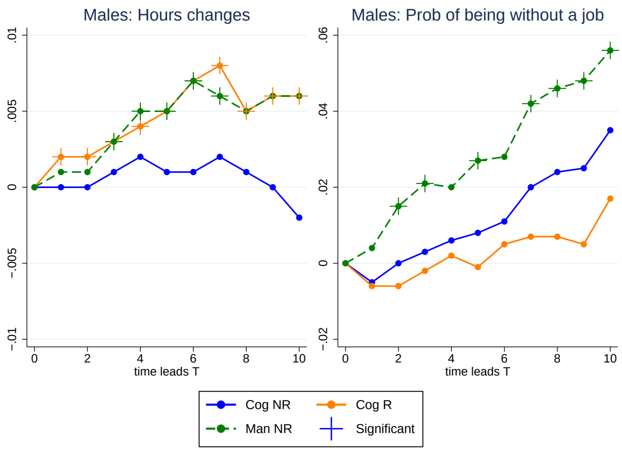

Figure 4.5: Changes in male labour supply
Picture shows changes in hours for men by initial occupation (left). Prob. of being without a job by initial occupation (right)

tenure might be more common among older workers. Younger routine manual workers might be more heterogeneous.

For the above reasons, we expect the wage growth differentials between non-routine cognitive and routine manual jobs to be smaller in magnitude for older workers. To check age differences, we divide the main sample into two: workers who are younger than 40 years old, and those who are at least 40. We estimate eq. 4.4 on these two subsamples. Our expectations are confirmed by Figure C.5 in the appendix. For the subsample of older individuals, the differential is not statistically significant. The wage differential of non-routine cognitive workers is positive and statistically significant only for the subsample of younger individuals. In addition, it becomes smaller and not statistically significant if we control for job tenure, as indicated by the thinner blue line in the left panel of the figure.

Next, we explore differences in terms of labour supply. The left panel of Fig 4.5 reports the coefficients of the specification in eq. 4.4, with hours of work as the left hand side variable. There are no differences in the change of worked hours between manual routine and cognitive non-routine workers. The coefficients are close to zero over all time horizons and not statistically significant. The figure suggests statistically significant differences with the workers who started in a cognitive routine or in a manual non-routine occupation. These are, however, small in magnitude: less than 0.1% after 10 years.

The right panel illustrates the coefficients of a Linear Probability Model, where the dependent variable is a dummy variable. The variable equals 1 if the worker is without a job at $t+T$ (for $T = 1, 2.., 10$) and 0 otherwise. The right-hand side of the equation is the same as eq. 4.4. The figure reports the difference in the probability of being without a job for those who started in a given occupation with respect to those who started with a manual routine job. The results suggest that in the medium and long period males who started with a manual routine job at time t are less likely to exit the labour force at $t+T$. The results, however, are only statistically significant with respect to non-routine manual workers.[23] Overall, we conclude that differential labour supply is not important in explaining differences in outcomes across tasks for men.

4.4.3 Changes in earnings by initial occupation: Women

We repeat the same exercises on the sample of females. Recall that our analysis of household income is based on male heads, and the female sample here is different from the sample of spouses. Nevertheless it is interesting to look at outcomes for women on

[23]Notice, however, that the probability of being unemployed is larger for manual routine workers than for the other types. The differences, however, are small in magnitude and they are statistically significant only in the long term and only with respect to manual non-routine workers. The results are not reported but they are available upon request.

their own. First, we estimate eq. 4.4. We then follow the procedure used for Figure 4.4 to construct Figure 4.6. The base category is now the cognitive routine occupation, which accounts for the majority of women in routine jobs.[24]

Overall, the initial occupation seems to have a higher predictive power for the earnings and wage changes of women. The left panel shows pronounced differences in earnings growth by initial occupation, holding fixed other observables. Women who started in a cognitive non-routine occupation experience a lower earnings growth than women in cognitive routine jobs. The differential increases monotonically to reach 9% after 10 years. The difference is statistically significant over all time horizons.

Perhaps most noteworthy is the manual non-routine group. These individuals have experienced the highest growth, both in terms of earnings and of wage. Specifically, the earnings change differential increases to 30% over 10 years. For the same time span, the difference in wage growth between manual non-routine and cognitive routine amounts to 12%. It indicates that workers in manual non-routine occupations experienced the higher growth on average over the period 1991-2008. Of course, it is worth mentioning this graph does not control for selection into employment.

Similarly to the case of men, we investigate the association between the initial occupation and change in employment and hours worked. The left panel of Figure 4.7 reports the estimates of eq. 4.4 for the differences in hours of work. Overall, the highlighted patterns are consistent with what observed for wages and earnings. This suggests that the changes in earnings are in part explained by changes in hours. Manual

[24]We chose manual routine for men and cognitive routine for women because these are the occupational groups with the larger number of observations.

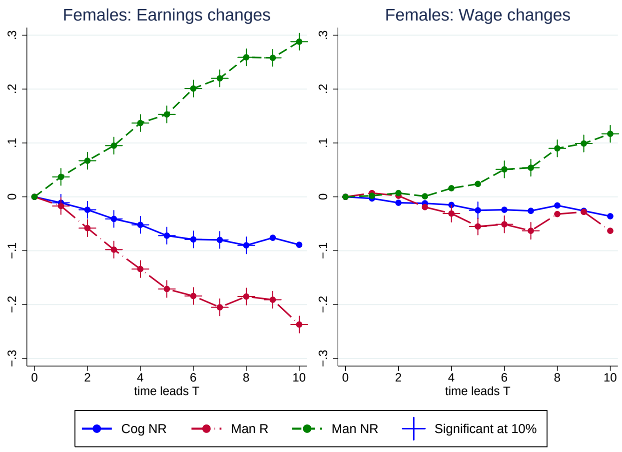

Figure 4.6: Changes in earnings and wages for women by initial occupation
Picture shows coefficients on future changes to income relative to cognitive routine workers after controlling for education, region of residence, marital status

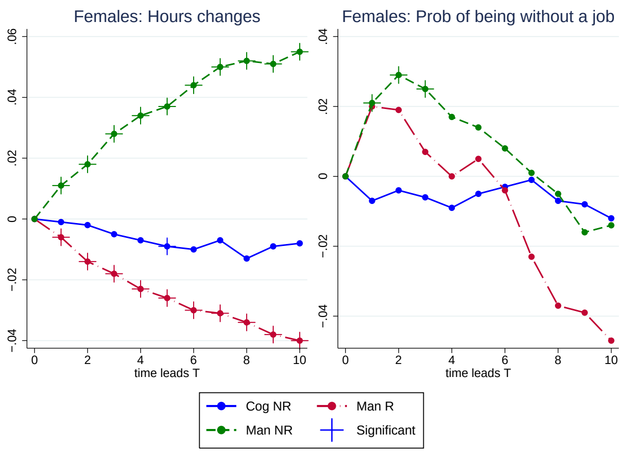

Figure 4.7: Changes in female labour supply
Picture shows changes in hours for women by initial occupation (left). Prob. of being without a job by initial occupation (right)

routine workers have a negative differential in worked hours change with respect to cognitive routine women. It is lower by 4% at $t+10$. Manual non-routine workers instead experience a higher growth in worked hours by 5.5% with respect to cognitive routine workers. Instead, the differential is not statistically significant for women starting in a cognitive non-routine job. This evidence reflects the important role of labour supply on the intensive margin in driving the link between wages and earnings for females in particular.

In conclusion, a striking result from this analysis is the positive differential for women in manual non-routine jobs. Our main hypothesis for the higher growth of earnings and wages is that it is caused by an increase in their wage premium. An alternative reason, which may also explain the positive differential in worked hours, is that we are just picking up differences in career trajectories across occupations. Therefore, women who switch from a manual non-routine job to another occupation after t may experience higher growth in terms of earnings, wages and hours. We attempt to control for this by estimating eq. 4.4 on the two subsamples of women: those who are younger than 40 years old, and those who are at least 40, like we did for men. We repeat this exercise for earnings, wages and worked hours. The appendix Figures C.6, C.7 and C.8 report the results on the changes in earnings, wages and worked hours, respectively. They show similar patterns for younger and older wives.[25] Therefore the results are at least not driven entirely by career trajectories but seem to reflect genuinely increasing wages for these types of workers. It should be remembered, of course, that during the period studied the UK saw the introduction of a minimum wage which likely affected these workers.[26]

4.5 Results of the Decomposition

In this section we decompose the growth in household income. We focus, in particular, on the role of changing occupational premia and occupational switches of males and

[25]The only exception is the change differential in worked hours for manual routine and cognitive non-routine workers. Although the coefficients are similar in magnitude, they are statistically different from zero only for the subsample of younger women.

[26]It is also worth noting that many manual non-routine workers are part time. In our sample, over 65% of manual non-routine female workers have a part-time job versus 30% of female workers in cognitive non-routine and manual routine, and 48% of cognitive routine workers. Their average earnings are also lower than those of the other occupations.

the spousal effects. As an aside, we estimate occupational premia and the effects of occupational switches for women also. In terms of spousal effects, we estimate the impact of the husband's occupation on the wife's earnings and labour supply. Although it is not possible to disentangle the effects due to assortative matching completely, we perform some additional exercises to try to further investigate the issue.

4.5.1 Occupational Prices

We estimate eq. 4.2 for males and females aged from 25 to 64 years old separately.[27] Figure 4.8 reports the estimated change differential in wage premia for workers in a non-routine occupation with respect to routine workers: specifically, manual routine workers for men and cognitive routine female workers. The existing literature for the UK, based on cross-sectional or short panel data suggest that the UK did not experience wage polarization (Salvatori, 2015). In contrast to the existing evidence, Figure 4.8 suggests that the wages of workers in non-routine occupations grew more than those of routine workers. The left panel indicates that for men, it is particularly true for cognitive non-routine occupations. For women, in the right panel, the change differential is positive and statistically significant also for manual non-routine workers.[28] In terms of quantities, the figure shows that the change differential in premia between cognitive non-routine and manual routine men for the period 1991-2008 is 13%. For women the coefficients amount to 19% between cognitive non-routine and cognitive routine and around 11% between manual non-routine and cognitive routine female workers.

[27]We exclude from the sample individuals with missing information about their job tenure and trade union membership.

[28]We do not report the wage change differential of cognitive routine males and of manual routine females as they are not statistically significant. Additionally, as mentioned previously, the number of workers belonging to this category is small.

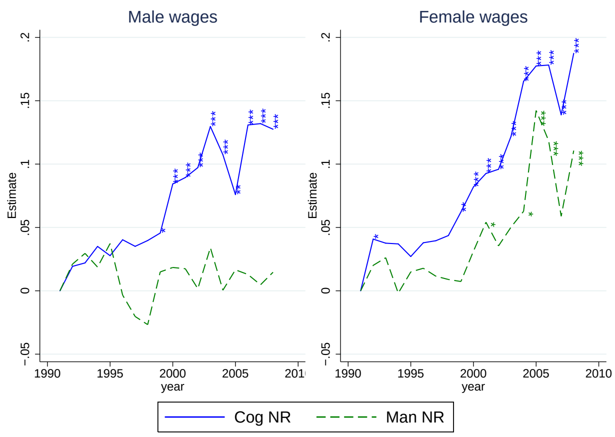

Figure 4.8: Estimated coefficients on occupation-year fixed effects
Picture shows coefficients for males and females by occupation with respect to the base occupation (manual routine for men and cognitive routine for women)

Table 4.2: Males: changes in wage premia for cognitive non routine workers with respect to changes for manual routine

	1		2		3		4	
Cog NR	0.328***	(0.0266)						
Cog R	0.100**	(0.0389)						
Man NR	-0.0179	(0.0354)						
1992 Cog NR	0.0268	(0.0253)	0.0193	(0.0221)	0.0243	(0.0268)	0.00314	(0.0307)
1993 Cog NR	0.0135	(0.0261)	0.0220	(0.0212)	0.0371	(0.0264)	0.0308	(0.0306)
1994 Cog NR	0.0461*	(0.0275)	0.0350	(0.0228)	0.0474*	(0.0265)	0.0268	(0.0315)
1995 Cog NR	0.0275	(0.0271)	0.0277	(0.0227)	0.0473*	(0.0282)	0.0291	(0.0317)
1996 Cog NR	0.0269	(0.0298)	0.0403	(0.0260)	0.0473	(0.0300)	0.0412	(0.0337)
1997 Cog NR	0.0106	(0.0286)	0.0351	(0.0239)	0.0515*	(0.0282)	0.0533	(0.0332)
1998 Cog NR	0.00183	(0.0287)	0.0397	(0.0248)	0.0571**	(0.0286)	0.0517	(0.0340)
1999 Cog NR	-0.0109	(0.0303)	0.0456*	(0.0272)	0.0615**	(0.0305)	0.0361	(0.0381)
2000 Cog NR	0.0151	(0.0299)	0.0844***	(0.0268)	0.0985***	(0.0301)	0.0873**	(0.0359)
2001 Cog NR	0.00152	(0.0316)	0.0894***	(0.0282)	0.0957***	(0.0317)	0.0922**	(0.0396)
2002 Cog NR	0.0284	(0.0318)	0.0973***	(0.0280)	0.0943***	(0.0317)	0.124***	(0.0373)
2003 Cog NR	0.0553	(0.0344)	0.130***	(0.0310)	0.135***	(0.0334)	0.132***	(0.0425)
2004 Cog NR	0.0239	(0.0323)	0.107***	(0.0291)	0.0965***	(0.0320)	0.123***	(0.0384)
2005 Cog NR	-0.00928	(0.0340)	0.0759**	(0.0306)	0.0897***	(0.0324)	0.0801*	(0.0414)
2006 Cog NR	0.0231	(0.0364)	0.131***	(0.0334)	0.133***	(0.0352)	0.147***	(0.0472)
2007 Cog NR	0.0184	(0.0351)	0.132***	(0.0325)	0.144***	(0.0349)	0.174***	(0.0442)
2008 Cog NR	0.0171	(0.0365)	0.128***	(0.0328)	0.123***	(0.0355)	0.185***	(0.0441)
Observations	25345		25345		25345		25345	
Adjusted R^2	0.348		0.230		0.230		0.231	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Clustered standard errors in parenthesis. For all models, controls include region, age and its squared, education, interaction between age and education, marital status, job tenure and year fixed effects. In 1, the baseline model is estimated with OLS; in 2, with panel fixed effects; in 3, model 2 is augmented with interaction terms between education and occupation, and education and year; in 4, model 2 is augmented with the interaction among occupation, year and job tenure. To make the table more readable, only the statistically significant coefficients are reported.

Table 4.3: Females: changes in wage premia for cognitive non routine workers with respect to changes for manual routine

	1		2		3		4	
Cog NR	0.246***	(0.03)						
Man R	-0.160***	(0.05)						
Man NR	-0.263***	(0.03)						
1992 Cog NR	0.050*	(0.03)	0.041*	(0.02)	0.044	(0.03)	0.076**	(0.03)
1992 Man NR	0.010	(0.03)	0.020	(0.03)	0.020	(0.03)	0.009	(0.04)
1994 Cog NR	0.068**	(0.03)	0.037	(0.03)	0.042	(0.03)	0.086**	(0.03)
1994 Man NR	-0.008	(0.03)	-0.002	(0.03)	-0.001	(0.03)	-0.000	(0.04)
1996 Cog NR	0.070**	(0.03)	0.038	(0.03)	0.049	(0.03)	0.084**	(0.03)
1996 Man NR	0.034	(0.03)	0.018	(0.03)	0.020	(0.03)	0.018	(0.04)
1998 Cog NR	0.085**	(0.03)	0.044	(0.03)	0.060*	(0.04)	0.112***	(0.04)
1998 Man NR	0.048	(0.03)	0.009	(0.03)	0.012	(0.03)	0.063	(0.04)
2000 Cog NR	0.076**	(0.03)	0.082***	(0.03)	0.096***	(0.04)	0.135***	(0.04)
2000 Man NR	0.037	(0.04)	0.031	(0.03)	0.034	(0.03)	0.026	(0.04)
2001 Cog NR	0.081**	(0.03)	0.093***	(0.03)	0.116***	(0.04)	0.148***	(0.04)
2001 Man NR	0.113***	(0.04)	0.054*	(0.03)	0.058*	(0.03)	0.065	(0.05)
2002 Cog NR	0.048	(0.04)	0.096***	(0.03)	0.098**	(0.04)	0.174***	(0.04)
2002 Man NR	0.058	(0.04)	0.035	(0.04)	0.037	(0.04)	0.060	(0.05)
2004 Cog NR	0.117***	(0.04)	0.165***	(0.04)	0.177***	(0.04)	0.246***	(0.04)
2004 Man NR	0.102***	(0.04)	0.063*	(0.03)	0.065*	(0.03)	0.087*	(0.05)
2006 Cog NR	0.107***	(0.04)	0.178***	(0.04)	0.169***	(0.04)	0.271***	(0.04)
2006 Man NR	0.134***	(0.04)	0.118***	(0.04)	0.120***	(0.04)	0.192***	(0.06)
2008 Cog NR	0.105***	(0.04)	0.187***	(0.04)	0.179***	(0.04)	0.285***	(0.04)
2008 Man NR	0.129***	(0.04)	0.111***	(0.04)	0.112***	(0.04)	0.177***	(0.06)
Observations	24885		24885		24885		24885	
Adjusted R^2	0.388		0.196		0.197		0.199	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Clustered standard errors in parenthesis. For all models, controls include region, age and its squared, education, interaction between age and education, marital status, job tenure and year fixed effects. In 1, the baseline model is estimated with OLS; in 2, with panel fixed effects; in 3, model 2 is augmented with interaction terms between education and occupation, and education and year; in 4, model 2 is augmented with the interaction among occupation, year and job tenure. To make the table more readable, only the statistically significant coefficients are reported.

We present these results in the second columns of tables 4.2 and 4.3. To check the robustness of our results, we add further control variables, with results shown in columns moving further to the right. In the third column, we add a series of dummies for completed education. We allow for changes in the returns to education by interacting education and year dummies. Although not reported, the coefficients in front of these interactions suggest a decrease in the returns to education over time, consistent with the existing literature, such as Blanden (2013).[29] Finally, in the fourth column we estimate eq. 4.3, which interacts the indicator of tenure with year dummies, to allow for changes in the returns of tenure over time.[30] In conclusion, for both men and women, the results are robust and similar to each other. In particular, overall, the coefficients are statistically significant in the second part of the period, in the 2000s.[31]

Perhaps most importantly, we also estimate the specifications according to the baseline specification by OLS. The results are reported in the first columns of the tables. Notice that, for men, the implied coefficients on tasks are completely different to those from the fixed effect regressions and are generally around zero in all years. This implies the importance of controlling for unobservables when estimating the prices on occupations. The results here imply that the cognitive non-routine occupation has been

[29]The decrease is higher for those with secondary or mid-vocational education, whereas the returns decrease less for those with the first degree or high vocational education. This holds especially for males. For females, the coefficients follow the same pattern as those of men in terms of sign, but their magnitude is smaller and they are not always statistically significant.

[30]Specifically, we introduce a proxy for occupational tenure. We use the retrospective question about employment history to control for years of job tenure.

[31]The tables in appendix C.3 present additional specifications. Additionally, the figures in the same appendix section estimate the baseline model on different samples (individuals from 16-64 years old and couples). The results are consistent with those presented here. Finally we estimate eq. 4.2 on a finer occupation classification. Specifically, we use the 9 categories of SOC 1990 at 1-digit level. Figure C.13 shows that the results are in line. They also suggest that the category driving the results for men is the category of general managers (major group 1 of SOC90).

increasingly filled with workers with lower (unobserved) skill. This result is in fact an implication of a standard Roy model which our regression equation captures. As the price on cognitive non-routine tasks increases, lower skill types switch to that occupation and average observed wages go down. The Roy model, however, does not itself predict what will be the quantitative importance of this effect. Our results imply that the quantitative effect is indeed very large.

4.5.2 Earnings Growth: Comparing Occupational Switches and Changes to Premia

We now estimate the effects of occupational premia and occupational switches on earnings of males and females between 25 and 64 years old. To do this we pool the data and examine changes at various leads ignoring year-specific effects. We are justified in doing this because the trends reported in the subsection above are approximately linear.

Figures 4.9 and 4.10 report the results. The results are interpreted as a double difference: the differential change in earnings for a worker in a given initial occupation with respect to a worker in the base category (manual routine for males and cognitive routine for females). Each figure is composed of three panels. In each panel, the solid green line reports the differential change in total earnings over time with respect to manual routine workers.[32] The dashed grey line indicates how much of the earnings differential is attributable to differences in occupational switches with respect to workers in manual routine jobs. Finally, the area between these two lines represents the

[32]For both men and women, this line is consistent with Figure 4.4 and Figure 4.8, where we analyse earnings and not wages.

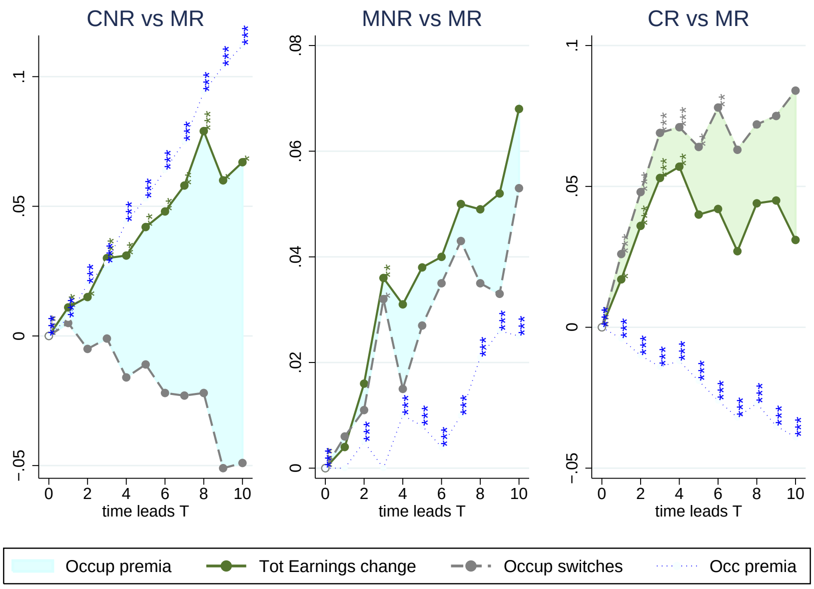

Figure 4.9: Earnings decomposition for males

Picture shows contributions of changes in occupational premia and occupational switches to the earning change differential for males, by initial occupation over time. The differential is with respect earnings changes of those in manual routine jobs. Occupational premia changes are identified by the light blue area. For further convenience, and in order to specify the significance level, changes in premia are also identified by the thin dotted blue line. The standard significance levels are indicated by the number of stars.

contribution of changes in the occupational premia. The blue dotted line represents an alternative way to report the changes in the occupational wage premia.

The first panel of Figure 4.9 shows one of our main results. It indicates that the earnings growth after 10 years is around 7% higher for those who started in a cognitive non-routine job with respect to those whose initial occupation was manual routine. The total result derives from two effects that partially offset each other. Specifically, it results from a positive occupational wage differential of 11% and a negative earnings change differential due to occupational switches of 5%. This implies that those starting in a cognitive non-routine occupation experienced higher wage increase by 11% with

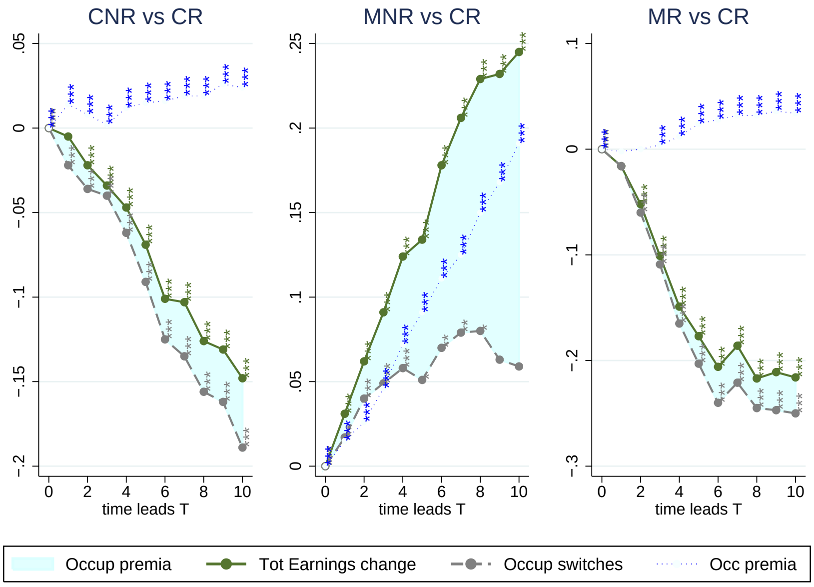

Figure 4.10: Earnings decomposition for females
Picture shows contributions of changes in occupational premia and occupational switches to the earning change differential for females, by initial occupation over time. The differential is with respect earnings changes of those in cognitive routine jobs. Occupational premia changes are identified by the light blue area. For further convenience, and in order to specify the significance level, changes in premia are also identified by the thin dotted blue line. The standard significance levels are indicated by the number of stars.

respect to manual routine workers. Instead, the increase in wage attributed to switching occupations over time is higher for manual routine workers by 5%, although not statistically significant.

By way of a full discussion, the second panel suggests a similar pattern in earnings differential for those who started in a manual non-routine job. However, the positive earnings change differential, 7% after 10 years, is mainly attributed to higher earnings growth through occupational switching, 5%, rather than through changes in occupational premia, which is only 2%. Finally, the positive earnings change differential between cognitive and manual routine workers, in the third panel, is determined by a positive differential in occupational switches and a negative differential in occupational premia.

For women, the decompositions are given in Figure 4.10. Recall that these results do not feature in our decomposition of household income. Nevertheless the figure indicates that the earnings of women who started in a cognitive non-routine job grew less than those of cognitive routine workers. The differential is statistically significant and negative. It reaches 15% after 10 years. This is mainly driven by occupational switches, whereas occupational premia of cognitive non-routine women increase over time to reach a positive differential of 2.4% at $t+10$. The third panel illustrates a similar pattern when comparing women in manual and in cognitive routine jobs. Consistently with Figure 4.8, workers who started in manual non-routine jobs experience positive earnings change differentials over all time horizons. Over time, the role of occupational premia increases with respect to that of occupational switches. For example, after 10 years occupational switches account for 6 percentage points of the overall increase in earnings, 25%. The remaining points are attributed to changes in occupational premia.

4.5.3 Spousal Effects

Returning to our decomposition, we now assess spousal effects. We do this by estimating a variant of eq. 4.4. The first dependent variable is the change in the wife's earnings as a share of household income. The second dependent variable is the change in worked hours, between t and $t+T$ ($T = 1, ..., 10$). The main regressor is the husband's occupation at time t.

Figure 4.11 illustrates the change differential in earnings, left panel, and in worked hours, right panel, for wives whose husbands are in a given occupation at t with respect to wives of manual routine workers. The patterns are similar for the two variables. Women with husbands who started in a cognitive non-routine occupation do not see significant differences in terms of earnings or worked hours with respect to those married with manual routine workers. Therefore, it seems, spousal effects do not explain much of flat growth in incomes between manual routine households and cognitive non-routine households. As for the other groups, wives with husbands in a manual non-routine job at time t experience a positive change differential in earnings and hours with respect to the wives of manual routine workers, the reference outcome. Women with men in cognitive routine jobs (a small category) experience lower growth over all time horizons with respect to those in the base category. Except for the case of cognitive routine husbands, the coefficients are small in magnitude and not statistically significant.

What explains these patterns? To explain them further, we need to look at the patterns of female earnings and mating patterns by occupation. The profiles for female earnings were shown in Figure 4.6 in the section 4.4. Figure 4.6 illustrates that the earnings growth differs according to the initial occupation. Women starting in cognitive routine or in manual non-routine jobs experience the highest increase in earnings. They are followed by women in cognitive non-routine jobs. Manual routine female workers experience the smallest changes.

In terms of assortative matching on occupations, Figure 4.12 provides a clear investigation.[33] Each panel corresponds to a subsample of husbands belonging to the same occupational group in a given year. For each sample, the figure reports the fraction of

[33] We use the term assortative matching in this paper to describe correlations between male and female occupations. Of course, this type of matching is different to that based on education, which likely involves substantial homophily, or matching based on preferences.

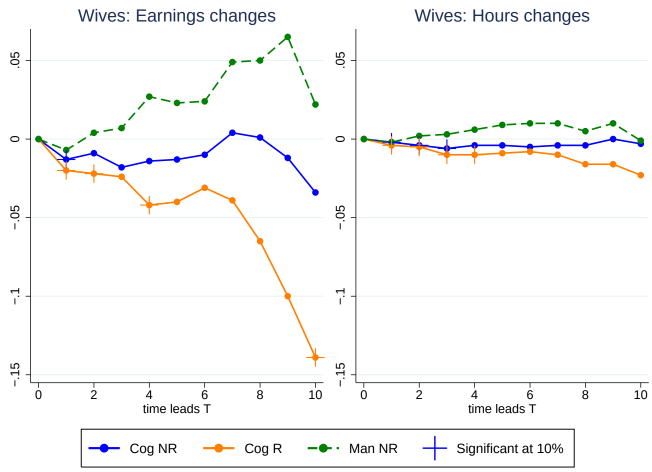

Figure 4.11: Spousal effects
Picture shows changes in wife's monthly earnings (left panel) and worked hours (right panel) from to t by husband initial occupation (at). The base category for the husband's occupation is manual routine.

spouses in a given group in a given year. To the four standard groups, we add a category for those who are either unemployed or out of the labour force. We consider that this category may be important for the dynamics of the household income. To avoid over-sampling retired spouses in this group, we restrict the sample to couples who are between 25 and 55 years of age.

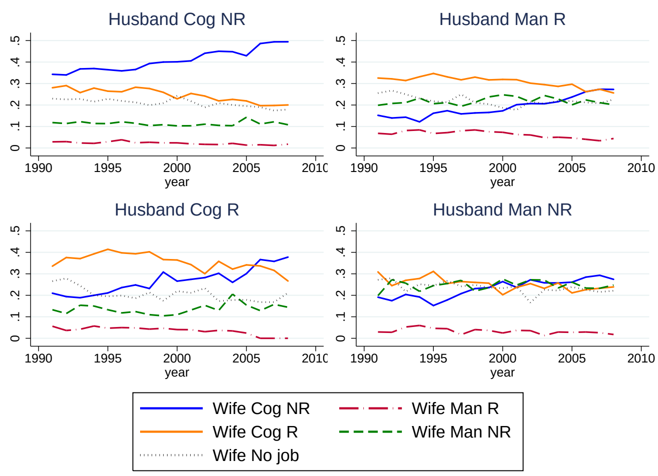

Figure 4.12: Wife task by husband's task

Figure 4.12 shows that for any of the four task-based groups, the fraction of spouses in that category is higher if the husband is in that group as well, at least in the first half of the period. For example, the percentage of cognitive non-routine women in 2008 is 50% with a husband in a cognitive non-routine occupation. In the same year, it is 40% with a cognitive routine partner, and around 30% in the other cases.

The four panels also suggest that conditional on the husband's occupation, the percentage of cognitive routine women decreases over time.[34] This implies that, conditional on the husband's occupation, in 2008, the percentage of cognitive routine workers is closer to that of cognitive non-routine, except if the husband has a cognitive non-routine occupation. In this case, the gap between the two types of cognitive female workers increases from 5 to over 30 percentage points over 1991-2008.

Finally, the fraction of spouses without a job does not seem to differ significantly across the husband's occupation.

Figure 4.12 shows how male and female occupations correlate. But it does not tell us if men in 'successful' occupations (i.e. those with high employment growth) are more or less likely to be married to women also in growing occupations. To investigate this, we use the Labour Force Survey to calculate the employment growth of each one-digit occupational group, or major groups of the 1990 Standard Occupational Classification, by sex and region from 1995 to 2000. We attribute the relevant employment growth to each man and woman in the sample using their occupational code at one-digit

[34]To a certain extent, this also applies to manual routine women. Instead, the percentage of cognitive non-routine women increases. However,the proportion of manual rouine women is small.

level. We run the following regression:

$$\Delta emp_{(2000,1995)} = \beta occupation_{it} + \delta X_{it} + \varepsilon_{it} \tag{4.5}$$

where $\Delta emp_{(2000,1995)}$ is the employment growth of a given occupation from 1995 to 2000 and *occupation* is the 1-digit occupation of the 1990 SOC. X is a matrix of control variables that include region of residence, education of both spouses, ages and squared ages. The correlation between the occupation of husbands and wives is illustrated in the appendix Figure C.14, which shows a positive association. In particular, the estimated correlation coefficient, computed fromβ of eq. 4.5, is 0.132.[35]

4.6 Conclusions

As in the US, the UK labour market has seen a large shift in occupational structure over at least the last 25 years. This shift has seen employment decline in middle-earning occupations, and grow in occupations at the tails of the wage distribution. We examine the effect of polarization on household welfare, by examining how it has affected earnings, working patterns and income, tracking households over time using panel data from the British Household Panel Survey over 1991-2008. Our sample covers a period when polarization was particularly pronounced.

We base our analysis around a decomposition of income growth into several components. These components capture effects from the following factors: changes in

[35]The correlation coefficient would be 0.267 if computed from a regression without extra control variables, i.e. if $\delta = 0$ in eq. 4.5.

occupational wage premia in the (male) head's initial occupation, changes to head earnings arising from occupational mobility, changes in spousal earnings, and changes to other income, potentially reflecting changes to the tax and transfer system. In this paper we focus on the first three components. We also partially decompose spousal effects into components coming from mating patterns across occupations and from labour supply responses. We estimate the occupational premia using wage equations that take into account selection across occupations using a fixed effects estimator, which is consistent with a simple Roy model. In the spirit of Acemoglu and Autor (2011), we segment workers into four categories, based on main task content of their occupation. Specifically, these four categories are based on dichotomies into cognitive vs non-cognitive and routine vs non-routine.

The large change in occupational structure sits amid apparently flat inequality and a flat earnings structure. Nevertheless, we find that behind this apparently flat earnings structure, job polarization has been driven by strong forces. Specifically, we find that when selection into occupations is taken into account, the price on professional (cognitive non-routine) jobs shows a large divergence from routine jobs, for both men and women. In fact over the period of the BHPS, the underlying price of professional jobs rose by around 15% compared to manual routine and cognitive routine jobs. This divergence between prices of professional jobs and routine jobs, together with the flat level of average earnings implies a strong sorting over time based on unobserved quality. Our findings also provide fresh evidence of polarization in wages: evidence that supports an increased demand for workers in professional occupations. In terms of the decomposition, we find important roles, therefore, for occupational premia, for occupational mobility, and a lesser role for spousal effects.

This paper suggests several avenues for future research. First, given that polarization has been observed around the world, it is important to investigate to what extent in other countries sorting into occupations drives average earnings levels. Second, consistently with evidence from around the world, polarization has been shown to be stronger for females than for males. It is therefore also important to extend the Roy framework to allow for selection into the labour market.

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Appendix A

"Intergenerational mobility across countries and methods"

A.1 Summary statistics and first stage regressions

Table A.1: Summary statistics for fathers

	DEs mean/sd	DEr mean/sd	ITs mean/sd	ITr mean/sd	UKs mean/sd	UKr mean/sd	USs mean/sd	USr mean/sd
F ln(LI)	10.12	9.45	9.60	8.99	10.20	9.40	10.79	10.42
	(0.63)	(0.47)	(0.62)	(0.40)	(0.66)	(0.42)	(0.98)	(0.44)
F Age	50.49	44.85	53.17	42.50	52.39	43.80	54.72	43.86
	(4.44)	(5.51)	(4.19)	(6.71)	(4.41)	(5.90)	(3.14)	(5.54)
F year of birth	1945.00	1932.87	1943.59	1926.60	1944.11	1930.09	1945.89	1932.83
	(3.59)	(8.63)	(4.22)	(9.51)	(3.91)	(8.86)	(2.75)	(8.69)
F university	0.24	0.12	0.12	0.03	0.12	0.09	0.16	0.36
	(0.43)	(0.32)	(0.32)	(0.18)	(0.33)	(0.28)	(0.37)	(0.48)
Observations	3625	21645	1655	6940	5005	14782	8683	8448

Notes: F stands for father. LI for labour income. Columns 1, 3, 5, 7 indicate the statistics for synthetic father; Columns 2, 4, 6, 8 indicate the statistics for for real fathers

Table A.2: Summary statistics for the sons

	Germany mean/sd	Italy mean/sd	UK mean/sd	US mean/sd
ln(LI)	10.47	9.80	10.45	10.79
	(0.82)	(0.62)	(0.70)	(0.91)
Age	41.42	42.50	40.63	39.63
	(7.24)	(6.71)	(6.58)	(6.67)
Year of birth	1962.72	1959.26	1959.88	1961.70
	(6.82)	(6.22)	(6.08)	(6.84)
Higher education	0.31	0.12	0.24	0.10
	(0.46)	(0.33)	(0.43)	(0.30)
Self-employed	0.13	0.24	0.11	0.11
	(0.33)	(0.43)	(0.31)	(0.32)
N of waves	9.04	3.89	14.41	9.91
	(3.90)	(2.48)	(3.98)	(3.82)
Observations	21645	6940	14782	8448

Table A.3: GSOEP: First stage regression

	ALL		AV3		A55		MIN40	
Turkish national	-0.044	(0.042)	-0.050	(0.053)	-0.059	(0.041)	0.069	(0.052)
F Intermediate school	0.154**	(0.065)	0.103	(0.094)	0.151**	(0.067)	0.321***	(0.068)
F Technical school	0.101	(0.120)	0.109	(0.151)	0.043	(0.120)	0.246**	(0.111)
F Upper secondary school	0.234**	(0.104)	0.192	(0.137)	0.239**	(0.108)	0.446***	(0.102)
F Other educ.	0.048	(0.048)	-0.004	(0.057)	0.028	(0.043)	0.014	(0.067)
F No degree	0.108**	(0.052)	0.083	(0.060)	0.066	(0.050)	0.055	(0.080)
Legislator, manager	0.219***	(0.067)	0.243*	(0.128)	0.171***	(0.065)	0.315***	(0.091)
Professional	0.118*	(0.069)	0.092	(0.110)	0.154**	(0.072)	0.064	(0.092)
Clerk	-0.117	(0.075)	-0.051	(0.108)	-0.092	(0.069)	-0.141	(0.101)
Service and sales workers	-0.130	(0.084)	-0.186	(0.118)	-0.120	(0.085)	-0.089	(0.104)
Skilled agr. and fishery	-0.513***	(0.156)	-0.463**	(0.234)	-0.478***	(0.163)	-0.336**	(0.153)
Crafts and rtld trade	-0.145***	(0.056)	-0.068	(0.084)	-0.120**	(0.057)	-0.041	(0.083)
Plant and machine operators	-0.174***	(0.059)	-0.077	(0.082)	-0.165***	(0.061)	-0.125	(0.080)
Elementary occupation	-0.321***	(0.068)	-0.243**	(0.099)	-0.250***	(0.071)	-0.345***	(0.114)
Workers	0.026	(0.063)	-0.086	(0.088)	0.052	(0.063)	-0.016	(0.088)
Self-employed	0.107	(0.074)	0.109	(0.110)	0.116	(0.074)	0.091	(0.086)
White collar	0.230***	(0.047)	0.205***	(0.071)	0.252***	(0.048)	0.173***	(0.058)
Voc. training	0.040	(0.037)	-0.012	(0.046)	0.040	(0.037)	-0.002	(0.051)
University	0.392***	(0.082)	0.314***	(0.114)	0.360***	(0.095)	0.410***	(0.083)
F y of birth	0.037***	(0.005)	0.057***	(0.007)	0.022***	(0.005)	0.039***	(0.006)
F age	-0.168***	(0.052)	-0.024	(0.100)	-0.210***	(0.077)	0.027	(0.058)
F age^2	0.002***	(0.001)	0.001	(0.001)	0.002***	(0.001)	-0.000	(0.001)
Observations	3625		456		2896		1244	
Adjusted R^2	0.4221		0.5584		0.3984		0.4044	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ ALL, A55: Clustered standard errors in parenthesis; AV3, MIN40: Robust standard errors in parenthesis

Table A.4: SHIW: First stage regression

	ALL		AV3		A55		MIN40	
No education	-0.539***	(0.115)	-0.455**	(0.184)	-0.484***	(0.138)	-0.269**	(0.132)
Primary ed.	-0.192***	(0.044)	-0.235***	(0.062)	-0.181***	(0.056)	-0.130***	(0.048)
Upper sec. ed.	0.142***	(0.045)	0.166***	(0.060)	0.139***	(0.050)	0.121**	(0.054)
University ed.	0.438***	(0.070)	0.384***	(0.092)	0.398***	(0.081)	0.512***	(0.085)
Production worker	-0.100**	(0.044)	-0.054	(0.063)	-0.120**	(0.048)	-0.144***	(0.054)
Junior manager	0.200***	(0.051)	0.163*	(0.086)	0.126**	(0.062)	0.182***	(0.062)
Manager	0.431***	(0.082)	0.538***	(0.096)	0.369***	(0.088)	0.357***	(0.088)
Self employed	-0.072	(0.048)	-0.050	(0.060)	-0.052	(0.056)	-0.101*	(0.054)
Industry	0.073**	(0.037)	0.073	(0.054)	0.063	(0.045)	0.059	(0.046)
Agriculture	-0.260***	(0.089)	-0.301*	(0.158)	-0.185*	(0.100)	-0.279***	(0.090)
Northern Italy	0.189***	(0.038)	0.127**	(0.052)	0.229***	(0.044)	0.232***	(0.042)
Central Italy	0.160***	(0.044)	0.132**	(0.060)	0.194***	(0.055)	0.135***	(0.050)
F age	-0.064	(0.067)	0.116	(0.132)	-0.208	(0.137)	-0.096	(0.066)
F age^2	0.001	(0.001)	-0.001	(0.001)	0.002	(0.001)	0.001*	(0.001)
Year of birth	0.018***	(0.004)	0.037***	(0.006)	-0.002	(0.005)	0.013***	(0.004)
Observations	1655		292		941		926	
Adjusted R^2	0.2968		0.4981		0.2502		0.2622	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ ALL, A55: Clustered standard errors in parenthesis; AV3, MIN40: Robust standard errors in parenthesis

Table A.5: BHPS: First stage regression

	ALL		AV3		A55		MIN40	
No completed education	-0.199***	(0.047)	-0.232***	(0.052)	-0.234***	(0.055)	-0.165***	(0.021)
Some ed.	-0.115***	(0.041)	-0.138***	(0.046)	-0.131***	(0.046)	-0.097***	(0.019)
University ed.	0.110	(0.068)	0.135**	(0.061)	0.099	(0.070)	0.061**	(0.029)
Legislator, manager	-0.012	(0.058)	0.043	(0.067)	0.020	(0.063)	-0.056*	(0.029)
Technician, Ass. prof.	-0.095*	(0.055)	-0.135*	(0.080)	-0.046	(0.061)	-0.152***	(0.032)
Clerk	-0.312***	(0.067)	-0.291***	(0.093)	-0.270***	(0.071)	-0.393***	(0.036)
Service worker, market sales	-0.380***	(0.114)	-0.302***	(0.114)	-0.307**	(0.131)	-0.526***	(0.054)
Skilled agr. and fishery	-0.768***	(0.141)	-0.849***	(0.164)	-0.706***	(0.167)	-0.956***	(0.101)
Crafts and rtld trade	-0.196***	(0.056)	-0.132*	(0.071)	-0.197***	(0.060)	-0.221***	(0.028)
Plant and machine operator	-0.244***	(0.058)	-0.169**	(0.069)	-0.227***	(0.062)	-0.277***	(0.030)
Elementary occupation	-0.367***	(0.073)	-0.329***	(0.087)	-0.356***	(0.076)	-0.456***	(0.036)
Born in England	-0.053	(0.070)	0.004	(0.087)	-0.114	(0.078)	-0.025	(0.037)
Born in Scotland	-0.167*	(0.090)	-0.043	(0.101)	-0.260***	(0.100)	-0.120***	(0.046)
Born in N.I.	0.004	(0.141)	-0.213	(0.330)	-0.169	(0.136)	0.034	(0.082)
Born in Ireland	0.117	(0.113)	0.104	(0.228)	0.001	(0.098)	0.195**	(0.077)
Born abroad	0.010	(0.155)	0.073	(0.163)	-0.093	(0.184)	0.060	(0.061)
Non white	-0.173	(0.122)	-0.198*	(0.119)	-0.196	(0.140)	-0.181***	(0.056)
Self-employed	-0.347***	(0.066)	-0.174***	(0.064)	-0.336***	(0.072)	-0.336***	(0.032)
Manager	0.117***	(0.043)	0.140**	(0.064)	0.096*	(0.049)	0.136***	(0.025)
Non manager	-0.193***	(0.033)	-0.170***	(0.046)	-0.169***	(0.038)	-0.189***	(0.018)
F age	-0.009	(0.049)	0.210*	(0.117)	-0.046	(0.088)	0.096***	(0.026)
F age^2	0.000	(0.000)	-0.002	(0.001)	0.001	(0.001)	-0.001***	(0.000)
F y of birth	0.040***	(0.004)	0.035***	(0.006)	0.036***	(0.005)	0.046***	(0.002)
Observations	5005		564		3558		6158	
Adjusted R^2	0.2852		0.4556		0.2699		0.3008	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ ALL, A55: Clustered standard errors in parenthesis; AV3, MIN40: Robust standard errors in parenthesis

Table A.6: PSID: First stage regression

	ALL		AV3		A55		MIN40	
Manager, Professional	0.063	(0.081)	0.140	(0.105)	0.035	(0.077)	0.315**	(0.127)
Sales	-0.213**	(0.105)	-0.222*	(0.132)	-0.252**	(0.104)	-0.060	(0.158)
Clerk	-0.141	(0.093)	-0.053	(0.122)	-0.124	(0.090)	-0.080	(0.169)
Services and military	-0.434***	(0.098)	-0.328***	(0.117)	-0.462***	(0.099)	-0.123	(0.160)
Agriculture and fishery	-0.590***	(0.138)	-0.371	(0.226)	-0.563***	(0.141)	-0.510**	(0.207)
Crafts and rtld trade	-0.186**	(0.085)	-0.136	(0.109)	-0.201**	(0.080)	0.051	(0.131)
Plant, machine operator	-0.386***	(0.089)	-0.276**	(0.112)	-0.374***	(0.086)	-0.200	(0.138)
Self-employed	-0.358***	(0.075)	-0.194	(0.313)	-0.316***	(0.072)	-0.340**	(0.139)
Up to 5 yrs ed.	-0.261***	(0.072)	-0.297***	(0.065)	-0.273***	(0.084)	-0.223**	(0.088)
From 6 to 8 yrs ed.	-0.208***	(0.053)	-0.224***	(0.050)	-0.260***	(0.057)	-0.256***	(0.075)
High school some train	0.151***	(0.047)	0.160***	(0.046)	0.122**	(0.050)	0.188***	(0.071)
High school+some college	0.308***	(0.061)	0.312***	(0.059)	0.270***	(0.060)	0.314***	(0.086)
University	0.569***	(0.067)	0.508***	(0.071)	0.564***	(0.067)	0.576***	(0.089)
Non-white	-0.108***	(0.040)	-0.080**	(0.040)	-0.119***	(0.041)	-0.042	(0.058)
Middle Atlantic	-0.231**	(0.095)	-0.092	(0.099)	-0.199**	(0.100)	-0.224*	(0.116)
East North Central	-0.198**	(0.093)	-0.124	(0.098)	-0.174*	(0.097)	-0.297***	(0.115)
West North Central	-0.280***	(0.095)	-0.160*	(0.096)	-0.292***	(0.102)	-0.400***	(0.118)
South Atlantic	-0.262***	(0.090)	-0.119	(0.096)	-0.240**	(0.094)	-0.333***	(0.111)
East South Central	-0.291***	(0.095)	-0.157	(0.098)	-0.250**	(0.099)	-0.371***	(0.117)
West South Central	-0.373***	(0.096)	-0.198**	(0.100)	-0.371***	(0.101)	-0.438***	(0.114)
Mountain	-0.447***	(0.119)	-0.339***	(0.125)	-0.425***	(0.121)	-0.494***	(0.140)
Pacific	-0.195**	(0.099)	-0.120	(0.107)	-0.178*	(0.105)	-0.319***	(0.123)
Agriculture	-0.228**	(0.111)	-0.208	(0.185)	-0.251**	(0.116)	-0.603***	(0.165)
Mining	0.172*	(0.097)	0.091	(0.133)	0.227**	(0.096)	0.051	(0.204)
Construction	-0.400***	(0.058)	-0.398***	(0.059)	-0.386***	(0.059)	-0.617***	(0.087)
Trade	-0.354***	(0.056)	-0.299***	(0.064)	-0.303***	(0.058)	-0.422***	(0.082)
Transport and commerce	-0.026	(0.044)	-0.012	(0.049)	-0.018	(0.046)	-0.112	(0.076)
Finance and insurance	-0.062	(0.076)	0.061	(0.081)	-0.030	(0.087)	-0.257**	(0.117)
Services	-0.413***	(0.048)	-0.407***	(0.051)	-0.359***	(0.052)	-0.558***	(0.068)
Public admin.	-0.156***	(0.054)	-0.147**	(0.062)	-0.111*	(0.059)	-0.339***	(0.112)
F age	0.087**	(0.043)	0.221***	(0.067)	0.029	(0.067)	0.045	(0.059)
F age^2	-0.001*	(0.000)	-0.002***	(0.001)	-0.000	(0.001)	-0.001**	(0.001)
Year of birth	0.009**	(0.004)	-0.002	(0.007)	0.010**	(0.005)	-0.068***	(0.016)
Observations	8683		1167		6957		1560	
Adjusted R^2	0.2383		0.3627		0.2409		0.2622	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ ALL, A55: Clustered standard errors in parenthesis; AV3, MIN40: Robust standard errors in parenthesis

A.2 Least square estimates

Table A.7: IGE on the PSID ALL sample with different instruments in the first stage

	Region+Age		Education+Age		Region+Educ+Age		Region+Educ+Age+Self-employed	
IGE	0.868***	[0.157]	0.600***	[0.068]	0.588***	[0.068]	0.556***	[0.071]
Observations	8448		8448		8448		8448	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrap standard errors in parenthesis. Controls include F and own age, age squared, year of birth, interactions with age

Table A.8: Model and sample selection for Germany

	Germany		Germany		West Germany	
Without interaction						
F ln(LI) for West Germany	0.300***	[0.040]	0.312***	[0.041]	0.300***	[0.041]
F ln(LI) for East Germany			0.049	[0.183]		
With interaction						
F ln(LI) for West Germany	0.437***	[0.057]	0.443***	[0.057]	0.437***	[0.057]
F ln(LI) for East Germany			0.233	[0.188]		
Observations	21645		21645		21192	
Controls	Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

Table A.9: TS2SLS, OLS estimation without the simultaneous bootstrapping

	Germany		Italy		UK		US	
F ln(LI)	0.437***	[0.020]	0.463***	[0.023]	0.317***	[0.021]	0.489***	[0.025]
F LI(Age-40)	0.008**	[0.003]	0.009***	[0.003]	-0.003	[0.002]	0.003	[0.003]
F LI(Age-40)^2	-0.004***	[0.000]						
F LI(Age-40)^3	0.000***	[0.000]						
F LI(F Age-40)	0.002	[0.002]			0.016***	[0.002]	0.008**	[0.004]
Observations	21645		6940		14782		8448	
Adjusted R^2	0.2586		0.2317		0.1244		0.0961	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

Table A.10: TS2SLS, OLS on the main sample reporting also the coefficients on the interaction terms

	(1) Germany		(2) Italy		(3) UK		(4) US	
F ln(LI)	0.437***	[0.057]	0.463***	[0.050]	0.317***	[0.058]	0.489***	[0.060]
F LI(Age-40)	0.008	[0.006]	0.009**	[0.004]	-0.003	[0.004]	0.003	[0.005]
F LI(Age-40)^2	-0.004***	[0.001]						
F LI(Age-40)^3	0.000***	[0.000]						
F LI(F Age-40)	0.002	[0.006]			0.016**	[0.006]	0.008	[0.009]
Observations	21645		6940		14782		8448	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

Table A.11: TS2SLS with education dummies

	Germany		Italy		UK		US	
F ln(LI)	0.206***	[0.048]	0.279***	[0.042]	0.154***	[0.054]	0.253***	[0.057]
F LI(Age-40)	0.011**	[0.005]	0.007**	[0.004]	-0.001	[0.004]	0.003	[0.005]
F LI(Age-40)^2	-0.003***	[0.001]						
F LI(Age-40)^3	0.000***	[0.000]						
F LI(F Age-40)	-0.006	[0.005]			0.013**	[0.006]	0.011	[0.008]
Observations	21645		6940		14782		8448	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age, dummies for education

A.2.1 Least square estimates in different regions

This section modifies eq. 2.7 to account for regional differences. Specifically, I augment the model by including regional dummies and interactions between these dummies and the paternal income. The goal is to further explore the existence of regional differences, which is somewhat suggested for the case of Germany. Several may be the possible mechanisms that explain differences in intergenerational transmissions across regions or states. Examples are the different share of public investment in education, cultural differences, or diverse labour market characteristics. To the best of my knowledge, the only relevant article on this topic is Chetty et al. (2014). For the United States, the authors find that higher mobility is in areas with lower income inequality, less residential segregation, better primary schools, greater family stability and social capital.

The appendix Table A.12 reports the results that indicate within-country geographical differences. Across Germany, the IGE appears lower in the Eastern regions. However, the number of observations is very limited and the coefficients are not statistically significant. Moreover, the sample of respondents living in East Germany are those who left West Germany after their studies. Therefore, they are more likely to be geographically distant from their fathers. The fact that geographical and intergenerational mobility are positively related is also supported by the fact that the lowest IGE of the Eastern regions is for those living in Berlin, where migration is assumed to be high. For Italy, as well, the lowest elasticity is in the Centre, where Rome lies. The highest values, instead, are in the islands. In Britain, the region where the association between the income of fathers and sons is higher are the Yorkshire and Humber and South East of England. Together with the North these are the only estimates to remain statistically significant after the introduction of education dummies. In the West Midlands and the South West the elasticity is lower, although in the latter the estimation is not precise, as the number of observations is small. Consistently with Chetty et al. (2014), the highest intergenerational association characterizes the region of East South Central, followed by South Atlantic (where Washington DC is). The Pacific and Middle Atlantic have the lowest elasticities.

Table A.12: TS2SLS by Region

	Germany		Italy		UK		US	
F ln(LI) for Region1	0.370^{***}	[0.075]	0.426^{***}	[0.074]	0.326^{***}	[0.096]	0.002	[0.273]
F ln(LI) for Region2	0.426^{***}	[0.071]	0.337^{***}	[0.065]	0.450^{***}	[0.100]	0.441^{**}	[0.177]
F ln(LI) for Region3	0.580^{***}	[0.101]	0.258^{***}	[0.066]	0.299^{**}	[0.153]	0.475^{***}	[0.143]
F ln(LI) for Region4	0.282^{**}	[0.121]	0.433^{***}	[0.071]	0.229^{*}	[0.128]	0.475^{***}	[0.136]
F ln(LI) for Region5	0.437^{***}	[0.079]	0.553^{***}	[0.094]	0.300^{**}	[0.131]	0.555^{***}	[0.104]
F ln(LI) for Region6	0.480^{***}	[0.076]			0.293^{*}	[0.160]	0.652^{***}	[0.208]
F ln(LI) for Region7	0.060	[0.172]			0.439^{***}	[0.098]	0.417^{***}	[0.142]
F ln(LI) for Region8	0.261	[0.513]			0.154	[0.118]	0.140	[0.161]
F ln(LI) for Region9	0.145	[0.205]			0.307^{***}	[0.093]	0.365^{**}	[0.151]
With dummies for education								
F ln(LI) for Region1	0.135^{**}	[0.068]	0.220^{***}	[0.067]	0.181^{*}	[0.095]	-0.131	[0.221]
F ln(LI) for Region2	0.201^{***}	[0.062]	0.154^{***}	[0.058]	0.247^{**}	[0.107]	0.228	[0.169]
F ln(LI) for Region3	0.323^{***}	[0.088]	0.083	[0.060]	0.096	[0.141]	0.241^{*}	[0.133]
F ln(LI) for Region4	0.095	[0.103]	0.200^{***}	[0.059]	0.028	[0.125]	0.267^{**}	[0.128]
F ln(LI) for Region5	0.164^{**}	[0.069]	0.306^{***}	[0.084]	0.144	[0.130]	0.321^{***}	[0.097]
F ln(LI) for Region6	0.273^{***}	[0.067]			0.099	[0.145]	0.363^{*}	[0.192]
F ln(LI) for Region7	-0.220	[0.177]			0.289^{***}	[0.088]	0.118	[0.149]
F ln(LI) for Region8	0.081	[0.422]			0.011	[0.118]	0.010	[0.156]
F ln(LI) for Region9	-0.061	[0.188]			0.140	[0.086]	0.199	[0.134]
Observations	21645		6940		14782		8448	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age. Regions by country: Germany 1: Schleswig-Holstein, Hamburg, Niedersachsen and Bremen; 2: Nordrhein-Westfalen; 3: Hessen; 4: Rheinland-Pfalz,Saarland; 5: Baden-Wuerttemberg; 6: Bayern; 7: Berlin; 8: Brandenburg and Mecklenburg-Vorpommern; 9: Sachsen, Sachsen-Anhalt and Thueringen. Italy 1: North-West; 2: North-East; 3: Centre; 4: South; 5: Islands. UK 1: North; 2: Yorkshire and Humber; 3: East Midlands; 4: West Midlands; 5: East of England; 6: London; 7: South East; 8: South West; 9: Wales; 10: Scotland. US 1: New England; 2: Middle Atlantic; 3: East North Central; 4: West North Central; 5: South Atlantic; 6: East South Central; 7: West South Central; 8: Mountain; 9: Pacific.

A.3 The IGE over time

Table A.13: TS2SLS, Cohorts

	Germany		Italy		UK		US	
ln(F LI)∗Cohort 1950	0.344***	[0.062]	0.418***	[0.050]	0.288***	[0.063]	0.503***	[0.062]
ln(F LI)∗Cohort 1951	0.334***	[0.062]	0.423***	[0.050]	0.301***	[0.063]	0.486***	[0.061]
ln(F LI)∗Cohort 1952	0.341***	[0.061]	0.421***	[0.050]	0.302***	[0.063]	0.495***	[0.063]
ln(F LI)∗Cohort 1953	0.360***	[0.061]	0.420***	[0.050]	0.288***	[0.062]	0.481***	[0.062]
ln(F LI)∗Cohort 1954	0.347***	[0.062]	0.426***	[0.050]	0.311***	[0.061]	0.480***	[0.062]
ln(F LI)∗Cohort 1955	0.386***	[0.061]	0.439***	[0.049]	0.307***	[0.061]	0.496***	[0.062]
ln(F LI)∗Cohort 1956	0.378***	[0.061]	0.440***	[0.050]	0.295***	[0.061]	0.477***	[0.063]
ln(F LI)∗Cohort 1957	0.378***	[0.060]	0.446***	[0.050]	0.297***	[0.060]	0.478***	[0.061]
ln(F LI)∗Cohort 1958	0.400***	[0.061]	0.451***	[0.050]	0.312***	[0.061]	0.492***	[0.061]
ln(F LI)∗Cohort 1959	0.408***	[0.061]	0.458***	[0.050]	0.325***	[0.061]	0.485***	[0.062]
ln(F LI)∗Cohort 1960	0.412***	[0.060]	0.459***	[0.050]	0.310***	[0.060]	0.488***	[0.061]
ln(F LI)∗Cohort 1961	0.424***	[0.059]	0.465***	[0.050]	0.316***	[0.060]	0.494***	[0.061]
ln(F LI)∗Cohort 1962	0.424***	[0.060]	0.474***	[0.049]	0.324***	[0.059]	0.481***	[0.062]
ln(F LI)∗Cohort 1963	0.421***	[0.059]	0.475***	[0.050]	0.317***	[0.059]	0.469***	[0.062]
ln(F LI)∗Cohort 1964	0.437***	[0.059]	0.470***	[0.050]	0.328***	[0.059]	0.494***	[0.063]
ln(F LI)∗Cohort 1965	0.449***	[0.058]	0.474***	[0.050]	0.332***	[0.059]	0.484***	[0.061]
ln(F LI)∗Cohort 1966	0.446***	[0.059]	0.481***	[0.050]	0.331***	[0.058]	0.489***	[0.062]
ln(F LI)∗Cohort 1967	0.449***	[0.058]	0.491***	[0.050]	0.332***	[0.058]	0.475***	[0.060]
ln(F LI)∗Cohort 1968	0.470***	[0.058]	0.502***	[0.050]	0.335***	[0.058]	0.478***	[0.060]
ln(F LI)∗Cohort 1969	0.468***	[0.058]	0.488***	[0.051]	0.341***	[0.057]	0.504***	[0.061]
ln(F LI)∗Cohort 1970	0.475***	[0.058]	0.501***	[0.050]	0.335***	[0.057]	0.506***	[0.060]
ln(F LI)∗Cohort 1971	0.490***	[0.058]	0.509***	[0.051]	0.343***	[0.058]	0.476***	[0.061]
ln(F LI)∗Cohort 1972	0.492***	[0.059]	0.489***	[0.055]	0.364***	[0.057]	0.484***	[0.060]
ln(F LI)∗Cohort 1973	0.503***	[0.058]	0.515***	[0.050]	0.359***	[0.057]	0.496***	[0.060]
ln(F LI)∗Cohort 1974	0.517***	[0.058]	0.528***	[0.050]	0.355***	[0.056]	0.493***	[0.063]
ln(F LI)∗Cohort 1975	0.495***	[0.058]	0.519***	[0.050]	0.352***	[0.057]	0.492***	[0.060]
ln(F LI)∗Cohort 1976	0.508***	[0.059]	0.524***	[0.051]	0.369***	[0.057]	0.519***	[0.062]
ln(F LI)∗Cohort 1977	0.517***	[0.060]	0.532***	[0.054]	0.382***	[0.057]	0.493***	[0.061]
ln(F LI)∗Cohort 1978	0.479***	[0.061]	0.536***	[0.050]	0.356***	[0.058]	0.507***	[0.064]
ln(F LI)∗Cohort 1979	0.501***	[0.062]						
ln(F LI)∗Cohort 1980	0.509***	[0.065]						
Observations	21645		6940		14782		8448	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

Table A.14: TS2SLS, Cohorts with education

	Germany		Italy		UK		US	
ln(F LI)∗Cohort 1950	0.097*	[0.053]	0.234***	[0.042]	0.125**	[0.058]	0.255***	[0.059]
ln(F LI)∗Cohort 1951	0.095*	[0.052]	0.236***	[0.043]	0.133**	[0.059]	0.249***	[0.058]
ln(F LI)∗Cohort 1952	0.101*	[0.052]	0.236***	[0.042]	0.138**	[0.058]	0.254***	[0.060]
ln(F LI)∗Cohort 1953	0.115**	[0.052]	0.237***	[0.042]	0.122**	[0.056]	0.238***	[0.059]
ln(F LI)∗Cohort 1954	0.104**	[0.053]	0.241***	[0.043]	0.148***	[0.057]	0.239***	[0.059]
ln(F LI)∗Cohort 1955	0.143***	[0.052]	0.251***	[0.042]	0.144**	[0.056]	0.253***	[0.059]
ln(F LI)∗Cohort 1956	0.139***	[0.052]	0.255***	[0.043]	0.131**	[0.056]	0.236***	[0.060]
ln(F LI)∗Cohort 1957	0.138***	[0.051]	0.259***	[0.043]	0.137**	[0.055]	0.240***	[0.059]
ln(F LI)∗Cohort 1958	0.157***	[0.052]	0.263***	[0.042]	0.150***	[0.056]	0.250***	[0.059]
ln(F LI)∗Cohort 1959	0.168***	[0.052]	0.269***	[0.043]	0.157***	[0.056]	0.248***	[0.059]
ln(F LI)∗Cohort 1960	0.175***	[0.051]	0.271***	[0.043]	0.148***	[0.055]	0.249***	[0.058]
ln(F LI)∗Cohort 1961	0.186***	[0.051]	0.278***	[0.043]	0.158***	[0.055]	0.260***	[0.058]
ln(F LI)∗Cohort 1962	0.190***	[0.051]	0.289***	[0.042]	0.164***	[0.054]	0.237***	[0.060]
ln(F LI)∗Cohort 1963	0.188***	[0.050]	0.288***	[0.043]	0.156***	[0.055]	0.228***	[0.059]
ln(F LI)∗Cohort 1964	0.207***	[0.050]	0.284***	[0.042]	0.169***	[0.054]	0.252***	[0.060]
ln(F LI)∗Cohort 1965	0.219***	[0.049]	0.287***	[0.043]	0.171***	[0.054]	0.249***	[0.058]
ln(F LI)∗Cohort 1966	0.213***	[0.050]	0.295***	[0.042]	0.171***	[0.054]	0.251***	[0.059]
ln(F LI)∗Cohort 1967	0.217***	[0.050]	0.305***	[0.042]	0.174***	[0.054]	0.240***	[0.058]
ln(F LI)∗Cohort 1968	0.237***	[0.049]	0.315***	[0.042]	0.170***	[0.054]	0.250***	[0.058]
ln(F LI)∗Cohort 1969	0.240***	[0.049]	0.300***	[0.044]	0.181***	[0.053]	0.269***	[0.058]
ln(F LI)∗Cohort 1970	0.244***	[0.049]	0.314***	[0.042]	0.174***	[0.053]	0.263***	[0.058]
ln(F LI)∗Cohort 1971	0.262***	[0.049]	0.321***	[0.044]	0.188***	[0.054]	0.240***	[0.058]
ln(F LI)∗Cohort 1972	0.261***	[0.050]	0.299***	[0.049]	0.203***	[0.053]	0.241***	[0.058]
ln(F LI)∗Cohort 1973	0.277***	[0.049]	0.326***	[0.042]	0.197***	[0.053]	0.264***	[0.057]
ln(F LI)∗Cohort 1974	0.286***	[0.049]	0.336***	[0.043]	0.197***	[0.052]	0.263***	[0.060]
ln(F LI)∗Cohort 1975	0.273***	[0.050]	0.329***	[0.042]	0.190***	[0.053]	0.259***	[0.058]
ln(F LI)∗Cohort 1976	0.287***	[0.050]	0.332***	[0.043]	0.205***	[0.052]	0.284***	[0.060]
ln(F LI)∗Cohort 1977	0.286***	[0.051]	0.340***	[0.046]	0.216***	[0.054]	0.259***	[0.059]
ln(F LI)∗Cohort 1978	0.258***	[0.053]	0.348***	[0.044]	0.206***	[0.053]	0.285***	[0.061]
ln(F LI)∗Cohort 1979	0.278***	[0.053]						
ln(F LI)∗Cohort 1980	0.293***	[0.056]						
Observations	21645		6940		14782		8448	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age, dummies for education

A.4 Mobility along the income distribution

A.4.1 Quantile regressions

Table A.15: TS2SLS, Quantile regressions

	Germany		Italy		UK		US	
q05								
F ln(LI)	0.219	[0.180]	0.608***	[0.086]	0.178	[0.127]	0.464***	[0.171]
q10								
F ln(LI)	0.319***	[0.088]	0.486***	[0.054]	0.127*	[0.077]	0.347***	[0.110]
q25								
F ln(LI)	0.393***	[0.056]	0.368***	[0.046]	0.274***	[0.069]	0.371***	[0.064]
q50								
F ln(LI)	0.461***	[0.056]	0.331***	[0.043]	0.345***	[0.056]	0.475***	[0.050]
q75								
F ln(LI)	0.477***	[0.057]	0.377***	[0.050]	0.363***	[0.069]	0.519***	[0.061]
q90								
F ln(LI)	0.487***	[0.068]	0.440***	[0.054]	0.355***	[0.080]	0.566***	[0.090]
q95								
F ln(LI)	0.530***	[0.085]	0.445***	[0.064]	0.347***	[0.113]	0.578***	[0.137]
Observations	21645		6940		14782		8448	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

A.4.2 Mobility matrices and generalised ordered logits

Figure A.1: Mobility matrices

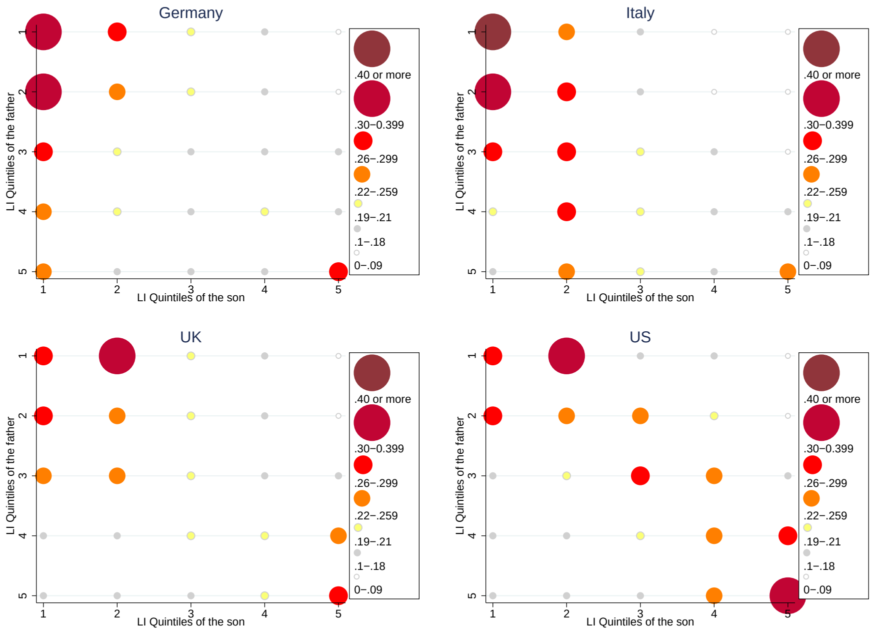

Table A.16: GSOEP Mobility matrices

	1st		2nd		3rd		4th		5th	
Whole sample										
1st	0.311***	(0.022)	0.265***	(0.019)	0.218***	(0.017)	0.158***	(0.017)	0.048***	(0.010)
2nd	0.307***	(0.012)	0.237***	(0.011)	0.210***	(0.012)	0.181***	(0.011)	0.066***	(0.012)
3rd	0.289***	(0.014)	0.214***	(0.010)	0.176***	(0.009)	0.174***	(0.009)	0.147***	(0.012)
4th	0.243***	(0.017)	0.205***	(0.012)	0.172***	(0.009)	0.197***	(0.011)	0.183***	(0.013)
5th	0.223***	(0.021)	0.184***	(0.014)	0.143***	(0.009)	0.186***	(0.011)	0.265***	(0.015)
Obs	21645									
Random										
1st	0.186***	(0.007)	0.208***	(0.007)	0.208***	(0.007)	0.199***	(0.007)	0.200***	(0.007)
2nd	0.198***	(0.007)	0.197***	(0.007)	0.211***	(0.007)	0.194***	(0.007)	0.199***	(0.007)
3rd	0.198***	(0.007)	0.207***	(0.008)	0.191***	(0.007)	0.200***	(0.008)	0.204***	(0.007)
4th	0.202***	(0.007)	0.216***	(0.007)	0.189***	(0.007)	0.191***	(0.007)	0.202***	(0.007)
5th	0.202***	(0.007)	0.190***	(0.007)	0.191***	(0.008)	0.217***	(0.007)	0.200***	(0.008)
Obs	15890									
Controls	Yes									

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Columns indicate quintiles of sons; rows of fathers. Bootstrap standard errors in parenthesis. Controls include F and own age, age squared, year of birth, interactions with age

Table A.17: SHIW Mobility matrices

	1st		2nd		3rd		4th		5th	
Whole sample										
1st	0.479***	(0.026)	0.225***	(0.020)	0.174***	(0.017)	0.086***	(0.011)	0.036***	(0.008)
2nd	0.352***	(0.025)	0.274***	(0.019)	0.184***	(0.016)	0.099***	(0.011)	0.091***	(0.014)
3rd	0.280***	(0.019)	0.299***	(0.017)	0.210***	(0.015)	0.137***	(0.013)	0.074***	(0.009)
4th	0.199***	(0.018)	0.295***	(0.016)	0.210***	(0.015)	0.187***	(0.014)	0.109***	(0.013)
5th	0.155***	(0.018)	0.239***	(0.015)	0.211***	(0.014)	0.171***	(0.012)	0.223***	(0.015)
Obs	6940									
Random										
1st	0.193***	(0.015)	0.195***	(0.015)	0.223***	(0.016)	0.204***	(0.015)	0.185***	(0.015)
2nd	0.208***	(0.017)	0.189***	(0.016)	0.197***	(0.016)	0.202***	(0.016)	0.204***	(0.016)
3rd	0.200***	(0.016)	0.206***	(0.016)	0.210***	(0.016)	0.221***	(0.015)	0.164***	(0.014)
4th	0.208***	(0.015)	0.197***	(0.014)	0.215***	(0.014)	0.210***	(0.015)	0.170***	(0.014)
5th	0.185***	(0.014)	0.207***	(0.015)	0.226***	(0.015)	0.203***	(0.015)	0.179***	(0.014)
Obs	4698									
Controls	Yes									

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Columns indicate quintiles of sons; rows of fathers. Bootstrap standard errors in parenthesis. Controls include F and own age, age squared, year of birth, interactions with age

Table A.18: BHPS Mobility matrices

	1st		2nd		3rd		4th		5th	
Whole sample										
1st	0.269***	(0.027)	0.305***	(0.026)	0.191***	(0.022)	0.139***	(0.021)	0.095***	(0.027)
2nd	0.278***	(0.022)	0.249***	(0.016)	0.218***	(0.017)	0.159***	(0.015)	0.097***	(0.020)
3rd	0.232***	(0.020)	0.225***	(0.014)	0.205***	(0.013)	0.178***	(0.012)	0.161***	(0.017)
4th	0.179***	(0.020)	0.174***	(0.014)	0.209***	(0.013)	0.212***	(0.013)	0.226***	(0.019)
5th	0.178***	(0.029)	0.151***	(0.017)	0.177***	(0.015)	0.204***	(0.016)	0.290***	(0.027)
Obs	14782									
Random										
1st	0.207***	(0.011)	0.197***	(0.011)	0.186***	(0.010)	0.200***	(0.010)	0.210***	(0.011)
2nd	0.195***	(0.011)	0.201***	(0.011)	0.204***	(0.011)	0.201***	(0.011)	0.199***	(0.011)
3rd	0.207***	(0.011)	0.180***	(0.010)	0.206***	(0.011)	0.212***	(0.011)	0.196***	(0.011)
4th	0.189***	(0.011)	0.206***	(0.010)	0.200***	(0.011)	0.209***	(0.011)	0.195***	(0.010)
5th	0.200***	(0.011)	0.211***	(0.011)	0.201***	(0.010)	0.206***	(0.010)	0.182***	(0.010)
Obs	8259									
Controls	Yes									

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Columns indicate quintiles of sons; rows of fathers. Bootstrap standard errors in parenthesis. Controls include F and own age, age squared, year of birth, interactions with age

Table A.19: PSID Mobility matrices

	1st		2nd		3rd		4th		5th	
Whole sample										
1st	0.299***	(0.025)	0.303***	(0.023)	0.188***	(0.019)	0.115***	(0.018)	0.094***	(0.020)
2nd	0.264***	(0.026)	0.237***	(0.020)	0.230***	(0.018)	0.191***	(0.021)	0.079***	(0.016)
3rd	0.183***	(0.022)	0.198***	(0.019)	0.261***	(0.021)	0.236***	(0.022)	0.122***	(0.019)
4th	0.101***	(0.014)	0.156***	(0.018)	0.207***	(0.021)	0.259***	(0.020)	0.278***	(0.029)
5th	0.141***	(0.020)	0.106***	(0.014)	0.139***	(0.019)	0.226***	(0.019)	0.388***	(0.031)
Obs	8448									
Random										
1st	0.155***	(0.019)	0.264***	(0.021)	0.218***	(0.020)	0.158***	(0.017)	0.204***	(0.020)
2nd	0.190***	(0.020)	0.190***	(0.020)	0.206***	(0.022)	0.183***	(0.021)	0.231***	(0.022)
3rd	0.187***	(0.022)	0.184***	(0.021)	0.193***	(0.022)	0.201***	(0.020)	0.235***	(0.020)
4th	0.204***	(0.019)	0.197***	(0.020)	0.207***	(0.020)	0.207***	(0.019)	0.186***	(0.020)
5th	0.213***	(0.021)	0.192***	(0.019)	0.210***	(0.021)	0.176***	(0.019)	0.209***	(0.021)
Obs	2034									
Controls	Yes									

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Columns indicate quintiles of sons; rows of fathers. Bootstrap standard errors in parenthesis. Controls include F and own age, age squared, year of birth, interactions with age

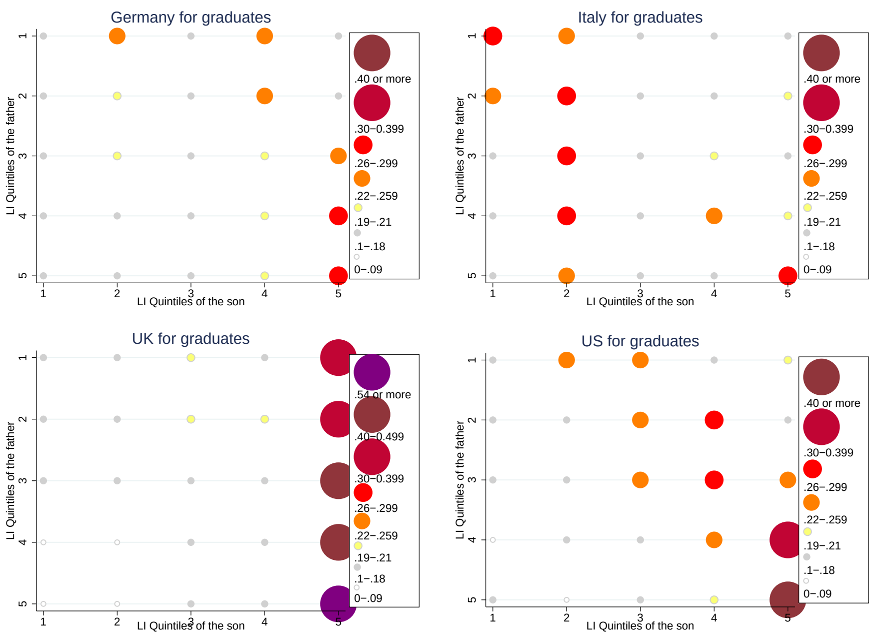

Figure A.2: Mobility matrices for a university graduate

Table A.20: Quintile mobility matrices for a university graduate

	1st		2nd		3rd		4th		5th	
Germany										
1st	0.178***	(0.019)	0.229***	(0.016)	0.187***	(0.021)	0.252***	(0.024)	0.153***	(0.027)
2nd	0.179***	(0.015)	0.211***	(0.012)	0.180***	(0.015)	0.259***	(0.020)	0.171***	(0.025)
3rd	0.185***	(0.014)	0.194***	(0.012)	0.156***	(0.012)	0.208***	(0.016)	0.256***	(0.020)
4th	0.168***	(0.017)	0.187***	(0.013)	0.160***	(0.011)	0.219***	(0.016)	0.266***	(0.020)
5th	0.174***	(0.019)	0.178***	(0.014)	0.155***	(0.012)	0.201***	(0.014)	0.292***	(0.018)
Obs	21645									
Italy										
1st	0.296***	(0.042)	0.232***	(0.031)	0.183***	(0.029)	0.172***	(0.025)	0.116***	(0.024)
2nd	0.229***	(0.036)	0.264***	(0.028)	0.166***	(0.026)	0.137***	(0.020)	0.204***	(0.028)
3rd	0.183***	(0.029)	0.273***	(0.025)	0.182***	(0.025)	0.199***	(0.022)	0.163***	(0.021)
4th	0.140***	(0.027)	0.264***	(0.023)	0.171***	(0.022)	0.230***	(0.022)	0.195***	(0.023)
5th	0.132***	(0.023)	0.229***	(0.022)	0.182***	(0.019)	0.178***	(0.017)	0.279***	(0.022)
Obs	6940									
UK										
1st	0.110***	(0.019)	0.155***	(0.024)	0.193***	(0.028)	0.189***	(0.042)	0.354***	(0.065)
2nd	0.116***	(0.018)	0.115***	(0.017)	0.202***	(0.021)	0.204***	(0.035)	0.361***	(0.051)
3rd	0.104***	(0.015)	0.102***	(0.015)	0.169***	(0.019)	0.179***	(0.027)	0.446***	(0.043)
4th	0.089***	(0.015)	0.079***	(0.013)	0.156***	(0.016)	0.181***	(0.025)	0.495***	(0.039)
5th	0.098***	(0.023)	0.068***	(0.015)	0.135***	(0.017)	0.162***	(0.026)	0.537***	(0.041)
Obs	14782									
US										
1st	0.153***	(0.027)	0.229***	(0.030)	0.239***	(0.031)	0.167***	(0.032)	0.211***	(0.047)
2nd	0.141***	(0.024)	0.163***	(0.025)	0.243***	(0.026)	0.272***	(0.034)	0.181***	(0.035)
3rd	0.101***	(0.020)	0.129***	(0.022)	0.248***	(0.028)	0.285***	(0.033)	0.237***	(0.042)
4th	0.064***	(0.014)	0.110***	(0.018)	0.189***	(0.025)	0.259***	(0.025)	0.378***	(0.041)
5th	0.118***	(0.020)	0.098***	(0.018)	0.159***	(0.023)	0.218***	(0.024)	0.406***	(0.039)
Obs	8448									
Controls	Yes									

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Columns indicate quintiles of sons; rows of fathers. Bootstrap standard errors in parenthesis. Controls include F and own age, age squared, year of birth, interactions with age

Table A.21: Probability differential for a 40-year-old graduate

	1st		2nd		3rd		4th		5th	
Germany										
1st	-0.006	(0.017)	0.035**	(0.016)	0.031	(0.021)	0.044*	(0.024)	-0.103***	(0.029)
2nd	-0.006	(0.011)	0.016	(0.011)	0.023	(0.015)	0.051**	(0.021)	-0.085***	(0.026)
4th	-0.016	(0.015)	-0.008	(0.010)	0.003	(0.012)	0.011	(0.016)	0.010	(0.022)
5th	-0.010	(0.018)	-0.016	(0.013)	-0.001	(0.013)	-0.007	(0.016)	0.035	(0.023)
Italy										
1st	0.053***	(0.010)	0.043***	(0.013)	0.025	(0.017)	-0.041**	(0.021)	-0.080***	(0.023)
2nd	0.013*	(0.008)	0.023**	(0.011)	0.013	(0.015)	-0.011	(0.018)	-0.038*	(0.020)
4th	-0.026***	(0.008)	-0.012	(0.010)	-0.013	(0.014)	-0.005	(0.018)	0.056***	(0.019)
5th	-0.024**	(0.010)	-0.025**	(0.011)	-0.042***	(0.014)	-0.032*	(0.019)	0.123***	(0.021)
UK										
1st	0.002	(0.014)	0.043**	(0.020)	0.053	(0.033)	0.017	(0.051)	-0.115	(0.078)
2nd	0.004	(0.012)	0.022	(0.014)	0.041*	(0.024)	0.042	(0.039)	-0.109*	(0.059)
4th	-0.015	(0.012)	-0.014	(0.012)	-0.018	(0.018)	-0.018	(0.027)	0.066	(0.044)
5th	0.004	(0.016)	-0.012	(0.013)	-0.030	(0.020)	-0.052*	(0.029)	0.090*	(0.049)
US										
1st	0.056***	(0.018)	0.067***	(0.024)	0.026	(0.033)	-0.054	(0.038)	-0.096**	(0.043)
2nd	0.043**	(0.017)	0.060***	(0.021)	-0.043	(0.029)	-0.053	(0.034)	-0.007	(0.044)
4th	0.001	(0.014)	-0.009	(0.019)	-0.092***	(0.026)	-0.075**	(0.031)	0.176***	(0.040)
5th	0.012	(0.016)	-0.018	(0.019)	-0.091***	(0.029)	-0.066**	(0.030)	0.163***	(0.042)
Controls	Yes									

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Columns indicate quintiles of sons; rows of fathers. Bootstrap standard errors in parenthesis. The coefficients indicate changes in the probabilities of being in a given income quintile for a 40-year-old son according to the paternal quintile with respect to the same probability with the father in the third quintile

Table A.22: GSOEP and SHIW decile mobility matrices

	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Germany										
1st	0.181	0.168	0.129	0.102	0.121	0.101	0.081	0.059	0.039	0.021
	(0.017)	(0.011)	(0.011)	(0.010)	(0.010)	(0.008)	(0.007)	(0.007)	(0.006)	(0.005)
2nd	0.139	0.154	0.143	0.097	0.102	0.106	0.109	0.077	0.046	0.028
	(0.016)	(0.010)	(0.011)	(0.008)	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)	(0.005)
3rd	0.162	0.152	0.137	0.103	0.094	0.106	0.092	0.085	0.044	0.027
	(0.017)	(0.010)	(0.013)	(0.009)	(0.009)	(0.008)	(0.007)	(0.008)	(0.006)	(0.006)
4th	0.137	0.152	0.111	0.125	0.108	0.115	0.094	0.077	0.050	0.032
	(0.011)	(0.010)	(0.009)	(0.010)	(0.009)	(0.009)	(0.007)	(0.008)	(0.008)	(0.006)
5th	0.142	0.156	0.111	0.104	0.096	0.089	0.083	0.085	0.088	0.046
	(0.015)	(0.010)	(0.008)	(0.007)	(0.009)	(0.007)	(0.006)	(0.008)	(0.010)	(0.008)
6th	0.122	0.145	0.123	0.105	0.081	0.084	0.093	0.099	0.082	0.067
	(0.015)	(0.010)	(0.009)	(0.009)	(0.008)	(0.007)	(0.009)	(0.010)	(0.010)	(0.012)
7th	0.101	0.139	0.104	0.099	0.098	0.092	0.087	0.090	0.095	0.094
	(0.013)	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.015)
8th	0.120	0.119	0.111	0.100	0.084	0.077	0.094	0.133	0.094	0.069
	(0.016)	(0.008)	(0.010)	(0.008)	(0.007)	(0.007)	(0.009)	(0.010)	(0.010)	(0.010)
9th	0.105	0.129	0.103	0.083	0.082	0.084	0.104	0.108	0.110	0.092
	(0.013)	(0.009)	(0.010)	(0.008)	(0.007)	(0.008)	(0.009)	(0.008)	(0.011)	(0.014)
10th	0.113	0.118	0.095	0.069	0.049	0.057	0.076	0.097	0.168	0.159
	(0.016)	(0.009)	(0.011)	(0.009)	(0.007)	(0.008)	(0.009)	(0.009)	(0.015)	(0.017)
Obs	21645									
Italy										
1st	0.350	0.196	0.137	0.081	0.088	0.055	0.040	0.022	0.022	0.009
	(0.032)	(0.017)	(0.016)	(0.012)	(0.011)	(0.009)	(0.006)	(0.005)	(0.005)	(0.003)
2nd	0.196	0.230	0.161	0.098	0.105	0.079	0.052	0.042	0.019	0.018
	(0.023)	(0.021)	(0.016)	(0.013)	(0.013)	(0.011)	(0.007)	(0.008)	(0.004)	(0.005)
3rd	0.201	0.191	0.158	0.129	0.096	0.050	0.050	0.049	0.044	0.032
	(0.026)	(0.021)	(0.016)	(0.015)	(0.011)	(0.009)	(0.008)	(0.008)	(0.007)	(0.006)
4th	0.159	0.171	0.152	0.116	0.111	0.107	0.072	0.043	0.039	0.031
	(0.028)	(0.020)	(0.017)	(0.012)	(0.012)	(0.012)	(0.009)	(0.007)	(0.007)	(0.006)
5th	0.123	0.162	0.163	0.142	0.109	0.101	0.073	0.053	0.040	0.033
	(0.018)	(0.019)	(0.017)	(0.016)	(0.015)	(0.010)	(0.009)	(0.008)	(0.006)	(0.006)
6th	0.114	0.155	0.140	0.139	0.121	0.087	0.082	0.076	0.049	0.037
	(0.015)	(0.019)	(0.015)	(0.016)	(0.012)	(0.011)	(0.010)	(0.009)	(0.007)	(0.006)
7th	0.092	0.114	0.163	0.146	0.110	0.094	0.090	0.075	0.061	0.055
	(0.017)	(0.016)	(0.019)	(0.018)	(0.016)	(0.010)	(0.012)	(0.010)	(0.008)	(0.009)
8th	0.079	0.107	0.143	0.138	0.124	0.101	0.102	0.089	0.066	0.051
	(0.015)	(0.016)	(0.015)	(0.015)	(0.014)	(0.012)	(0.012)	(0.011)	(0.009)	(0.010)
9th	0.068	0.104	0.123	0.143	0.121	0.114	0.069	0.082	0.092	0.084
	(0.014)	(0.015)	(0.014)	(0.017)	(0.013)	(0.013)	(0.008)	(0.011)	(0.012)	(0.012)
10th	0.061	0.074	0.117	0.086	0.108	0.083	0.101	0.095	0.125	0.151
	(0.013)	(0.013)	(0.016)	(0.011)	(0.014)	(0.011)	(0.014)	(0.013)	(0.016)	(0.016)
Obs	6940									

Bootstrap standard errors in parenthesis. Columns indicate quintiles of sons; rows of fathers

Table A.23: BHPS and PSID decile mobility matrices

	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
UK										
1st	0.155	0.153	0.150	0.140	0.107	0.093	0.070	0.064	0.042	0.025
	(0.027)	(0.017)	(0.019)	(0.014)	(0.013)	(0.012)	(0.010)	(0.011)	(0.008)	(0.007)
2nd	0.132	0.157	0.144	0.134	0.099	0.092	0.083	0.069	0.056	0.033
	(0.020)	(0.018)	(0.015)	(0.012)	(0.011)	(0.011)	(0.011)	(0.010)	(0.011)	(0.014)
3rd	0.113	0.123	0.143	0.123	0.125	0.107	0.090	0.079	0.062	0.035
	(0.018)	(0.018)	(0.014)	(0.012)	(0.012)	(0.011)	(0.010)	(0.010)	(0.009)	(0.011)
4th	0.138	0.150	0.124	0.102	0.092	0.109	0.087	0.093	0.060	0.045
	(0.022)	(0.019)	(0.014)	(0.010)	(0.010)	(0.014)	(0.009)	(0.013)	(0.010)	(0.011)
5th	0.117	0.127	0.113	0.119	0.119	0.104	0.094	0.078	0.068	0.060
	(0.018)	(0.015)	(0.012)	(0.013)	(0.012)	(0.011)	(0.011)	(0.009)	(0.010)	(0.013)
6th	0.101	0.111	0.099	0.119	0.102	0.101	0.090	0.095	0.085	0.097
	(0.017)	(0.016)	(0.012)	(0.011)	(0.011)	(0.010)	(0.012)	(0.011)	(0.013)	(0.021)
7th	0.134	0.076	0.085	0.094	0.099	0.096	0.106	0.103	0.094	0.112
	(0.019)	(0.012)	(0.012)	(0.011)	(0.010)	(0.010)	(0.012)	(0.010)	(0.011)	(0.021)
8th	0.083	0.070	0.074	0.084	0.115	0.112	0.114	0.103	0.123	0.122
	(0.017)	(0.012)	(0.011)	(0.011)	(0.010)	(0.010)	(0.012)	(0.011)	(0.012)	(0.017)
9th	0.108	0.076	0.073	0.086	0.098	0.094	0.103	0.104	0.130	0.128
	(0.021)	(0.013)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.012)	(0.015)	(0.023)
10th	0.067	0.045	0.050	0.070	0.085	0.108	0.121	0.117	0.158	0.179
	(0.016)	(0.011)	(0.010)	(0.010)	(0.009)	(0.012)	(0.014)	(0.014)	(0.016)	(0.031)
Obs	14782									
US										
1st	0.154	0.188	0.175	0.145	0.086	0.075	0.062	0.037	0.041	0.037
	(0.024)	(0.025)	(0.021)	(0.023)	(0.013)	(0.013)	(0.014)	(0.009)	(0.014)	(0.014)
2nd	0.118	0.136	0.158	0.108	0.115	0.086	0.090	0.071	0.074	0.044
	(0.024)	(0.022)	(0.024)	(0.015)	(0.020)	(0.015)	(0.016)	(0.019)	(0.019)	(0.020)
3rd	0.155	0.132	0.124	0.114	0.118	0.107	0.092	0.097	0.037	0.024
	(0.029)	(0.024)	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)	(0.021)	(0.010)	(0.013)
4th	0.123	0.107	0.123	0.111	0.114	0.123	0.109	0.085	0.040	0.063
	(0.028)	(0.020)	(0.016)	(0.016)	(0.017)	(0.021)	(0.019)	(0.014)	(0.013)	(0.019)
5th	0.092	0.098	0.084	0.110	0.130	0.139	0.111	0.125	0.077	0.034
	(0.017)	(0.020)	(0.016)	(0.018)	(0.018)	(0.018)	(0.023)	(0.020)	(0.022)	(0.012)
6th	0.084	0.085	0.099	0.104	0.123	0.132	0.139	0.103	0.085	0.045
	(0.021)	(0.016)	(0.018)	(0.016)	(0.017)	(0.016)	(0.019)	(0.017)	(0.017)	(0.017)
7th	0.072	0.055	0.068	0.122	0.103	0.115	0.129	0.120	0.111	0.105
	(0.014)	(0.012)	(0.011)	(0.019)	(0.016)	(0.020)	(0.017)	(0.018)	(0.021)	(0.028)
8th	0.039	0.046	0.039	0.082	0.096	0.099	0.109	0.142	0.187	0.161
	(0.009)	(0.011)	(0.008)	(0.015)	(0.017)	(0.021)	(0.014)	(0.018)	(0.023)	(0.027)
9th	0.056	0.069	0.069	0.049	0.068	0.057	0.087	0.132	0.179	0.235
	(0.015)	(0.019)	(0.014)	(0.010)	(0.016)	(0.014)	(0.014)	(0.023)	(0.025)	(0.044)
10th	0.087	0.060	0.045	0.037	0.059	0.088	0.109	0.131	0.172	0.211
	(0.019)	(0.011)	(0.008)	(0.008)	(0.012)	(0.017)	(0.015)	(0.017)	(0.025)	(0.029)
Obs	8448									

Bootstrap standard errors in parenthesis. Columns indicate quintiles of sons; rows of fathers

A.5 Robustness checks: different samples

Table A.24: Summary statistics for fathers by sample

	DEs	DEr	ITs	ITr	UKs	UKr	USs	USr
AV3								
F Age	50.39	44.90	52.54	43.31	52.15	43.56	50.55	43.83
	(3.88)	(5.50)	(2.76)	(6.02)	(2.508)	(5.71)	(2.17)	(5.46)
F year of birth	1944.56	1933.21	1944.35	1926.23	1944.55	1931.79	1945.54	1935.43
	(3.85)	(8.80)	(3.38)	(9.58)	(3.21)	(9.22)	(2.95)	(8.75)
F Higher education	0.24	0.11	0.08	0.03	0.14	0.09	0.16	0.10
	(0.43)	(0.31)	(0.27)	(0.17)	(0.34)	(0.29)	(0.36)	(0.30)
F ln(LI)	10.16	9.47	9.67	8.90	10.29	9.40	10.87	10.63
	(0.53)	(0.50)	(0.50)	(0.61)	(0.49)	(0.50)	(0.62)	(0.44)
Observations	438	2539	211	1030	492	1322	1017	882
A55								
F Age	49.26	44.19	50.91	43.44	50.25	44.03	52.25	43.58
	(3.61)	(4.88)	(3.35)	(5.39)	(3.40)	(5.10)	(2.13)	(5.16)
F year of birth	1945.49	1932.14	1944.37	1925.80	1945.02	1928.46	1946.85	1931.73
	(3.18)	(7.69)	(3.57)	(9.13)	(3.15)	(7.69)	(1.89)	(7.89)
F Higher education	0.20	0.11	0.10	0.03	0.14	0.08	0.16	0.09
	(0.40)	(0.31)	(0.30)	(0.17)	(0.35)	(0.28)	(0.37)	(0.29)
F ln(LI)	10.11	9.66	9.59	9.49	10.19	9.49	10.86	10.40
	(0.60)	(0.38)	(0.56)	(0.35)	(0.63)	(0.37)	(0.92)	(0.43)
Observations	2855	15220	941	5924	3568	10509	6957	5811
MIN40								
F Age	50.33	45.42	52.61	41.68	49.49	43.60	53.46	44.05
	(5.22)	(6.03)	(4.55)	(5.71)	(4.88)	(5.88)	(3.60)	(5.60)
F year of birth	1944.60	1933.62	1942.67	1927.39	1942.12	1930.73	1945.43	1937.48
	(3.83)	(9.42)	(4.60)	(9.52)	(4.85)	(8.85)	(3.44)	(7.64)
F Higher education	0.26	0.12	0.09	0.04	0.11	0.09	0.13	0.10
	(0.44)	(0.33)	(0.28)	(0.18)	(0.32)	(0.28)	(0.34)	(0.30)
F ln(LI)	9.99	9.63	9.55	9.07	10.06	9.55	9.96	11.09
	(0.65)	(0.44)	(0.60)	(0.36)	(0.63)	(0.39)	(1.38)	(0.58)
Observations	1057	3641	722	2765	742	1417	1373	964

Notes: F stands for father. LI for labour income. Columns 1, 3, 5, 7 report the statistics for syntethic father; Columns 2, 4, 6, 8 report the statistics for for real fathers

Table A.25: Summary statistics for sons by sample

	Germany mean/sd	Italy mean/sd	UK mean/sd	US mean/sd
AV3				
ln(LI)	10.55	9.92	10.51	10.80
	(0.67)	(0.45)	(0.54)	(0.65)
Age	41.18	43.31	39.83	37.45
	(6.83)	(6.02)	(5.06)	(4.19)
Year of birth	1963.11	1959.01	1961.35	1964.25
	(7.11)	(6.01)	(6.77)	(6.90)
Self-employed	0.13	0.24	0.11	0.07
	(0.34)	(0.43)	(0.31)	(0.25)
N of waves	9.39	4.05	11.95	10.89
	(4.18)	(2.05)	(4.63)	(3.53)
Observations	2539	1030	1322	882
A55				
ln(LI)	10.56	9.82	10.50	10.82
	(0.78)	(0.61)	(0.70)	(0.94)
Age	43.36	43.44	42.62	43.62
	(5.56)	(5.39)	(5.27)	(5.51)
Year of birth	1961.33	1958.60	1958.49	1960.30
	(5.90)	(5.72)	(5.42)	(5.91)
Self-employed	0.13	0.24	0.11	0.12
	(0.34)	(0.43)	(0.31)	(0.33)
N of waves	8.07	3.62	12.76	8.16
	(3.51)	(2.25)	(4.14)	(3.74)
Observations	15220	5924	10509	5811
MIN40				
ln(LI)	10.32	9.74	10.37	10.77
	(0.89)	(0.65)	(0.82)	(0.94)
Age	39.76	41.68	39.54	38.74
	(5.49)	(5.71)	(2.11)	(2.91)
Year of birth	1964.04	1959.76	1960.33	1966.53
	(7.64)	(6.29)	(6.14)	(5.51)
Self-employed	0.13	0.26	0.14	0.13
	(0.34)	(0.44)	(0.35)	(0.34)
Observations	3641	2765	1417	964

Table A.26: AV3: TS2SLS, OLS

	Germany		Italy		UK		US	
Interaction of age and F's age with ln(LI)								
F ln(LI)	0.438***	[0.088]	0.387***	[0.082]	0.308***	[0.070]	0.504***	[0.070]
F LI(Age-40)	0.016	[0.010]	0.001	[0.004]	-0.018**	[0.008]	0.003	[0.011]
F LI$(\text{Age-40})^2$	-0.005***	[0.001]						
F LI$(\text{Age-40})^3$	0.000	[0.000]						
F LI(F Age-40)	0.004	[0.008]			0.021**	[0.008]	0.009	[0.009]
F's year of birth and interaction of age with ln(LI)								
F ln(LI)	0.452***	[0.079]	0.387***	[0.082]	0.376***	[0.081]	0.537***	[0.065]
F LI(Age-40)	0.016*	[0.010]	0.001	[0.004]	-0.009	[0.009]	0.003	[0.011]
F LI$(\text{Age-40})^2$	-0.004***	[0.001]						
F LI$(\text{Age-40})^3$	0.000	[0.000]						
No interaction								
F ln(LI)	0.291***	[0.056]	0.390***	[0.082]	0.372***	[0.080]	0.533***	[0.062]
Observations	2539		1030		1322		882	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrapped standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

Table A.27: A55: TS2SLS, OLS

	Germany		Italy		UK		US	
Interaction of age and F's age with ln(LI)								
F ln(LI)	0.430***	[0.074]	0.514***	[0.066]	0.358***	[0.073]	0.506***	[0.073]
F LI(Age-40)	0.023**	[0.009]	0.009	[0.006]	-0.005	[0.006]	-0.003	[0.007]
F LI$(\text{Age-40})^2$	-0.003*	[0.002]						
F LI$(\text{Age-40})^3$	0.000	[0.000]						
F LI(F Age-40)	0.005	[0.009]			0.013	[0.008]	0.011	[0.012]
F's year of birth and interaction of age with ln(LI)								
F ln(LI)	0.451***	[0.060]	0.514***	[0.066]	0.407***	[0.064]	0.551***	[0.068]
F LI(Age-40)	0.023**	[0.009]	0.009	[0.006]	-0.003	[0.006]	-0.002	[0.007]
F LI$(\text{Age-40})^2$	-0.003	[0.002]						
F LI$(\text{Age-40})^3$	-0.000	[0.000]						
No interaction								
F ln(LI)	0.399***	[0.053]	0.553***	[0.068]	0.397***	[0.063]	0.545***	[0.070]
Observations	15220		5924		10509		5811	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrapped standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

Table A.28: MIN40: TS2SLS, OLS

	Germany		Italy		UK		US	
Interaction of age and F's age with ln(LI)								
F ln(LI)	0.394***	[0.065]	0.565***	[0.067]	0.395***	[0.097]	0.520***	[0.074]
F LI(Age-40)	0.018	[0.011]	0.012*	[0.006]	-0.013	[0.021]	0.083***	[0.023]
F LI(Age-40)^2	-0.003***	[0.001]						
F LI(Age-40)^3	0.000	[0.000]						
F LI(F Age-40)	-0.005	[0.007]			0.009	[0.011]	0.006	[0.008]
F's year of birth and interaction of age with ln(LI)								
F ln(LI)	0.367***	[0.059]	0.565***	[0.067]	0.430***	[0.086]	0.544***	[0.069]
F LI(Age-40)	0.016	[0.011]	0.012*	[0.006]	-0.013	[0.021]	0.082***	[0.023]
F LI(Age-40)^2	-0.003***	[0.001]						
F LI(Age-40)^3	0.000	[0.000]						
No interaction								
F ln(LI)	0.285***	[0.051]	0.596***	[0.069]	0.431***	[0.086]	0.488***	[0.066]
Observations	3641		2765		1417		964	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrapped standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

Table A.29: TS2SLS with education

	Germany		Italy		UK		US	
F ln(LI)	0.196***	[0.058]	0.209***	[0.060]	0.135**	[0.058]	0.264***	[0.062]
F LI(Age-40)	0.019**	[0.009]	0.000	[0.004]	-0.013*	[0.008]	0.003	[0.011]
F LI(Age-40)^2	-0.004***	[0.001]						
F LI(Age-40)^3	0.000	[0.000]						
F LI(F Age-40)	-0.005	[0.005]			0.016**	[0.007]	0.009	[0.008]
Observations	2978		1241		1815		1901	
A55								
F ln(LI)	0.166***	[0.063]	0.315***	[0.053]	0.191***	[0.064]	0.260***	[0.070]
F LI(Age-40)	0.027***	[0.008]	0.007	[0.006]	-0.002	[0.006]	-0.003	[0.007]
F LI(Age-40)^2	-0.004**	[0.002]						
F LI(Age-40)^3	0.000	[0.000]						
F LI(F Age-40)	-0.003	[0.008]			0.007	[0.007]	0.009	[0.011]
Observations	15220		5924		10509		5811	
MIN40								
F ln(LI)	0.168***	[0.052]	0.339***	[0.053]	0.207**	[0.094]	0.301***	[0.069]
F LI(Age-40)	0.023**	[0.010]	0.012**	[0.006]	-0.005	[0.020]	0.073***	[0.020]
F LI(Age-40)^2	-0.003***	[0.001]						
F LI(Age-40)^3	0.000	[0.000]						
F LI(F Age-40)	-0.009*	[0.005]			0.007	[0.011]	0.003	[0.008]
Observations	3641		2765		1417		964	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrapped standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

Table A.30: AV3: TS2SLS, Cohorts

	Germany		Italy		UK		US	
ln(F LI)∗Cohort 1950	0.305***	[0.095]	0.339***	[0.084]	0.294***	[0.074]	0.523***	[0.072]
ln(F LI)∗Cohort 1951	0.299***	[0.095]	0.337***	[0.084]	0.296***	[0.074]	0.507***	[0.071]
ln(F LI)∗Cohort 1952	0.316***	[0.094]	0.335***	[0.083]	0.300***	[0.074]	0.515***	[0.072]
ln(F LI)∗Cohort 1953	0.337***	[0.094]	0.338***	[0.083]	0.282***	[0.072]	0.500***	[0.070]
ln(F LI)∗Cohort 1954	0.322***	[0.093]	0.347***	[0.083]	0.306***	[0.073]	0.499***	[0.072]
ln(F LI)∗Cohort 1955	0.373***	[0.093]	0.359***	[0.083]	0.293***	[0.072]	0.506***	[0.073]
ln(F LI)∗Cohort 1956	0.356***	[0.093]	0.354***	[0.084]	0.292***	[0.071]	0.494***	[0.073]
ln(F LI)∗Cohort 1957	0.359***	[0.092]	0.359***	[0.084]	0.299***	[0.071]	0.496***	[0.073]
ln(F LI)∗Cohort 1958	0.387***	[0.092]	0.372***	[0.083]	0.303***	[0.070]	0.505***	[0.073]
ln(F LI)∗Cohort 1959	0.395***	[0.092]	0.376***	[0.083]	0.311***	[0.071]	0.504***	[0.074]
ln(F LI)∗Cohort 1960	0.402***	[0.091]	0.376***	[0.084]	0.300***	[0.070]	0.507***	[0.074]
ln(F LI)∗Cohort 1961	0.412***	[0.091]	0.387***	[0.083]	0.303***	[0.069]	0.520***	[0.075]
ln(F LI)∗Cohort 1962	0.414***	[0.091]	0.393***	[0.083]	0.310***	[0.069]	0.512***	[0.076]
ln(F LI)∗Cohort 1963	0.411***	[0.090]	0.391***	[0.083]	0.308***	[0.068]	0.498***	[0.075]
ln(F LI)∗Cohort 1964	0.426***	[0.090]	0.386***	[0.083]	0.307***	[0.069]	0.524***	[0.077]
ln(F LI)∗Cohort 1965	0.436***	[0.090]	0.393***	[0.083]	0.318***	[0.070]	0.511***	[0.075]
ln(F LI)∗Cohort 1966	0.435***	[0.089]	0.400***	[0.083]	0.326***	[0.069]	0.517***	[0.075]
ln(F LI)∗Cohort 1967	0.439***	[0.089]	0.398***	[0.083]	0.315***	[0.068]	0.507***	[0.075]
ln(F LI)∗Cohort 1968	0.459***	[0.089]	0.425***	[0.083]	0.328***	[0.069]	0.510***	[0.074]
ln(F LI)∗Cohort 1969	0.455***	[0.088]	0.415***	[0.085]	0.335***	[0.069]	0.534***	[0.075]
ln(F LI)∗Cohort 1970	0.466***	[0.089]	0.411***	[0.082]	0.330***	[0.068]	0.535***	[0.075]
ln(F LI)∗Cohort 1971	0.476***	[0.089]	0.444***	[0.084]	0.337***	[0.069]	0.519***	[0.076]
ln(F LI)∗Cohort 1972	0.473***	[0.090]	0.423***	[0.084]	0.359***	[0.069]	0.515***	[0.075]
ln(F LI)∗Cohort 1973	0.484***	[0.090]	0.427***	[0.082]	0.355***	[0.069]	0.531***	[0.076]
ln(F LI)∗Cohort 1974	0.502***	[0.090]	0.437***	[0.082]	0.353***	[0.069]	0.534***	[0.078]
ln(F LI)∗Cohort 1975	0.483***	[0.090]			0.339***	[0.069]	0.529***	[0.076]
ln(F LI)∗Cohort 1976	0.494***	[0.092]			0.368***	[0.069]		
ln(F LI)∗Cohort 1977	0.499***	[0.093]						
ln(F LI)∗Cohort 1978	0.463***	[0.096]						
F LI(F Age-40)	0.006	[0.008]			0.018**	[0.008]	0.009	[0.009]
Observations	2978		1241		1815		1901	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrapped standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

Table A.31: MIN40: TS2SLS, Cohorts

	Germany		Italy		UK		US	
ln(F LI)∗Cohort 1950	0.227***	[0.067]	0.516***	[0.067]	0.389***	[0.103]	0.511***	[0.072]
ln(F LI)∗Cohort 1951	0.221***	[0.067]	0.530***	[0.067]	0.376***	[0.103]	0.489***	[0.073]
ln(F LI)∗Cohort 1952	0.233***	[0.066]	0.531***	[0.067]	0.376***	[0.102]	0.504***	[0.073]
ln(F LI)∗Cohort 1953	0.265***	[0.065]	0.521***	[0.067]	0.344***	[0.102]	0.485***	[0.075]
ln(F LI)∗Cohort 1954	0.233***	[0.066]	0.526***	[0.067]	0.385***	[0.102]	0.468***	[0.073]
ln(F LI)∗Cohort 1955	0.274***	[0.066]	0.534***	[0.066]	0.372***	[0.101]	0.497***	[0.074]
ln(F LI)∗Cohort 1956	0.279***	[0.066]	0.546***	[0.067]	0.364***	[0.101]	0.483***	[0.073]
ln(F LI)∗Cohort 1957	0.277***	[0.065]	0.545***	[0.067]	0.387***	[0.100]	0.494***	[0.076]
ln(F LI)∗Cohort 1958	0.299***	[0.065]	0.551***	[0.067]	0.391***	[0.099]	0.514***	[0.077]
ln(F LI)∗Cohort 1959	0.295***	[0.065]	0.551***	[0.067]	0.392***	[0.100]	0.514***	[0.076]
ln(F LI)∗Cohort 1960	0.302***	[0.065]	0.551***	[0.067]	0.371***	[0.100]	0.539***	[0.077]
ln(F LI)∗Cohort 1961	0.303***	[0.064]	0.566***	[0.067]	0.369***	[0.099]	0.527***	[0.076]
ln(F LI)∗Cohort 1962	0.352***	[0.065]	0.568***	[0.067]	0.394***	[0.099]	0.528***	[0.079]
ln(F LI)∗Cohort 1963	0.353***	[0.064]	0.580***	[0.067]	0.384***	[0.097]	0.505***	[0.079]
ln(F LI)∗Cohort 1964	0.367***	[0.064]	0.571***	[0.067]	0.392***	[0.098]	0.544***	[0.081]
ln(F LI)∗Cohort 1965	0.369***	[0.063]	0.573***	[0.066]	0.396***	[0.098]	0.533***	[0.079]
ln(F LI)∗Cohort 1966	0.378***	[0.064]	0.587***	[0.067]	0.410***	[0.099]	0.541***	[0.080]
ln(F LI)∗Cohort 1967	0.373***	[0.063]	0.599***	[0.067]	0.402***	[0.098]	0.536***	[0.079]
ln(F LI)∗Cohort 1968	0.394***	[0.063]	0.608***	[0.067]	0.417***	[0.097]	0.538***	[0.080]
ln(F LI)∗Cohort 1969	0.372***	[0.063]	0.594***	[0.067]	0.413***	[0.098]	0.559***	[0.079]
ln(F LI)∗Cohort 1970	0.391***	[0.063]	0.603***	[0.066]	0.400***	[0.090]	0.552***	[0.080]
ln(F LI)∗Cohort 1971	0.393***	[0.063]	0.607***	[0.065]	0.410***	[0.097]	0.531***	[0.080]
ln(F LI)∗Cohort 1972	0.402***	[0.063]	0.601***	[0.068]	0.433***	[0.095]	0.530***	[0.079]
ln(F LI)∗Cohort 1973	0.408***	[0.063]	0.613***	[0.067]	0.416***	[0.097]	0.538***	[0.078]
ln(F LI)∗Cohort 1974	0.432***	[0.063]	0.634***	[0.066]	0.430***	[0.096]	0.530***	[0.081]
ln(F LI)∗Cohort 1975	0.418***	[0.064]	0.611***	[0.067]	0.437***	[0.095]	0.532***	[0.080]
ln(F LI)∗Cohort 1976	0.434***	[0.063]	0.631***	[0.068]	0.429***	[0.100]	0.558***	[0.081]
ln(F LI)∗Cohort 1977	0.441***	[0.065]	0.631***	[0.067]	0.461***	[0.095]	0.552***	[0.078]
ln(F LI)∗Cohort 1978	0.412***	[0.067]					0.552***	[0.081]
ln(F LI)∗Cohort 1979	0.417***	[0.068]						
ln(F LI)∗Cohort 1980	0.437***	[0.069]						
F LI(F Age-40)	-0.003	[0.007]			0.009	[0.011]	0.008	[0.008]
Observations	4736		3487		2159		2337	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrapped standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

Table A.32: A55: TS2SLS, Cohorts

	Germany		Italy		UK		US	
ln(F LI)∗Cohort 1950	0.317***	[0.076]	0.470***	[0.066]	0.317***	[0.079]	0.520***	[0.075]
ln(F LI)∗Cohort 1951	0.321***	[0.076]	0.474***	[0.066]	0.332***	[0.078]	0.505***	[0.074]
ln(F LI)∗Cohort 1952	0.321***	[0.075]	0.473***	[0.066]	0.334***	[0.077]	0.512***	[0.076]
ln(F LI)∗Cohort 1953	0.347***	[0.076]	0.475***	[0.066]	0.320***	[0.077]	0.498***	[0.074]
ln(F LI)∗Cohort 1954	0.327***	[0.077]	0.479***	[0.066]	0.339***	[0.077]	0.497***	[0.075]
ln(F LI)∗Cohort 1955	0.366***	[0.076]	0.491***	[0.066]	0.341***	[0.077]	0.511***	[0.074]
ln(F LI)∗Cohort 1956	0.367***	[0.076]	0.493***	[0.066]	0.326***	[0.076]	0.494***	[0.076]
ln(F LI)∗Cohort 1957	0.360***	[0.076]	0.497***	[0.066]	0.325***	[0.075]	0.496***	[0.075]
ln(F LI)∗Cohort 1958	0.383***	[0.076]	0.501***	[0.066]	0.340***	[0.076]	0.496***	[0.075]
ln(F LI)∗Cohort 1959	0.392***	[0.076]	0.507***	[0.066]	0.356***	[0.076]	0.500***	[0.075]
ln(F LI)∗Cohort 1960	0.396***	[0.075]	0.508***	[0.066]	0.343***	[0.075]	0.502***	[0.075]
ln(F LI)∗Cohort 1961	0.408***	[0.075]	0.514***	[0.066]	0.350***	[0.075]	0.512***	[0.073]
ln(F LI)∗Cohort 1962	0.410***	[0.076]	0.521***	[0.066]	0.349***	[0.074]	0.501***	[0.076]
ln(F LI)∗Cohort 1963	0.405***	[0.074]	0.521***	[0.066]	0.348***	[0.074]	0.477***	[0.075]
ln(F LI)∗Cohort 1964	0.423***	[0.075]	0.520***	[0.066]	0.362***	[0.074]	0.515***	[0.078]
ln(F LI)∗Cohort 1965	0.435***	[0.075]	0.522***	[0.066]	0.364***	[0.074]	0.504***	[0.075]
ln(F LI)∗Cohort 1966	0.443***	[0.074]	0.534***	[0.065]	0.361***	[0.074]	0.509***	[0.075]
ln(F LI)∗Cohort 1967	0.452***	[0.074]	0.542***	[0.066]	0.368***	[0.073]	0.487***	[0.074]
ln(F LI)∗Cohort 1968	0.469***	[0.074]	0.560***	[0.066]	0.372***	[0.073]	0.487***	[0.073]
ln(F LI)∗Cohort 1969	0.464***	[0.074]	0.543***	[0.066]	0.375***	[0.073]	0.516***	[0.073]
ln(F LI)∗Cohort 1970	0.468***	[0.074]	0.550***	[0.066]	0.366***	[0.072]	0.520***	[0.073]
ln(F LI)∗Cohort 1971	0.475***	[0.074]	0.561***	[0.066]	0.379***	[0.072]	0.503***	[0.074]
ln(F LI)∗Cohort 1972	0.467***	[0.075]	0.552***	[0.068]	0.396***	[0.072]	0.492***	[0.073]
ln(F LI)∗Cohort 1973	0.474***	[0.074]	0.561***	[0.066]	0.374***	[0.073]	0.509***	[0.074]
ln(F LI)∗Cohort 1974	0.485***	[0.074]	0.573***	[0.066]	0.386***	[0.072]	0.508***	[0.078]
ln(F LI)∗Cohort 1975	0.460***	[0.076]	0.552***	[0.066]	0.366***	[0.072]		
F LI(F Age-40)	0.006	[0.009]			0.015*	[0.008]	0.011	[0.012]
Observations	15220		5924		10509		5811	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrapped standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

A.6 Additional robustness checks: outlying observations and the role of self-employment

The following two sections control if the results are robust to an additional series of sample or model modifications. Specifically, section A.6.1 investigates the effect of excluding the outlying observations, whereas section A.6.2 explicitly accounts for self-employment.

In order to better appreciate the data, notice that the natural logarithm of 1,200, or a monthly labour income of 100 dollars, equals to 7.09, whereas for example $ln(22,000) \approx 10$. At the other extreme, the number 15 is the natural logarithm of 3,269,000.

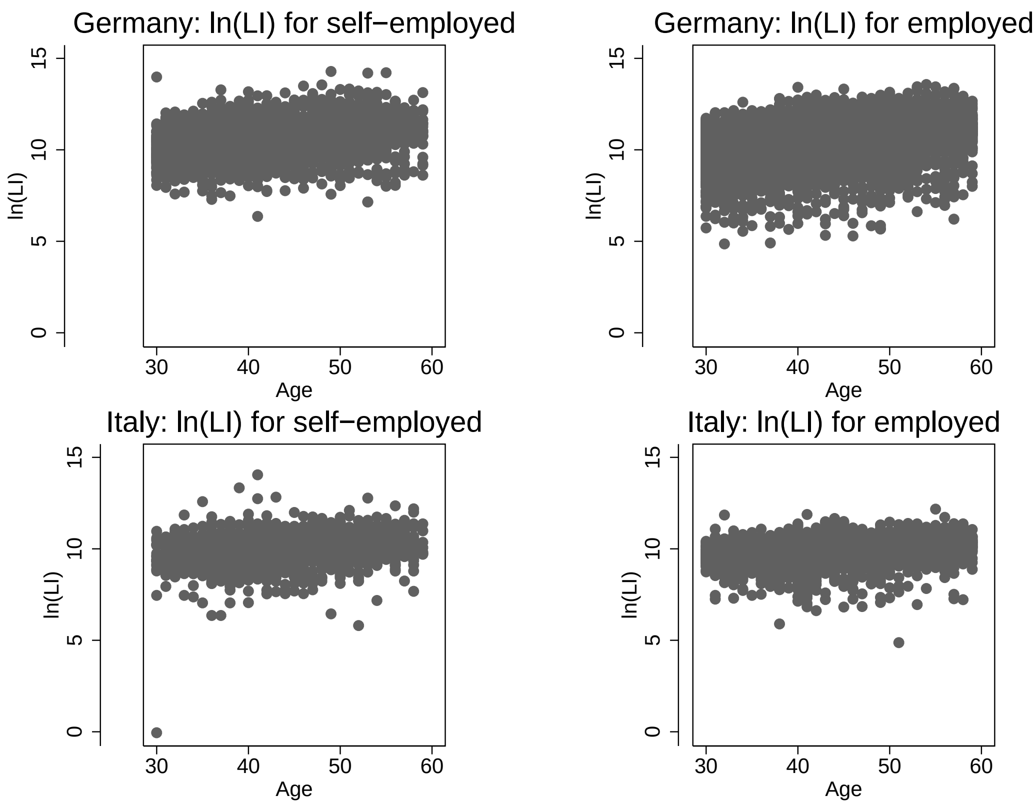

Figure A.3: Distribution of ln(LI) by type of employment in Italy and Germany

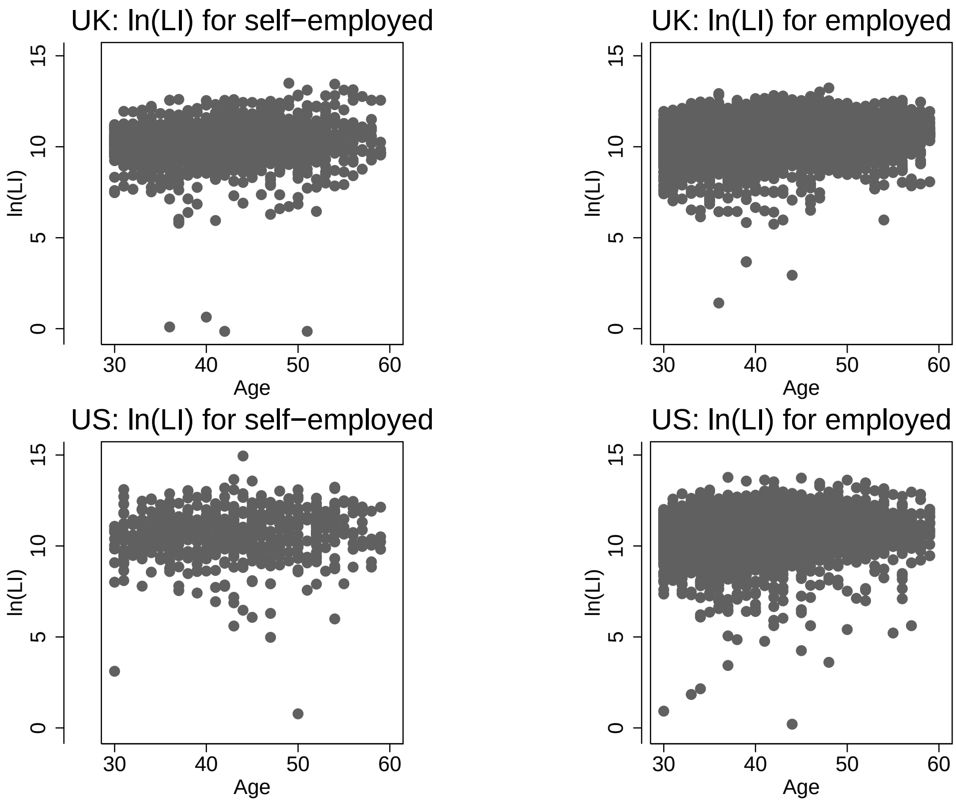

Figure A.4: Distribution of ln(LI) by type of employment in the UK and US

A.6.1 Outliers

Lee and Solon (2009) and Hertz (2007) exclude from their investigations the individuals with an income lower than 700 USD or higher than 700,000 USD in 2000 USD. The level of earnings is not a sample selection criterion for this analysis. Consequently, the sample includes some individuals that report an annual income lower than one USD. The reason is to avoid setting up an additional rule to select the observations included in the analysis. Particularly because it would be based on an arbitrary decision about the labour income threshold. Nonetheless, it may be worth to check the impact of these observations on the estimations. Especially considering that the low figures might result from a reporting or measurement error. Thus, this sections performs the same analysis of the main document on a reduced sample. Specifically, it excludes the top and the bottom percentiles. The summary statistics are reported in is reported in Table A.33.

Table A.33: Summary statistics for fathers without outliers

	DEs mean/sd	DEr mean/sd	ITs mean/sd	ITr mean/sd	UKs mean/sd	UKr mean/sd	USs mean/sd	USr mean/sd
F Age	50.47	44.81	53.15	42.48	52.35	43.77	54.70	43.86
	(4.44)	(5.50)	(4.18)	(6.69)	(4.40)	(5.88)	(3.14)	(5.54)
F year of birth	1944.98	1932.92	1943.59	1926.61	1944.11	1930.08	1945.87	1932.86
	(3.60)	(8.59)	(4.22)	(9.52)	(3.90)	(8.84)	(2.76)	(8.69)
F Higher Education	0.22	0.12	0.11	0.03	0.13	0.09	0.16	0.09
	0.22	0.12	(0.31)	(0.18)	(0.34)	(0.28)	(0.37)	(0.29)
F ln(LI)	10.13	9.47	9.61	9.12	10.21	9.48	10.82	10.43
	(0.55)	(0.44)	(0.56)	(0.34)	(0.56)	(0.39)	(0.75)	(0.41)
Observations	3511	20952	1485	6801	4904	10801	6411	8232

Notes: F stands for father. LI for labour income. Columns 1, 3, 5, 7 indicate the statistics for syntethic father; Columns 2, 4, 6, 8 indicate the statistics for for real fathers

The results are presented in the tables below. Table A.35 illustrates the value of the elasticity in each country, with and without controlling for education. A comparison with Tables 2.1 and suggests that the extremes observations have a limited impact on the

Table A.34: Summary statistics for the sons without the outliers

	Germany mean/sd	Italy mean/sd	UK mean/sd	US mean/sd
ln(LI)	10.50	9.82	10.46	10.79
	(0.71)	(0.52)	(0.58)	(0.76)
Age	41.40	42.48	40.63	41.97
	(7.22)	(6.69)	(6.57)	(7.17)
F Age	44.81		43.77	43.86
	(5.50)		(5.88)	(5.54)
Year of birth	1962.74	1959.28	1959.85	1961.73
	(6.80)	(6.22)	(6.08)	(6.86)
Self-employed	0.12	0.24	0.11	0.11
	(0.33)	(0.43)	(0.31)	(0.31)
N of waves	8.98	3.87	14.28	9.79
	(3.90)	(2.47)	(4.03)	(3.84)
Observations	20952	6801	12978	8232

slope coefficients. A similar picture emerges when the education dummies are included (comparable with the Appendix Table A.11).

Similar results to the main analysis emerge from the investigation of the IGE trend, which remains unchanged. In Germany, Italy and the United Kingdom the impact of paternal income on the offspring’s earnings increases across cohorts, whereas in the United States it is not possible to detect a statistically significant trend (Figure A.5 and Table A.37).

Finally, Table A.38 illustrates the transition probabilities computed for a 40-year-old individual. The matrix is computed using the methodology and the covariates described in Section 2.6.4. Similarly to the conclusions of the previous exercises, the exclusions of the outlying observations does not appear to affect the mobility patterns.

Table A.35: Intergenerational elasticity with and without education on the sample without outliers

	Germany		Italy		UK		US	
F ln(LI)	0.450***	[0.055]	0.506***	[0.049]	0.318***	[0.056]	0.460***	[0.055]
F LI(Age-40)	0.005	[0.005]	0.006*	[0.004]	-0.008**	[0.004]	-0.002	[0.005]
F LI(Age-40)^2	-0.004***	[0.001]						
F LI(Age-40)^3	0.000***	[0.000]						
F LI(F Age-40)	0.003	[0.005]			0.017***	[0.005]	0.005	[0.007]
With education dummies								
F ln(LI)	0.214***	[0.045]	0.308***	[0.040]	0.148***	[0.051]	0.238***	[0.054]
F LI(Age-40)	0.008*	[0.005]	0.005	[0.003]	-0.006	[0.004]	-0.002	[0.005]
F LI(Age-40)^2	-0.004***	[0.000]						
F LI(Age-40)^3	0.000***	[0.000]						
F LI(F Age-40)	-0.004	[0.004]			0.013***	[0.005]	0.008	[0.007]
Observations	20952		6801		12978		8232	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age, dummies for education

Table A.36: TS2SLS by Region

	Germany		Italy		UK		US	
F ln(LI) for Region1	0.391***	[0.073]	0.429***	[0.069]	0.289***	[0.093]	0.005	[0.243]
F ln(LI) for Region2	0.449***	[0.068]	0.372***	[0.064]	0.468***	[0.098]	0.404**	[0.157]
F ln(LI) for Region3	0.549***	[0.099]	0.341***	[0.078]	0.327**	[0.133]	0.381***	[0.126]
F ln(LI) for Region4	0.345***	[0.112]	0.493***	[0.076]	0.204	[0.131]	0.436***	[0.122]
F ln(LI) for Region5	0.438***	[0.074]	0.617***	[0.098]	0.275**	[0.121]	0.584***	[0.103]
F ln(LI) for Region6	0.495***	[0.071]			0.289*	[0.161]	0.445***	[0.148]
F ln(LI) for Region7	0.167	[0.141]			0.453***	[0.101]	0.457***	[0.128]
F ln(LI) for Region8	0.590	[0.396]			0.149	[0.118]	0.242	[0.154]
F ln(LI) for Region9	0.123	[0.165]			0.280***	[0.082]	0.372**	[0.155]
With dummies for education								
F ln(LI) for Region1	0.155**	[0.064]	0.208***	[0.063]	0.142	[0.092]	-0.140	[0.195]
F ln(LI) for Region2	0.210***	[0.058]	0.165***	[0.058]	0.260**	[0.107]	0.203	[0.153]
F ln(LI) for Region3	0.295***	[0.087]	0.135*	[0.071]	0.125	[0.120]	0.158	[0.115]
F ln(LI) for Region4	0.157	[0.097]	0.229***	[0.062]	-0.000	[0.124]	0.234**	[0.111]
F ln(LI) for Region5	0.162**	[0.064]	0.336***	[0.087]	0.114	[0.116]	0.360***	[0.095]
F ln(LI) for Region6	0.282***	[0.062]			0.092	[0.146]	0.181	[0.134]
F ln(LI) for Region7	-0.130	[0.147]			0.298***	[0.091]	0.174	[0.130]
F ln(LI) for Region8	0.362	[0.331]			0.002	[0.115]	0.108	[0.148]
F ln(LI) for Region9	-0.096	[0.148]			0.109	[0.073]	0.204	[0.136]
Observations	20952		6801		12978		8232	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age. Regions by country: Germany 1: Schleswig-Holstein, Hamburg, Niedersachsen and Bremen; 2: Nordrhein-Westfalen; 3: Hessen; 4: Rheinland-Pfalz,Saarland; 5: Baden-Wuerttemberg; 6: Bayern; 7: Berlin; 8: Brandenburg and Mecklenburg-Vorpommern; 9: Sachsen, Sachsen-Anhalt and Thueringen. Italy 1: North-West; 2: North-East; 3: Centre; 4: South; 5: Islands. UK 1: North; 2: Yorkshire and Humber; 3: East Midlands; 4: West Midlands; 5: East of England; 6: London; 7: South East; 8: South West; 9: Wales; 10: Scotland. US 1: New England; 2: Middle Atlantic; 3: East North Central; 4: West North Central; 5: South Atlantic; 6: East South Central; 7: West South Central; 8: Mountain; 9: Pacific.

Table A.37: The IGE across cohorts without the outliers

	Germany		Italy		UK		US	
ln(F LI)∗Cohort 1950	0.355***	[0.059]	0.471***	[0.048]	0.296***	[0.061]	0.477***	[0.057]
ln(F LI)∗Cohort 1951	0.355***	[0.058]	0.470***	[0.048]	0.305***	[0.060]	0.462***	[0.057]
ln(F LI)∗Cohort 1952	0.359***	[0.058]	0.469***	[0.048]	0.306***	[0.060]	0.474***	[0.058]
ln(F LI)∗Cohort 1953	0.376***	[0.058]	0.472***	[0.048]	0.298***	[0.060]	0.458***	[0.057]
ln(F LI)∗Cohort 1954	0.365***	[0.058]	0.476***	[0.048]	0.315***	[0.059]	0.459***	[0.057]
ln(F LI)∗Cohort 1955	0.397***	[0.058]	0.490***	[0.048]	0.314***	[0.059]	0.476***	[0.057]
ln(F LI)∗Cohort 1956	0.392***	[0.058]	0.488***	[0.048]	0.304***	[0.058]	0.462***	[0.057]
ln(F LI)∗Cohort 1957	0.395***	[0.057]	0.495***	[0.048]	0.304***	[0.058]	0.454***	[0.057]
ln(F LI)∗Cohort 1958	0.412***	[0.058]	0.500***	[0.048]	0.317***	[0.059]	0.474***	[0.057]
ln(F LI)∗Cohort 1959	0.416***	[0.057]	0.506***	[0.048]	0.326***	[0.058]	0.459***	[0.057]
ln(F LI)∗Cohort 1960	0.423***	[0.057]	0.503***	[0.048]	0.313***	[0.057]	0.465***	[0.057]
ln(F LI)∗Cohort 1961	0.436***	[0.057]	0.507***	[0.048]	0.321***	[0.058]	0.470***	[0.056]
ln(F LI)∗Cohort 1962	0.435***	[0.057]	0.518***	[0.048]	0.327***	[0.057]	0.461***	[0.059]
ln(F LI)∗Cohort 1963	0.436***	[0.056]	0.520***	[0.048]	0.320***	[0.057]	0.445***	[0.057]
ln(F LI)∗Cohort 1964	0.447***	[0.056]	0.517***	[0.048]	0.336***	[0.057]	0.464***	[0.057]
ln(F LI)∗Cohort 1965	0.460***	[0.056]	0.520***	[0.048]	0.337***	[0.057]	0.460***	[0.057]
ln(F LI)∗Cohort 1966	0.458***	[0.056]	0.522***	[0.048]	0.335***	[0.057]	0.464***	[0.057]
ln(F LI)∗Cohort 1967	0.459***	[0.056]	0.529***	[0.048]	0.337***	[0.056]	0.450***	[0.056]
ln(F LI)∗Cohort 1968	0.480***	[0.056]	0.538***	[0.048]	0.339***	[0.055]	0.456***	[0.056]
ln(F LI)∗Cohort 1969	0.479***	[0.055]	0.534***	[0.048]	0.344***	[0.056]	0.475***	[0.057]
ln(F LI)∗Cohort 1970	0.485***	[0.055]	0.543***	[0.048]	0.340***	[0.055]	0.480***	[0.056]
ln(F LI)∗Cohort 1971	0.499***	[0.055]	0.547***	[0.048]	0.346***	[0.055]	0.456***	[0.057]
ln(F LI)∗Cohort 1972	0.503***	[0.056]	0.553***	[0.049]	0.361***	[0.055]	0.456***	[0.056]
ln(F LI)∗Cohort 1973	0.511***	[0.055]	0.555***	[0.048]	0.364***	[0.055]	0.470***	[0.057]
ln(F LI)∗Cohort 1974	0.524***	[0.056]	0.566***	[0.048]	0.355***	[0.055]	0.458***	[0.058]
ln(F LI)∗Cohort 1975	0.510***	[0.056]	0.558***	[0.048]	0.352***	[0.055]	0.467***	[0.057]
ln(F LI)∗Cohort 1976	0.513***	[0.056]	0.563***	[0.050]	0.376***	[0.055]	0.492***	[0.058]
ln(F LI)∗Cohort 1977	0.527***	[0.057]	0.569***	[0.051]	0.381***	[0.055]	0.466***	[0.058]
ln(F LI)∗Cohort 1978	0.493***	[0.057]	0.572***	[0.048]	0.355***	[0.056]	0.479***	[0.060]
ln(F LI)∗Cohort 1979	0.522***	[0.060]						
ln(F LI)∗Cohort 1980	0.514***	[0.064]						
Observations	20952		6801		12978		8232	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

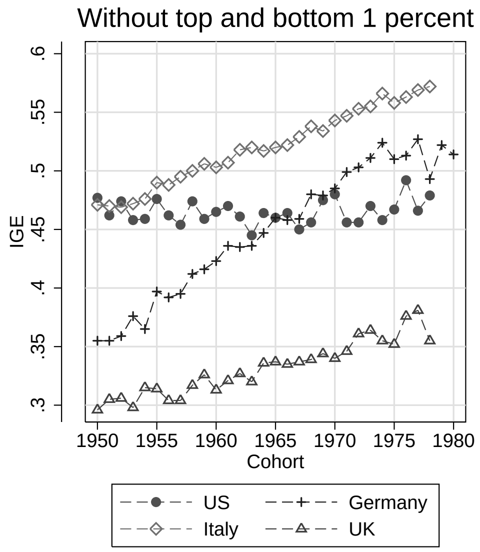

Figure A.5: IGE trend on a reduced sample

Table A.38: Quintile mobility matrices without the top and bottom 1 percent

	1st		2nd		3rd		4th		5th	
Germany										
1st	0.312***	(0.023)	0.267***	(0.018)	0.213***	(0.017)	0.154***	(0.017)	0.053***	(0.011)
2nd	0.310***	(0.012)	0.242***	(0.012)	0.213***	(0.012)	0.179***	(0.012)	0.056***	(0.010)
3rd	0.278***	(0.014)	0.213***	(0.012)	0.181***	(0.009)	0.179***	(0.009)	0.149***	(0.013)
4th	0.241***	(0.016)	0.208***	(0.012)	0.172***	(0.009)	0.194***	(0.011)	0.184***	(0.014)
5th	0.209***	(0.023)	0.191***	(0.015)	0.140***	(0.010)	0.183***	(0.010)	0.277***	(0.015)
Obs	20952									
Italy										
1st	0.476***	(0.026)	0.224***	(0.020)	0.169***	(0.016)	0.093***	(0.011)	0.038***	(0.008)
2nd	0.344***	(0.023)	0.281***	(0.020)	0.179***	(0.016)	0.112***	(0.012)	0.084***	(0.013)
3rd	0.295***	(0.020)	0.294***	(0.018)	0.198***	(0.015)	0.136***	(0.012)	0.078***	(0.010)
4th	0.206***	(0.018)	0.290***	(0.017)	0.204***	(0.015)	0.190***	(0.013)	0.111***	(0.012)
5th	0.151***	(0.019)	0.249***	(0.017)	0.217***	(0.014)	0.169***	(0.012)	0.213***	(0.015)
Obs	6801									
UK										
1st	0.261***	(0.028)	0.332***	(0.027)	0.187***	(0.022)	0.134***	(0.021)	0.087***	(0.022)
2nd	0.262***	(0.020)	0.262***	(0.017)	0.223***	(0.016)	0.167***	(0.016)	0.086***	(0.019)
3rd	0.250***	(0.022)	0.207***	(0.013)	0.196***	(0.012)	0.183***	(0.013)	0.163***	(0.018)
4th	0.185***	(0.021)	0.171***	(0.015)	0.211***	(0.012)	0.212***	(0.013)	0.221***	(0.018)
5th	0.193***	(0.028)	0.154***	(0.016)	0.174***	(0.014)	0.201***	(0.017)	0.278***	(0.025)
Obs	12978									
US										
1st	0.303***	(0.027)	0.296***	(0.024)	0.198***	(0.021)	0.115***	(0.018)	0.088***	(0.022)
2nd	0.238***	(0.026)	0.234***	(0.020)	0.227***	(0.018)	0.220***	(0.023)	0.081***	(0.015)
3rd	0.194***	(0.024)	0.207***	(0.017)	0.255***	(0.021)	0.211***	(0.021)	0.133***	(0.019)
4th	0.105***	(0.017)	0.156***	(0.018)	0.201***	(0.023)	0.263***	(0.020)	0.275***	(0.030)
5th	0.143***	(0.020)	0.107***	(0.015)	0.141***	(0.019)	0.227***	(0.019)	0.382***	(0.031)
Obs	8232									
Controls	Yes									

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Columns indicate quintiles of sons; rows of fathers. Bootstrap standard errors in parenthesis. Controls include F and own age, age squared, year of birth, interactions with age

Table A.39: Quintile mobility matrices for a university graduate

	1st		2nd		3rd		4th		5th	
Germany										
1st	0.184***	(0.019)	0.226***	(0.017)	0.184***	(0.021)	0.237***	(0.024)	0.169***	(0.030)
2nd	0.188***	(0.015)	0.207***	(0.013)	0.182***	(0.016)	0.264***	(0.020)	0.159***	(0.024)
3rd	0.183***	(0.016)	0.187***	(0.013)	0.157***	(0.012)	0.209***	(0.017)	0.264***	(0.022)
4th	0.175***	(0.018)	0.183***	(0.013)	0.157***	(0.012)	0.211***	(0.016)	0.274***	(0.020)
5th	0.171***	(0.021)	0.181***	(0.016)	0.150***	(0.012)	0.192***	(0.014)	0.306***	(0.019)
Obs	20952									
Italy										
1st	0.300***	(0.041)	0.234***	(0.030)	0.169***	(0.029)	0.178***	(0.025)	0.120***	(0.026)
2nd	0.222***	(0.033)	0.270***	(0.028)	0.162***	(0.025)	0.154***	(0.022)	0.191***	(0.026)
3rd	0.200***	(0.031)	0.272***	(0.027)	0.166***	(0.023)	0.191***	(0.021)	0.170***	(0.023)
4th	0.146***	(0.025)	0.260***	(0.024)	0.166***	(0.022)	0.229***	(0.021)	0.199***	(0.024)
5th	0.130***	(0.023)	0.238***	(0.022)	0.184***	(0.019)	0.177***	(0.017)	0.271***	(0.023)
Obs	6801									
UK										
1st	0.099***	(0.017)	0.178***	(0.027)	0.199***	(0.028)	0.191***	(0.037)	0.334***	(0.055)
2nd	0.110***	(0.018)	0.124***	(0.017)	0.204***	(0.023)	0.228***	(0.037)	0.334***	(0.054)
3rd	0.114***	(0.017)	0.096***	(0.014)	0.161***	(0.017)	0.187***	(0.025)	0.443***	(0.041)
4th	0.089***	(0.014)	0.078***	(0.013)	0.157***	(0.015)	0.186***	(0.024)	0.491***	(0.037)
5th	0.108***	(0.023)	0.072***	(0.015)	0.133***	(0.017)	0.162***	(0.027)	0.525***	(0.043)
Obs	12978									
US										
1st	0.153***	(0.028)	0.222***	(0.032)	0.244***	(0.033)	0.173***	(0.033)	0.209***	(0.046)
2nd	0.130***	(0.023)	0.164***	(0.023)	0.231***	(0.025)	0.296***	(0.034)	0.179***	(0.032)
3rd	0.110***	(0.022)	0.145***	(0.021)	0.250***	(0.027)	0.251***	(0.029)	0.244***	(0.037)
4th	0.066***	(0.015)	0.114***	(0.018)	0.187***	(0.026)	0.263***	(0.027)	0.370***	(0.038)
5th	0.117***	(0.020)	0.100***	(0.018)	0.160***	(0.022)	0.223***	(0.024)	0.400***	(0.037)
Obs	8232									
Controls	Yes									

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Columns indicate quintiles of sons; rows of fathers. Bootstrap standard errors in parenthesis. Controls include F and own age, age squared, year of birth, interactions with age

A.6.2 Self-employment

An additional robustness check consists in considering the role of self-employment. The sample includes all types of workers: employed, self-employed, full-time and part-time workers. The decision to include all these categories in the main analysis relates to the fact that the type of job might also be affected by the social origin. Thus, excluding for example part-time workers and self-employed might deprive the analysis of important characteristics. Nonetheless, in this section I explore how and whether these characteristics influence the results. Whereas data limitation on SHIW prevent from discriminating between full- and part-timers, it is possible to account for self-employment. For the purpose of this research, this concern is also the most relevant: it is of particular interest to control for the possibility that a direct channel of labour income transmission between the father and his offspring is through business inheritance, if the father is self-employed. If this happened often, the IGE might be overestimated. Additionally, labour income from self-employment might be more susceptible of measurement error. This might be the case of Italy where it is a common practice to under-report the income from self-employment to pay fewer taxes.

For the reasons mentioned above, this section performs the main analysis on a sub-sample of employed sons and fathers. Less than ten percent of the sons report a self-employed father in all datasets, whereas the percentage of self-employed sons ranges from eleven to twenty-four percent, according to the dataset.

The estimations reported in Table A.40, suggest that excluding self-employed individuals does not affect the IGE in most countries. The only change worth mentioning is in the UK, where the IGE increases from 0.32 to 0.38. The same patterns emerge after controlling for education. The IGE is also slightly higher in Italy and in the US, although the differences with Table 2.1 are not statistically significant.

Figure A.6 and Table A.42 illustrate that the IGE trend across cohorts when only employed individuals are considered is consistent with that uncovered on the whole sample (Figure 2.3). It is interesting to notice that for the earlier cohorts the IGE in Germany and in the UK are very similar to each other. The difference between these two countries starts to widen from the 1955 cohort. From the 1960 cohort the IGE in Germany catches up with the IGE in Italy and it appears to overtake it for the latest cohorts.

Table A.40: TS2SLS, OLS for employed respondents with employed fathers

	Germany		Italy		UK		US	
Only employed								
F ln(LI)	0.415***	[0.061]	0.501***	[0.068]	0.377***	[0.058]	0.515***	[0.060]
F LI(Age-40)	0.004	[0.007]	0.005	[0.004]	-0.003	[0.005]	0.005	[0.005]
F LI(Age-40)^2	-0.004***	[0.001]						
F LI(Age-40)^3	0.000***	[0.000]						
F LI(F Age-40)	0.008	[0.007]			0.010*	[0.006]	0.008	[0.008]
Observations	16127		5136		11354		7681	
With education								
F ln(LI)	0.177***	[0.049]	0.312***	[0.053]	0.185***	[0.054]	0.290***	[0.058]
F LI(Age-40)	0.009	[0.006]	0.003	[0.004]	0.000	[0.004]	0.005	[0.005]
F LI(Age-40)^2	-0.003***	[0.001]						
F LI(Age-40)^3	0.000***	[0.000]						
F LI(F Age-40)	-0.002	[0.006]			0.006	[0.005]	0.010	[0.007]
Observations	16127		5136		11354		7681	
Employed and self-employed								
F ln(LI)	0.432***	[0.060]	0.439***	[0.050]	0.356***	[0.060]	0.518***	[0.059]
F ln(LI)(Self)	-0.026	[0.097]	0.064	[0.071]	-0.065	[0.130]	-0.015	[0.159]
F ln(LI)(Age-40)Self	-0.000	[0.001]	0.001*	[0.000]	-0.001	[0.001]	-0.000	[0.001]
F's ln(LI)(F Age-40)Self	-0.001	[0.001]			-0.001	[0.001]	-0.000	[0.001]
F ln(LI)(F Self)	0.012	[0.087]	-0.033	[0.208]	-0.192	[0.137]	-0.677**	[0.301]
F's ln(LI)(Age-40)F Self	0.001**	[0.000]	-0.001	[0.001]	0.000	[0.001]	-0.000	[0.001]
F's ln(LI)(F Age-40)F Self	-0.001	[0.001]			0.001	[0.001]	-0.001	[0.003]
F LI(Age-40)	0.008	[0.006]	0.009**	[0.004]	0.002	[0.005]	0.004	[0.005]
F LI(Age-40)^2	-0.004***	[0.001]						
F LI(Age-40)^3	0.000***	[0.000]						
F LI(F Age-40)	0.002	[0.006]			0.015**	[0.006]	0.008	[0.009]
Observations	21645		6940		14782		8448	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

Table A.41: TS2SLS with self-employment, OLS

	Germany		Italy		UK		US	
F ln(LI) for Region1	0.376***	[0.079]	0.480***	[0.077]	0.344***	[0.096]	0.332	[0.248]
F ln(LI) for Region2	0.373***	[0.078]	0.376***	[0.075]	0.466***	[0.089]	0.451**	[0.176]
F ln(LI) for Region3	0.577***	[0.128]	0.357***	[0.084]	0.370***	[0.126]	0.481***	[0.152]
F ln(LI) for Region4	0.189	[0.156]	0.405***	[0.091]	0.347***	[0.133]	0.501***	[0.136]
F ln(LI) for Region5	0.447***	[0.090]	0.675***	[0.126]	0.467***	[0.131]	0.591***	[0.102]
F ln(LI) for Region6	0.436***	[0.079]			0.351**	[0.177]	0.538***	[0.190]
F ln(LI) for Region7	0.188	[0.159]			0.401***	[0.099]	0.412***	[0.144]
F ln(LI) for Region8	0.398	[0.737]			0.192	[0.117]	0.185	[0.168]
F ln(LI) for Region9	-0.019	[0.230]			0.306***	[0.086]	0.469***	[0.141]
Observations	16127		5136		11354		7681	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

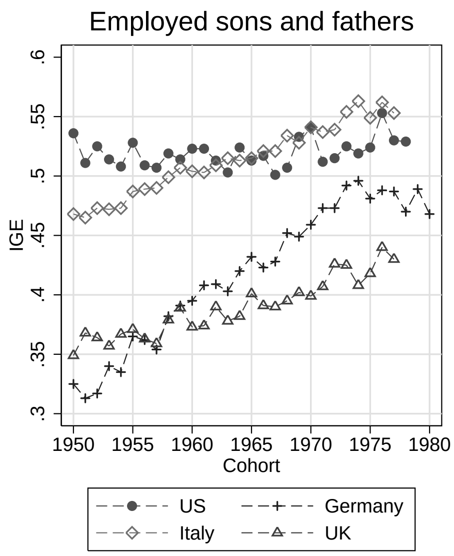

Figure A.6: IGE trend by cohort of employed individuals with employed fathers

Table A.42: The IGE across cohorts for employed sons and fathers

	Germany		Italy		UK		US	
ln(F LI)∗Cohort 1950	0.325^{***}	[0.065]	0.468^{***}	[0.069]	0.349^{***}	[0.063]	0.536^{***}	[0.062]
ln(F LI)∗Cohort 1951	0.313^{***}	[0.065]	0.465^{***}	[0.069]	0.368^{***}	[0.062]	0.511^{***}	[0.061]
ln(F LI)∗Cohort 1952	0.317^{***}	[0.064]	0.473^{***}	[0.069]	0.364^{***}	[0.063]	0.525^{***}	[0.062]
ln(F LI)∗Cohort 1953	0.340^{***}	[0.066]	0.472^{***}	[0.068]	0.357^{***}	[0.062]	0.514^{***}	[0.062]
ln(F LI)∗Cohort 1954	0.335^{***}	[0.066]	0.473^{***}	[0.069]	0.367^{***}	[0.061]	0.508^{***}	[0.062]
ln(F LI)∗Cohort 1955	0.365^{***}	[0.065]	0.487^{***}	[0.068]	0.371^{***}	[0.062]	0.528^{***}	[0.061]
ln(F LI)∗Cohort 1956	0.362^{***}	[0.065]	0.489^{***}	[0.069]	0.363^{***}	[0.061]	0.509^{***}	[0.063]
ln(F LI)∗Cohort 1957	0.354^{***}	[0.064]	0.490^{***}	[0.068]	0.359^{***}	[0.061]	0.507^{***}	[0.062]
ln(F LI)∗Cohort 1958	0.382^{***}	[0.064]	0.499^{***}	[0.069]	0.379^{***}	[0.060]	0.519^{***}	[0.061]
ln(F LI)∗Cohort 1959	0.391^{***}	[0.064]	0.507^{***}	[0.068]	0.389^{***}	[0.061]	0.514^{***}	[0.062]
ln(F LI)∗Cohort 1960	0.395^{***}	[0.063]	0.504^{***}	[0.068]	0.373^{***}	[0.060]	0.523^{***}	[0.061]
ln(F LI)∗Cohort 1961	0.408^{***}	[0.063]	0.503^{***}	[0.068]	0.374^{***}	[0.060]	0.523^{***}	[0.061]
ln(F LI)∗Cohort 1962	0.409^{***}	[0.064]	0.509^{***}	[0.069]	0.390^{***}	[0.059]	0.513^{***}	[0.063]
ln(F LI)∗Cohort 1963	0.403^{***}	[0.062]	0.515^{***}	[0.069]	0.378^{***}	[0.059]	0.503^{***}	[0.062]
ln(F LI)∗Cohort 1964	0.420^{***}	[0.063]	0.513^{***}	[0.068]	0.382^{***}	[0.059]	0.524^{***}	[0.062]
ln(F LI)∗Cohort 1965	0.432^{***}	[0.062]	0.515^{***}	[0.069]	0.401^{***}	[0.059]	0.513^{***}	[0.061]
ln(F LI)∗Cohort 1966	0.423^{***}	[0.062]	0.521^{***}	[0.068]	0.391^{***}	[0.059]	0.517^{***}	[0.062]
ln(F LI)∗Cohort 1967	0.428^{***}	[0.062]	0.521^{***}	[0.068]	0.390^{***}	[0.058]	0.501^{***}	[0.060]
ln(F LI)∗Cohort 1968	0.452^{***}	[0.062]	0.534^{***}	[0.068]	0.395^{***}	[0.058]	0.507^{***}	[0.060]
ln(F LI)∗Cohort 1969	0.449^{***}	[0.062]	0.528^{***}	[0.069]	0.402^{***}	[0.058]	0.533^{***}	[0.061]
ln(F LI)∗Cohort 1970	0.459^{***}	[0.061]	0.541^{***}	[0.068]	0.399^{***}	[0.057]	0.541^{***}	[0.061]
ln(F LI)∗Cohort 1971	0.473^{***}	[0.062]	0.537^{***}	[0.068]	0.407^{***}	[0.058]	0.512^{***}	[0.060]
ln(F LI)∗Cohort 1972	0.473^{***}	[0.062]	0.539^{***}	[0.070]	0.426^{***}	[0.058]	0.515^{***}	[0.060]
ln(F LI)∗Cohort 1973	0.492^{***}	[0.062]	0.554^{***}	[0.068]	0.425^{***}	[0.058]	0.525^{***}	[0.061]
ln(F LI)∗Cohort 1974	0.496^{***}	[0.062]	0.563^{***}	[0.068]	0.408^{***}	[0.057]	0.519^{***}	[0.063]
ln(F LI)∗Cohort 1975	0.481^{***}	[0.063]	0.549^{***}	[0.068]	0.418^{***}	[0.057]	0.524^{***}	[0.061]
ln(F LI)∗Cohort 1976	0.488^{***}	[0.063]	0.562^{***}	[0.069]	0.440^{***}	[0.058]	0.553^{***}	[0.061]
ln(F LI)∗Cohort 1977	0.487^{***}	[0.063]	0.553^{***}	[0.068]	0.430^{***}	[0.057]	0.530^{***}	[0.062]
ln(F LI)∗Cohort 1978	0.470^{***}	[0.066]					0.529^{***}	[0.063]
ln(F LI)∗Cohort 1979	0.489^{***}	[0.065]						
ln(F LI)∗Cohort 1980	0.468^{***}	[0.068]						
Observations	16127		5136		11354		7681	
Controls	Yes		Yes		Yes		Yes	

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father. LI for predicted labour income. Controls include F and own age, age squared, year of birth, interactions with age

The final step of this exercise consists in estimating the ordered logit transition matrices. The findings suggest that excluding self-employed does not affect the main conclusions. In fact, Table A.43 is very similar to the conclusions of the main analysis, in the appendix section A.4.

Table A.43: Generalised Ordered Logit Transition Matrices, for employed individuals with employed fathers

	1st		2nd		3rd		4th		5th	
Germany										
1st	0.291^{***}	(0.023)	0.250^{***}	(0.020)	0.242^{***}	(0.020)	0.161^{***}	(0.018)	0.056^{***}	(0.015)
2nd	0.307^{***}	(0.013)	0.218^{***}	(0.012)	0.216^{***}	(0.013)	0.186^{***}	(0.013)	0.074^{***}	(0.014)
3rd	0.278^{***}	(0.015)	0.208^{***}	(0.012)	0.173^{***}	(0.010)	0.179^{***}	(0.011)	0.161^{***}	(0.014)
4th	0.243^{***}	(0.019)	0.202^{***}	(0.014)	0.160^{***}	(0.010)	0.192^{***}	(0.012)	0.203^{***}	(0.016)
5th	0.210^{***}	(0.020)	0.192^{***}	(0.015)	0.135^{***}	(0.010)	0.194^{***}	(0.011)	0.270^{***}	(0.015)
Obs	16127									
Italy										
1st	0.494^{***}	(0.037)	0.197^{***}	(0.029)	0.184^{***}	(0.023)	0.097^{***}	(0.014)	0.029^{***}	(0.009)
2nd	0.405^{***}	(0.027)	0.259^{***}	(0.021)	0.190^{***}	(0.020)	0.095^{***}	(0.013)	0.051^{***}	(0.012)
3rd	0.322^{***}	(0.029)	0.287^{***}	(0.023)	0.182^{***}	(0.018)	0.135^{***}	(0.014)	0.074^{***}	(0.011)
4th	0.240^{***}	(0.024)	0.311^{***}	(0.020)	0.211^{***}	(0.017)	0.146^{***}	(0.012)	0.091^{***}	(0.011)
5th	0.153^{***}	(0.022)	0.261^{***}	(0.023)	0.233^{***}	(0.017)	0.153^{***}	(0.013)	0.200^{***}	(0.016)
Obs	5136									
United Kingdom										
1st	0.281^{***}	(0.031)	0.334^{***}	(0.030)	0.203^{***}	(0.025)	0.100^{***}	(0.021)	0.082^{**}	(0.032)
2nd	0.281^{***}	(0.025)	0.251^{***}	(0.018)	0.211^{***}	(0.019)	0.165^{***}	(0.017)	0.093^{***}	(0.022)
3rd	0.267^{***}	(0.026)	0.214^{***}	(0.015)	0.198^{***}	(0.013)	0.187^{***}	(0.015)	0.133^{***}	(0.017)
4th	0.150^{***}	(0.022)	0.164^{***}	(0.015)	0.212^{***}	(0.014)	0.226^{***}	(0.016)	0.248^{***}	(0.021)
5th	0.182^{***}	(0.035)	0.140^{***}	(0.020)	0.172^{***}	(0.021)	0.214^{***}	(0.021)	0.292^{***}	(0.033)
Obs	11354									
United States										
1st	0.287^{***}	(0.028)	0.309^{***}	(0.025)	0.194^{***}	(0.021)	0.115^{***}	(0.017)	0.096^{***}	(0.023)
2nd	0.265^{***}	(0.026)	0.236^{***}	(0.020)	0.228^{***}	(0.019)	0.205^{***}	(0.023)	0.066^{***}	(0.014)
3rd	0.180^{***}	(0.024)	0.193^{***}	(0.020)	0.267^{***}	(0.024)	0.233^{***}	(0.023)	0.128^{***}	(0.021)
4th	0.092^{***}	(0.015)	0.160^{***}	(0.018)	0.211^{***}	(0.022)	0.250^{***}	(0.021)	0.287^{***}	(0.030)
5th	0.136^{***}	(0.020)	0.094^{***}	(0.014)	0.137^{***}	(0.019)	0.223^{***}	(0.021)	0.410^{***}	(0.032)
Obs	7681									
Controls	Yes									

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ Columns indicate quintiles of sons; rows of fathers. Bootstrap standard errors in parenthesis. Controls include F and own age, age squared, year of birth, interactions with age

Appendix B

"Intergenerational mobility over the income distribution: the role of social networks"

B.1 Theory

B.1.1 Modelling π

This Appendix provides an interpretation of π based on the urn-ball model within the search and matching framework.[1] If jobs are found through own search and job contacts, the probability of finding a job of type l (where $l = H, M, L$) is composed of two terms:

$$\pi^l = \kappa^l + (1 - \kappa^l)\rho^l \tag{B.1}$$

where κ^l is the probability of finding a job with formal (or own) search and includes all activities that can be performed through formal channels, such as applying to vacancies through the internet or through job centres. ρ^l is the probability of finding a job through job contacts. Notice that for simplification I omit the index l for the remaining of the appendix.

[1] As explained by the review article of Petrongolo and Pissarides (2001) the urn-ball framework constitutes the micro-foundations of the macroeconomic matching function. In its simplest version, unemployed workers (the balls) know the location of the vacancies (the firms being the urns). Some examples of theoretical articles that model the role of job informational networks for job search are Cahuc and Fontaine (2009), Calvó-Armengol and Zenou (2005), and Calvó-Armengol and Jackson (2007).

I assume that individuals differ from each other only in terms of education and that each type of job requires a given education level. If individuals only apply to the vacancies (V) matching their education level, each vacancy receives applications from similar candidates. Consequently, firms select the first applicant. Additionally, for each job type, vacancies are homogeneous. Therefore, unemployed workers are happy with any suitable job offer. As timing is fundamental in this setting, people will only apply to the first relevant vacancy they are aware of. They becomes aware of a vacancy through own search or because they are informed by an employed contact. For a given job type, the probability of finding a job through formal search, κ:

$$\kappa = 1 - \left(1 - \frac{1}{U}\right)^{V} \approx 1 - e^{-\frac{V}{U}} \tag{B.2}$$

where U is the number of unemployed workers of a given type, $\frac{1}{U}$ is the probability of being the first to apply to a given vacancy, and $\left(1 - \frac{1}{U}\right)^{V}$ is the probability of not being the first to apply to any vacancy.[2]

If a vacancy first reaches an employed worker, they transmit the information to an unemployed contact. I assume that the information is passed instantaneously. Consequently, the applicant will be the first to apply if the friend who helped him/her with the vacancy was the first to know about it. Also, only the employed connections of type l can help in the search of type-l jobs. This is because an employee of a given type will hear sooner about a vacancy of that type than another employee. For each type, the probability of getting a job through a friend is composed of the probability that one's

[2] If L is large enough, a good approximation is $e^{-V/L}$.

relevant job contacts (s_{it}) are the first to know about a vacancy (c) and that they decide to pass her that information (which depends on d):

$$\rho = \sum_{d=1}^{(1-u)s_{it}} c^d \tag{B.3}$$

where u is the unemployment rate and $(1-u)s_{it}$ is the fraction of relevant employed contacts. Particularly, c is the probability that an employed individual is the first to know about a vacancy and $0 < c < 1$. c is constructed in the same way as κ:

$$c = 1 - (1 - \frac{1}{L})^V \approx 1 - e^{-\frac{V}{L}} \tag{B.4}$$

where L is the total labour force (employed and unemployed workers). c^d is the probability of being the first to receive an information about a vacancy from an employed contact, where $1 \leq d \leq (1-u)s_{it}$. The probability is weighted by the position (d) that the connection occupies in i's network. The closer the friend, the lower d and the higher the probability. For example, $d = 1$ for the best friend.

As ρ is a sum of geometric series and $0 < c < 1$, it is possible to further simplify it:

$$\rho = \frac{c\left(1 - c^{(1-u)s_{it}}\right)}{1-c} \tag{B.5}$$

The partial derivatives of π with respect to s_{it}:

$$\pi_s : \frac{c^{1+a}(1-\kappa)(1-u)\ln c}{c-1} \tag{B.6}$$

$$\pi_{ss}: \frac{c^{1+a}(1-\kappa)(1-u)^2 \ln c^2}{c-1} \tag{B.7}$$

where $a = (1-u)s_{it}$. Eq. B.6 and B.7 refer to the change in π when the parental investments in the number of friends of a given type (s_{it}) increase by one unit. The probability increases with s_{it}, at an increasing rate. In fact, $\pi_s > 0$ and $\pi_{ss} > 0$. In fact, both the numerator and the denominator of the two equations are negative.

B.1.2 Optimal education

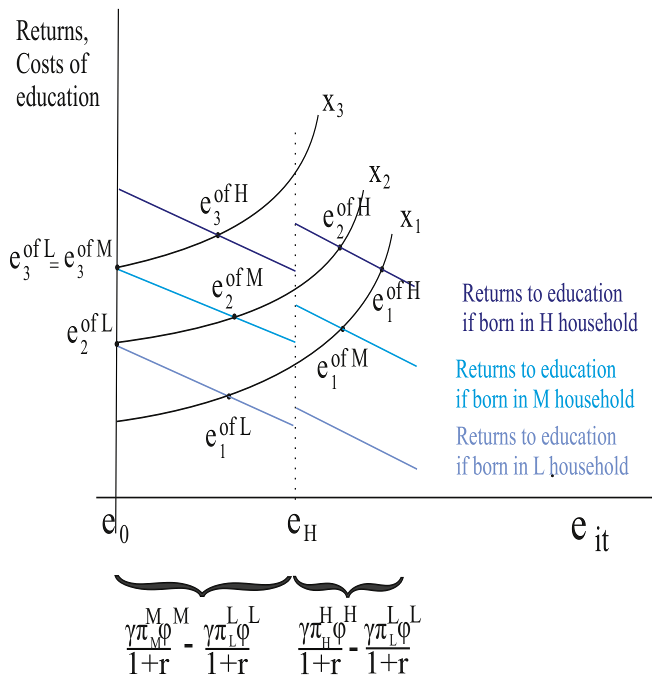

Figure B.1: Investments in education by type of parent

Figure B.1 shows the possible education choices of H, M and L households with three different cost locuses (x_1, x_2 and x_3). With a cost function equal to x_1, the offspring of unskilled parents would get some education, whereas individuals born in H and M household would be highly educated. However, if the locus shifted to the left

(x_2), unskilled parents would not invest in skilled education and medium-skilled parents would only invest in some education. Finally, with a further increase (x_3), only the offspring of highly skilled parents would get some education.[3]

B.1.3 Deriving the IGE

This Appendix provides the details on the derivation of the intergenerational elasticities of Section 3.2.4. It should be mentioned that the following exercise is based on a series of simplifications and assumptions, partly based on Solon (2004).

Assuming the following utility function (eq. B.8):

$$U(z_{it}, y_{it+1}) = \ln z_{it} + \frac{\alpha}{1+r} E\left[\ln w_{it+1}\right] \tag{B.8}$$

subject to:

$$z_{it} + e_{it}\left(X - g_{it}\right) + I_{it} = w_{it} + R_t s_{it} \tag{B.9}$$

where $(X - g_{it})\, e_{it}$ are the total private investments in education. X is the unit cost of education and g_{it} is the public contribution.

Like in Solon (2004), the wage function is a semi-logs earning function, where the logarithm underlines the decreasing returns to education:

$$\ln w_{it+1} = \mu + \gamma\chi\left(\ln e_{it} + B_{it+1}\right) \tag{B.10}$$

An educational level equal to the compulsory one implies no private investments and a wage at the bottom end of the wage distribution, whereas a job requiring an

[3]For example, the locus could shift with a lower level of ability or of public spending (g_{it}).

educational level higher than e_H is associated with a top wage. Any education between these two thresholds is for jobs in the middle of the income distribution. As explained in the main analysis, parents cannot predict with certainty their offspring's future labour income.[4] The expected wage is:

$$E\left[\ln w_{it+1}\right] = \mu + \gamma\chi\left[\pi^{l}\ln e_{it} + B_{it+1}\right] \tag{B.11}$$

$$\text{where} \begin{cases} w_{it+1} \leq w_0 \text{ and } l = L & \text{if } e_{it} = e_0 \\ w_0 < w_{it+1} < w_H \text{ and } l = M & \text{if } e_0 < e_{it} < e_H \\ w_{it+1} \geq w_H \text{ and } l = H & \text{if } e_{it} \geq e_H \end{cases}$$

π^l is the likelihood that the offspring have a job matching their education for their whole working life[5]. Its structure does not change across education or workers' types, even though the contribution of some of its components may differ. Therefore, to make things simpler I drop the index l and I consider a household, of an unspecified type, investing in any level of education. Throughout the analysis, I highlight the differences in the probability when a specific job type is considered.

In general, π has two components.[6]

$$\pi = \kappa\left(u,v\right) + \left(1-\kappa\right)\sum_{d=1}^{(1-u)s_{it}} c^{d} \tag{B.12}$$

The first, $\kappa\left(u,v\right)$, is the likelihood of finding a suitable job through formal search channels. For a given job type, κ depends on the specific labour market conditions.

[4] Refer to Section 3.2.2 for further details.

[5] Appendix B.1.1 provides an interpretation of π based on the search and matching framework.

[6] Refer to section B.1.1 for an interpretation in terms of an urn-balls matching function.

Specifically, it is a negative function of the unemployment rate, u, and it positively depends on the vacancy rate, v.

The second component accounts for the role of job contacts. It is bounded between 0 and 1. The likelihood of having a job of a given type depends on the number of employed job contacts of that type, $(1-u)s_{it}$. It is also a function of the effectiveness of connections in a given economy for a given skill-level. In other words, it depends on the probability that a friend can help with the job search (c). As mentioned in Section 3.2.2, ceteris paribus, one may prefer to help a closer friend. Therefore, c is weighted by the position (d) that a given friend occupies in the network. The weaker the relationship (i.e. the higher the position) the lower c^d.

The intergenerational elasticity β (that is the coefficient in the regression $\ln w_{it+1} = \alpha + \beta \ln w_{it} + v_{it}$) is computed by deriving and substituting the optimal amount of education into the wage equation (eq. B.10).

B.1.3.1 IGE with perfect credit markets: Cases 1 and 2

With perfect credit markets, the optimal amount of education is the following:

$$e_{it} = \frac{\pi\gamma\chi}{(1+r)(X-g_{it})} \tag{B.13}$$

I substitute eq. B.13 in eq. B.10 to obtain:

$$\ln w_{it+1} = \mu + \gamma\chi \ln \frac{\pi\gamma\chi}{(1+r)(X-g_{it})} + \gamma\chi B_{it+1} \tag{B.14}$$

After simplification, this equation is:

$$\ln w_{it+1} = \mu + \gamma\chi \ln \pi\gamma\chi - \gamma\chi \ln(1+r) - \gamma\chi \ln X \left(1 - \frac{g_{it}}{X}\right) + \gamma\chi B_{it+1} \tag{B.15}$$

where $\frac{g_{it}}{X}$ is the share of public contribution relative to the costs. If we assume a society where skilled education is mainly financed privately, following Solon (2004), $\ln\left(1 - \frac{g_{it}}{X}\right) \approx -\frac{g_{it}}{X}$. We also consider that public investments in education are progressive, that $\frac{g_{it}}{X}$ is a positive function of the cost and is negatively associated to the wage. Like in Solon (2004), $\frac{g_{it}}{X}$ is approximated to $X - \eta \ln w_{it}$. After further rearranging, eq. B.15 becomes:

$$\begin{aligned} \ln w_{it+1} &\approx m + \gamma\chi \ln \pi - \gamma\chi\eta \ln w_{it} + \gamma\chi B_{it+1} \qquad \text{(B.16)} \\ \text{where } m &= \mu + \gamma\chi \ln \gamma\chi - \gamma\chi \ln(1+r) - \gamma\chi \ln X + \gamma\chi X \end{aligned}$$

I derive the intergenerational elasticity by simplifying and further rearranging eq. B.16, after substituting for π. For simplicity, I consider two extreme cases.

Case 1: Own search Within this framework, $c = 0$ and $\pi = \kappa$. In this context, eq. B.16 becomes:

$$\ln w_{it+1} = m + \gamma\chi \ln \kappa - \gamma\chi\eta \ln w_{it} + \gamma\chi B_{it+1} \tag{B.17}$$

Further simplification results in:

$$\begin{aligned} \ln w_{it+1} &= m_1 - \gamma\chi\eta \ln w_{it} + \gamma\chi B_{it+1} \\ \text{where } m_1 &= m + \gamma\chi \ln \kappa \end{aligned} \tag{B.18}$$

Solon (2004) explains that B_{it+1} is correlated with $\ln w_{it}$ through the parental endowments B_{it-1}. The author considers eq. B.18 as a first-order autoregression of $\ln w_{it+1}$ with a serially correlated error term ($\gamma\chi B_{it+1}$, from eq. 3.5). Considering that in the steady state $\ln w_{it+1}$ and $\ln w_{it}$ have equal variances, the slope of a regression of the former on the latter and the correlation coefficient are the same. Specifically, the intergenerational coefficient is derived as the sum of the two autoregressive parameters ($\gamma\chi\eta$ in eq. B.18 and $\gamma\chi h$ from eqs. B.18 and 3.5), divided by 1 plus their product. Therefore, the steady state IGE is β_1:

$$\beta_1 = \frac{\gamma\chi\,(h-\eta)}{1-\gamma^2\chi^2\eta h} \tag{B.19}$$

If job search only occurs through formal methods and families are not constrained, the only effect of parents on the offspring's labour income is through inherited characteristics. In particular, the extent of the parental influence depends on their degree of transmissibility (h). Moreover, β_1 decreases with the progressivity of the public investment in education (η) and it could be negative if $h < \eta$. The intuition is that with no credit constraints, the completed level of education does not depend on the parental income. If the returns to education, $\gamma\chi$, increase, the impact of an extra year of education on the potential earnings is higher. This may amplify the difference between the offspring's and the parental income (upwards or downwards). In fact, the family plays no role in the child's future income, except through transmitted ability and social values. Therefore, with perfect credit markets higher returns to education can promote equality of opportunities and reduce intergenerational inequality. In the extreme case, where $h = \eta$, the mobility across generations is perfect.

Case 2: Job search through the social network Case 2 examines the implications on the IGE when search occurs only through job contacts. When $\kappa = 0$, eq. B.16 becomes:

$$\ln w_{it+1} = m + \gamma\chi \ln \frac{c\left(1 - c^{(1-u)s_{it}}\right)}{1-c} - \gamma\chi\eta \ln w_{it} + \gamma\chi B_{it+1} \tag{B.20}$$

If $c^{(1-u)s_{it}}$ is small enough, $\ln\left(1 - c^{(1-u)s_{it}}\right) \approx -c^{(1-u)s_{it}}$. After further simplification:

$$\ln w_{it+1} \approx m + \gamma\chi \ln \frac{c}{1-c} - \gamma\chi c^{(1-u)s_{it}} - \gamma\chi\eta \ln w_{it} + \gamma\chi B_{it+1} \tag{B.21}$$

Figure 3.1 in Section 3.2 suggests that, ceteris paribus, the agent of a given type invests more in friends of the same type. It also indicates that there are differences across households and acrosss friends' types. Assume it is possible to express the number of relevant friends as a function of the wage, $\Omega(l, s^l) \ln w_{it}$. $\Omega(.)$ lies between zero and one and can be considered as the technology that relates the type of friend to the type of household. The higher the correlation between one's earnings and the type of friends one has, the higher $\Omega(.)$. The strength of the relationship depends on both the parent's and the relevant friend's types. For example, highly skilled households are very likely to have many highly skilled friends, whereas it is very unlikely they have many unskilled contacts. The same (reverse) scenario applies to low-skilled households. Instead, medium-skilled households have a more diversified network. Therefore, ceteris paribus, medium-skilled parents have a lower $\Omega(l)$. Medium-skilled friends are more common in all households. Consequently, $\Omega(s^l)$ is lower when the relevant friends are the medium-skilled contacts. This is the case for parents who invest in some non-compulsory education and for whom the offspring's success implies a stable medium-skilled job. These parents in fact will consider π^M, where the relevant contacts are medium-skilled.

Eq. B.21 suggests that the higher s_{it}, the lower $c^{(1-u)s_{it}}$. Specifically, that amount increases with the unemployment rate (u) and the effectiveness of each connection in helping with the job search (c), whereas it decreases with the number of relevant contacts. Assume that it is possible to approximate this expression with $-\theta(u,c)\Omega(.)\ln w_{it}$, where $\theta(u,c)$ increases with the unemployment rate and with the role that each connection plays in the job search. This would transform eq. B.21 into:

$$\ln w_{it+1} \approx m + \gamma\chi \ln \frac{c}{1-c} + \gamma\chi\theta(.)\Omega(.)\ln w_{it} - \gamma\chi\eta \ln w_{it} + \gamma\chi B_{it+1} \tag{B.22}$$

Further simplification results in:

$$\begin{aligned} \ln w_{it+1} &\approx m_2 + \gamma\chi\theta(.)\Omega(.)\ln w_{it} - \gamma\chi\eta \ln w_{it} + \gamma\chi B_{it+1} \qquad \text{(B.23)} \\ \text{where } m_2 &= m + \gamma\chi \ln \frac{c}{1-c} \end{aligned}$$

Following the same reasoning as for Case 1, the IGE coefficient β_2 is :

$$\beta_2 \approx \frac{\gamma\chi\,(h+\theta\,(.)\,\Omega(.)-\eta)}{1+\gamma^2\chi^2(\theta\,(.)\,\Omega(.)-\eta)h} \tag{B.24}$$

Similarly to β_1, β_2 is increasing in h and decreasing in η. The IGE increases in the effectiveness of the network, $\theta\,(.)$, and in the technology that relates the type of friend to the type of household, $\Omega(.)$. Both lie between zero and one. $\theta\,(u,c)$ is a positive function of the unemployment rate and of the role that each connection plays in the job search (c). The intuition is that the more effective the contact, the higher the parental influence (through their network). With a higher unemployment rate, competition for jobs is higher and parental income (through its association with the parental network) can play a greater role in determining one's income. $\Omega(l,s^l)$ increase with the correlation between one's earnings and the type of friends one chooses. Notice that if $\Omega(.)$ is zero, β_2 equals β_1. Instead, if $\Omega(.)$ is positive, β_2 is larger than β_1. Implication 2 in the previous section suggests that the strength of this association depends on one's own type (l) and on the relevant friends' type (s^l). Ceteris paribus, medium-skilled parents have a lower $\Omega(l)$ because their network is more diversified.$\Omega(s^l)$ is also lower for the offspring with medium-skilled jobs.[7]

Case 3: extension of Case 2 This paragraph considers the possible implications on the IGE with perfect credit markets and search through job contacts, if the offspring's own network is included. Assume the following scenario: the parental friends live for

[7]Medium-skilled friends are more common in all households. Consequently, $\Omega(s^l)$ is lower when the relevant friends are the medium-skilled contacts. This is the case for the likelihood of having a medium-skilled job (π^M).

one additional period, $t+1$. At $t+1$, offspring work and, among other things, invest in new contacts. At the end of $t+1$, they search for a new job. The new friends met at $t+1$ and the parental friends made at t are useful job contacts[8]. π becomes:

$$\pi = \kappa + (1-\kappa)\left[\frac{c\left(1-c^{(1-u)(s_{it+1}+s_{it})}\right)}{1-c}\right] \tag{B.25}$$

where $s_{it+1}+s_{it}$ is the total number of relevant contacts at the end of $t+1$.

It is easy to show that the IGE in the case of no job referrals would be the same as in Case 1 (eq. B.19).

Without formal search, $\kappa = 0$, and after substituting eq. B.25 into eq. B.21:

$$\ln w_{it+1} \approx m + \gamma\chi \ln\frac{c}{1-c} - \gamma\chi c^{(1-u)(s_{it+1}+s_{it})} - \gamma\chi\eta \ln w_{it} + \gamma\chi B_{it+1} \tag{B.26}$$

Following the same reasoning for Case 2, assume that this term can be approximated to:

$$c^{(1-u)(s_{it+1}+s_{it})} \approx -\theta(.)\left[\Omega(.)\ln w_{it} + \Omega_1(.)\ln w_{it+1}\right] \tag{B.27}$$

where $\theta(.)$ and $\Omega(.)$ are the same as in Case 2. $\Omega_1(.)$ is the technology that relates the type of friend to the offspring's type. $\Omega_1(.)$ lies between zero and one. The model in Section 3.2 suggests that the optimal amount of investment in contacts of a given type is negatively correlated to the stock of contacts of that type (through the marginal

[8]An alternative way to consider this case is to consider that after working in $t+1$, children decide/have to change jobs. Therefore, in $t+2$ they find a new job by using the new contacts formed in $t+1$. The shortcoming of this approach is that it augments the present value of the lifetime wealth of the household by an additional period, $t+2$. Additionally, when calculating the IGE, both w_{it+1} and w_{it+2} have to be considered.

costs). Therefore, $\Omega_1(.)$ is negatively affected by the reactiveness of the marginal costs for a type of friend to the stock of friends of that type. I substitute for eq. B.27 into eq. B.26 and isolate $\ln w_{it+1}$ on the left-hand side. The rearranged version of the intergenerational equation is the following:

$$\ln w_{it+1} \approx m_3 + \frac{\gamma\chi\left[\theta(.)\Omega(.)-\eta\right]}{1-\gamma\chi\theta(.)\Omega_1(.)}\ln w_{it} + \frac{\gamma\chi}{1-\gamma\chi\theta(.)\Omega_1(.)}B_{it+1} \tag{B.28}$$
$$\text{where } m_3 = \frac{m_2}{1-\gamma\chi\theta(.)\Omega_1(.)}$$

After further simplification, the IGE is:

$$\beta_3 \approx \frac{\gamma\chi\left(h+\theta(.)\Omega(.)-\eta\right)\left[1-\gamma\chi\theta(.)\Omega_1(.)\right]}{\left[1-\gamma\chi\theta(.)\Omega_1(.)\right]^2+\gamma^2\chi^2 h\left[\theta(.)\Omega(.)-\eta\right]} \tag{B.29}$$

The elasticity is higher than β_2 if the decrease in the denominator is larger than the decrease in the numerator. It is not possible to establish a priori if this is the case. Consider the case that individuals at the beginning of $t+1$ find the same type of job as their parents. Their wage at $t+1$ is the same as their parent's wage at t. We assume that eq. B.27 can be modified as follows:

$$c^{(1-u)(s_{it+1}+s_{it})} \approx -\theta(.)\left[\Omega(.)+\Omega_1(.)\right]\ln w_{it} \tag{B.30}$$

the wage-generating equation becomes:

$$\ln w_{it+1} \approx m_2 + \gamma\chi\left[\theta(.)\left[\Omega(.)+\Omega_1(.)\right]-\eta\right]\ln w_{it} + \gamma\chi B_{it+1} \tag{B.31}$$

where m_2 is the intercept in Case 2. And the IGE is:

$$\beta_{31} \approx \frac{\gamma\chi\left[h+\theta\left(.\right)\left[\Omega(.)+\Omega_1(.)\right]-\eta\right]}{1+\gamma^2\chi^2\left[\theta\left(.\right)\left[\Omega(.)+\Omega_1(.)\right]-\eta\right]h} \tag{B.32}$$

In this case, the IGE is clearly larger than β_2. The intuition is that if the friends that the offspring meet at $t+1$ are similar to the parental connections, the former would just reinforce the role of the latter.

B.1.3.2 IGE with imperfect credit markets: Case 4 and Case 5

With imperfect credit markets, households simultaneously make consumption and investment decisions in order to maximise their utility. The optimal amount of education (resulting from solving the optimization problem in eq. B.8 subject to the budget constraint in eq, B.9) does not only depend on the costs and returns from education. Although there is no explicit solution for the optimal education, eq. B.33 indicates that the investment in the offspring's human capital is also positively correlated to the degree of altruism and to the available income, which is the wage plus the net returns from the optimal investment in friends. It decreases with the interest rate and with the cost of education.

$$e_{it} = \frac{\alpha\gamma\chi\pi\left[w_{it}+R_t s^*_{it}-I^*_{it}\right]}{\left(X-g_{it}\right)\left[1+r+\alpha\gamma\chi\pi\right]} \tag{B.33}$$

In order to proceed, we need simplify eq. B.33. It can be shown that the optimal amount of friends positively depends on the available income and on the net benefits from the investment. Assume that it is possible to rewrite $w_{it}+R_t s^*_{it}-I^*_{it}$ as $\left(1-N\right)w_{it}$, where $0 < N < 1$. The term indicates the available income after investing in friendship.[9] I also assume that I can rewrite $\frac{\alpha\gamma\chi\pi}{1+r+\alpha\gamma\chi\pi}$ as $\varepsilon\alpha\gamma\chi\pi$, where $0 < \varepsilon < 1$ and it decreases with the interest rate r.[10]

Like in the previous section, I substitute the optimal education into the wage equation to obtain:

$$\ln w_{it+1} \approx \mu + \gamma\chi \ln \frac{\varepsilon\alpha\gamma\chi\pi\,(1-N)\,w_{it}}{X - g_{it}} + \gamma\chi B_{it+1} \tag{B.34}$$

and:

$$\ln w_{it+1} \approx \mu + \gamma\chi \ln \varepsilon\alpha\gamma\chi\pi + \gamma\chi \ln (1-N)\, w_{it} - \gamma\chi \ln X \left(1 - \frac{g_{it}}{X}\right) + \gamma\chi B_{it+1} \tag{B.35}$$

where $\frac{g_{it}}{X}$ is the share of public contribution relative to the costs. Following the reasoning on public funding applied for Case 1 and Case 2, and after substituting and rearranging, the above equation becomes:

$$\begin{aligned} \ln w_{it+1} &\approx m^* + \gamma\chi\,(1-\eta)\ln w_{it} + \gamma\chi \ln \pi + \gamma\chi B_{it+1} \qquad \text{(B.36)} \\ \text{where } m^* &= \mu + \gamma\chi \ln \varepsilon\alpha\gamma\chi + \gamma\chi \ln (1-N) - \gamma\chi \ln X + \gamma\chi X \end{aligned}$$

Now I consider the two extreme cases.

[9] Education and friendship investments should be determined simultaneously. We consider that N indicates the optimal net investment in friendship. This simplification should not affect the results we are intereseted in, as we don't need the exact s^*_{it}.

[10] This is another simplification needed in order to proceed with the estimation of the elasticity. The intuition is that $\frac{\alpha\gamma\chi\pi}{1+r+\alpha\gamma\chi\pi}$ is smaller than 1. Consequently, the exact amount is an increasing function of $\alpha\gamma\chi\pi$ and a decreasing function of r. This explains the chosen approximation.

Case 4: Own search Firstly, and similarly to Case 1, Case 4 derives the IGE when job search only occurs through formal channels. The probability π is equal to κ and eq. B.36 simplifies to:

$$\begin{aligned} \ln w_{it+1} &\approx m_4 + \gamma\chi\,(1-\eta)\ln w_{it} + \gamma\chi B_{it+1} \qquad \text{(B.37)} \\ \text{where } m_4 &= m^* + \gamma\chi \ln\kappa \end{aligned}$$

It is easy to show that with credit constraints and no search through networks, the IGE is:

$$\beta_4 \approx \frac{\gamma\chi(h+1-\eta)}{1+\gamma^2\chi^2(1-\eta)h} \qquad \text{(B.38)}$$

The intergenerational elasticity β_4 increases with the degree of inheritability of the endowments (h), with the returns to human capital ($\gamma\chi$) and it decreases with the progressivity of public investment (η). β_4 is larger than β_1, with perfect credit markets and no search through job contacts.[11] This is very similar to the elasticity in Solon (2004).

Case 5: Job contacts Secondly, I consider the case where the individuals search for a job with the help of their friends. Under these circumstances, $\ln\pi = \ln\frac{c}{1-c}\left(1-c^{(1-u)s_{it}}\right)$. I follow the same reasoning as in Case 2 to simplify this term. Like before, I argue that a good approximation of $\ln\left(1-c^{(1-u)s_{it}}\right)$ is $\theta\,(.)\,\Omega(.)\ln w_{it}$. Therefore, eq. B.36 can be simplified as:

[11] In fact the numerator in β_4 increases by a larger amount ($\gamma\chi$) than the denominator (augmented by $\gamma^2\chi^2$).

$$\begin{aligned} \ln w_{it+1} &\approx m_5 + \gamma\chi\,(1-\eta)\ln w_{it} + \gamma\chi\theta\,(.)\,\Omega(.)\ln w_{it} + \gamma\chi B_{it+1} \quad \text{(B.39)} \\ \text{where } m_5 &= m^* + \gamma\chi \ln\frac{c}{1-c} \end{aligned}$$

This implies that the IGE, β_5 is:

$$\beta_5 \approx \frac{\gamma\chi(h+1-\eta+\theta\,(.)\,\Omega(.))}{1+\gamma^2\chi^2(1-\eta+\theta\,(.)\,\Omega(.))h} \quad \text{(B.40)}$$

β_5 increases with h, $\gamma\chi$, $\Omega(.)$ and θ and decreases with η. Ceteris paribus, β_5 is larger than β_2 (where networks are used to find a job but families are not financially constrained). β_5 is also larger than β_4. Notice that the parameter due to credit constraints (1) is larger than that associated with genetics (h) or social networks ($\theta\,(.)\,\Omega(.)$).

B.1.3.3 Case 6: Perfect credit markets, social networks and no uncertainty

This paragraph computes β in a framework where there is no uncertainty about the future wage. This section investigates the consequences on the IGE in a society where the families are not credit-constrained and the economic environment allows a perfect match between the acquired qualification and the job. For example, this might be the case for a society without unemployment or overeducation.

With $\pi = 1$, the optimal investment in skilled education would satisfy the following condition:

$$\frac{\gamma\chi}{(1+r)\,(X-g_{it})} = e_{it} \quad \text{(B.41)}$$

By substituting eq. B.41 in the wage-generating equation and after applying the same approximation for public funding as for Cases 1, 2, 3 and 4:

$$\ln w_{it+1} \approx \mu + \gamma\chi e_{t0} + \gamma\chi \ln \gamma\chi - \gamma\chi \ln(1+r) - \gamma\chi \ln X + \gamma\chi (X - \eta \ln w_{it}) + \gamma\chi B_{it+1} \tag{B.42}$$

Therefore, the equation simplifies to:

$$\ln w_{it+1} \approx m - \gamma\chi\eta \ln w_{it} + \gamma\chi B_{it+1} \tag{B.43}$$

where m is the same as in eq. B.16.

The intergenerational elasticity with perfect capital markets, no uncertainty and social networks:

$$\beta_6 = \frac{\gamma\chi(h-\eta)}{1-\gamma^2\chi^2\eta h} \tag{B.44}$$

which is the same as the IGE of Case 1, with uncertainty but no job contacts (β_1). Therefore, in a society with perfect credit markets, and with a perfect match between job and education level, parents only affect the offspring's future income through the inherited ability. Therefore, the IGE is the same as in Case 1, where search occurs only through formal channels.

Case 6 could be considered the extension of Becker and Tomes (1979, 1986) and Solon (2004). Indeed, Solon (2004) uses this framework to compute the IGE for a society with imperfect financial markets.

B.2 Derivation of the main variable

The main variable is derived from the information provided by BHPS on the occupation and the mean earnings by occupation in NES-ASHE. Occupations in BHPS are coded in terms of two Standard Occupational Classifications (SOCs): the 1990 and 2000 SOC. The 1990 occupational codes are available for the majority of observations, but not for all. For most respondents the information is available in terms of 1990 SOC for all the waves, whereas for friends the 1990 SOC is available only until 2004.

There is no perfect correspondence between the two. Out of 353 codes in the 2000 SOC, only 96 are perfectly matched to the corresponding SOC90 code. Therefore, a cross-walk from 2000 SOC to 1990 SOC could only be created by using some arbitrary criteria (for example, by selecting the median 1990 occupational code for each 2000 SOC unit). Additionally, this might also reduce the variability.[12] It is not possible to exclude the observations for which an exact correspondence is missing either, because of the selection bias.

The adopted solution consists in using the earnings predicted using the 1990 occupational codes until 2001, and in relying on the income computed by 2000 SOC from 2002. Moreover, earnings in ASHE are provided in terms of 1990 SOC only until 2001, but the information about the occupational code of friends in BHPS is in terms of 1990 SOC until 2004. Therefore, the occupational income of 2004 is predicted using the available data from 1990 to 2001 and taking into account the Consumer Price Index. This might imply that the mean earnings for a given occupation might differ over the

[12] It is interesting to notice, however, that the overall results do not change if the main variable is predicted using this methodology

years just because of how the variable is constructed. It should be highlighted, however, that this should not affect the results in a significant way for this study, as it is based on cross-sectional comparisons.

The main variable is based on the minor groups of the Standard Occupational Classifications for two reasons. Firstly, data at a finer aggregation level are not available for certain occupations. Secondly, the occupation of some friends is only available at this level.

Table B.1 illustrates the predicted income by SOC minor group for males and females. Figure B.2 illustrates the correspondence between the real and predicted income.

Table B.1: Summary statistics of mean earnings by SOC minor group by year (Source: own calculations from NES-ASHE)

Variable	N	Mean	Std. Dev.	Min	Max	Variable	N	Mean	Std. Dev.	Min	Max
Male mean earnings by SOC 90 minor group by year											
1992	76	406.15	147.31	187.42	851.56	1999	76	450.73	187.59	243.55	1060.89
1994	76	414.38	158.36	203.20	966.13	2000	76	465.08	204.37	243.82	1184.75
1997	76	430.17	170.55	210.81	936.45	2002	76	478.93	209.73	248.20	1307.64
1998	76	444.73	184.31	221.51	1049.95	2004	76	494.41	179.20	282.07	1045.01
Male mean earnings by SOC 00 minor group by year											
2006	81	533.60	265.56	245.75	2066.86	2008	81	535.84	258.59	248.11	2029.22
Female mean earnings by SOC 90 minor group by year											
1992	76	310.02	118.17	163.32	691.39	1999	76	357.02	138.10	195.77	757.10
1994	76	320.20	122.84	178.91	693.32	2000	76	369.34	142.02	203.22	778.63
1997	76	340.78	127.99	184.28	709.59	2002	76	382.74	150.96	199.47	843.52
1998	76	345.13	130.52	186.39	720.75	2004	76	398.81	132.04	245.35	794.14
Female mean earnings by SOC 00 minor group by year											
2006	81	441.80	176.23	232.45	1202.35	2008	81	441.30	167.42	232.07	1078.06

To test the robustness of the results based on NES-ASHE, I create alternative variables. One is the mean (or median) monthly labour income by gender and occupational group from BHPS. Another variable is the Hope-Goldthorpe (HG, hereafter) score, indicating the occupational prestige of a given occupation[13]. They are created using all the BHPS respondents (in all waves) working full-time. The advantage of using BHPS

[13] The HG score is based on a survey conducted in England and Wales about the social desirability of occupations.

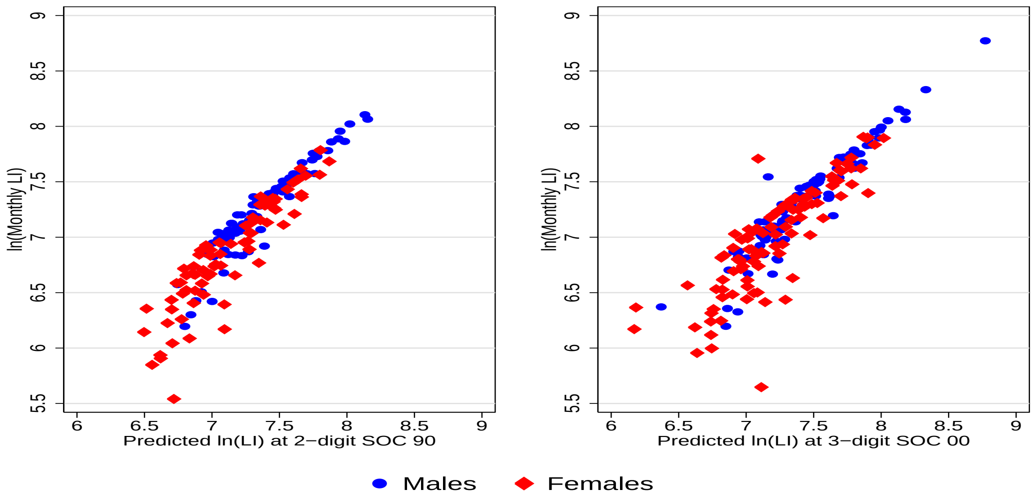

Figure B.2: Comparison between individual and occupational weekly earnings for males and females

would have been that fewer observations are lost as it allows keeping the additional codes of the survey (78 for minor groups for BHPS 1990 SOC and 100 for BHPS 2000 SOC versus 77 and 81 of the standard version). However, the sample size would not allow to predict the occupational income by year. Additionally, the number of observations by occupational minor group is extremely limited for certain occupations, especially for the monthly income of females. The HG score could be derived on a larger number of observations.[14] However, it only has a maximum of 143 categories. Additionally, although it has been used for males and females, it is based on a 1971 survey considering male occupations. Finally, it is not clear what criteria are used to attribute the prestige score to each individual in BHPS.

For information, Table B.2, indicates the sample on which these were created.

[14]In fact the HG score is available for the first, the current, the paternal and maternal occupations.

Table B.2: Sample available to derive the median HG score and the median annual labour income

	Obs	Mean	Std. Dev.	Min	Max
Males					
3-digit SOC 2000	43337	495.1127	265.9139	111	999
2-digit SOC 1990	256276	55.08425	26.90605	10	99
Real HG score	252903	45.29125	15.00723	17.52	82.05
Pred HG score by SOC 90	256275	44.81534	14.29744	18.36	76.29
Pred HG score by SOC 00	43330	47.21739	14.91835	18	76.29
Annual Labour Income	61401	20982.94	16243.97	0.3035302	733819.7
Pred Annual LI by SOC 90	256276	17746.96	5451.668	8862.846	39507.83
Pred Annual LI by SOC 00	43333	20030.98	6540.129	1.106069	60833.77
Females					
3-digit SOC 2000	29067	463.945	240.3505	111	999
2-digit SOC 1990	162442	56.71753	24.93857	10	99
Real HG score	157946	41.50495	15.10114	17.52	82.05
Pred HG score by SOC 90	162441	39.36047	14.45771	18.36	76.29
Pred HG score by SOC 00	29055	47.28752	13.83487	18	76.29
Annual Labour Income	40085	15605.34	14351.13	0.2233583	1231039
Pred Annual LI by SOC 90	162442	12438.4	4922.082	6694.708	37148.7
Pred Annual LI by SOC 00	29062	15542.1	5879.903	5274.059	36342

B.3 Empirical results

B.3.1 Summary statistics, IGE and transition matrices

Table B.3: Samples used in the analysis

Sample	Sons	Daughters	Characteristics
1	4,186	3,570	Matched triplets of respondents with their mother and father , where at least one parent works
2	3,434	2,959	Matched triplets of respondents with their mother and father, with both working parents
Ref. sample	1,153	1,017	Matched triplets of respondents with their mother and father, with non-missing information about the parents' best friends
4	861	761	Reference sample with non-missing information about own best friends
5	22,751	25,656	Respondents with information about their best friends

Table B.4: Summary statistics

	Sons N=1,153		Daughters N=1,017		Sample homophily N=48,407	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	21.34	4.22	20.44	3.60	39.13	12.46
Year of birth	1978.43	6.50	1979.87	6.41	1961.69	13.28
Degree or higher	0.09	0.29	0.11	0.31	0.17	0.38
LI	292.09	121.28	228.83	106.42	328.94	164.09
Friend LI	269.95	140.41	254.93	151.43	325.80	156.72
Friend age	21.50	5.72	21.96	6.02	40.06	13.86
Friend Female	0.29	0.45	0.66	0.47	0.55	0.50
F LI	380.81	168.32	390.24	170.96	361.11	172.72
F age	50.03	5.84	49.80	5.46	53.43	8.93
F Year of birth	1949.78	7.21	1950.55	7.28	1931.33	15.29
F friend LI	369.50	158.13	371.96	149.22	316.69	179.14
F friend age	48.95	9.81	49.29	9.56	50.99	11.28
F Friend Female	0.09	0.29	0.09	0.29	0.14	0.35
M LI	253.01	120.75	250.45	105.85	204.17	144.54
M age	48.03	5.48	47.78	5.20	51.51	10.13
M Year of birth	1951.78	6.69	1952.54	6.85	1934.56	15.02
M friend LI	263.87	126.90	267.87	120.31	241.27	144.87
M friend age	47.40	10.52	48.23	10.43	50.49	12.98
M Friend Female	0.95	0.22	0.94	0.23	0.91	0.28
Female	0	0	1	0	0.53	0.50

Table B.5: Intergenerational elasticities

	Real ln(LI)	P ln(LI) ASHE	P ln(LI) BHPS	Real ln(HG)	P ln(HG) BHPS	P ln(LI) ASHE sample
Sons						
F Variable	0.298***	0.223***	0.237***	0.265***	0.203***	0.327***
	(0.064)	(0.071)	(0.062)	(0.071)	(0.071)	(0.111)
M Variable	0.042	-0.017	0.018	-0.051	0.016	-0.056
	(0.059)	(0.066)	(0.055)	(0.066)	(0.062)	(0.082)
(F Variable)(Age-30)	0.030***	0.016**	0.020***	0.017**	0.012*	0.024**
	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.010)
(M Variable)(Age-30)	0.008	0.003	0.009*	0.001	0.008	-0.004
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)
Observations	2584	2584	2584	2584	2584	1153
Adjusted R^2	0.3425	0.2964	0.1017	0.0879	0.0675	0.4055
Daughters						
F Variable	0.259***	0.419***	0.332***	0.253***	0.119	0.526***
	(0.097)	(0.042)	(0.096)	(0.040)	(0.130)	(0.113)
M Variable	0.134	-0.064	-0.033	-0.088	-0.026	-0.087
	(0.120)	(0.068)	(0.133)	(0.069)	(0.090)	(0.122)
(F Variable)(Age-30)	0.027***	0.032***	0.027***	0.022***	0.006	0.040***
	(0.010)	(0.004)	(0.010)	(0.006)	(0.012)	(0.010)
(M Variable)(Age-30)	0.017	-0.009	-0.005	-0.009**	-0.001	-0.018
	(0.012)	(0.006)	(0.011)	(0.005)	(0.008)	(0.011)
Observations	2260	2260	2260	2260	2260	1017
Adjusted R^2	0.3909	0.4461	0.2146	0.1631	0.1434	0.5617

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Bootstrap standard errors in parenthesis. Controls include ages, year of birth, interaction between parental variables and age. The elasticity refers to a thirty year old individual. The variable on which the elasticity is computed differs according to the model: in the 1st column it is the ln of LI; in the 2nd the ln of the mean LI by year and by occupation computed on ASHE; in the 3rd on ln of the mean LI by occupation computed on all the available observations from BHPS; in the 4th, the ln of the Hope-Goldthorpe prestige score; in the 5th on the mean HG score by occupation computes on BHPS; in the 6th it is the same variable as the 2nd col but on the reference sample.

Table B.6: Intergenerational elasticities of family average occupational-related measure

	Real ln(LI)	P ln(LI) ASHE	P ln(LI) BHPS	Real ln(HG)	P ln(HG) BHPS	P ln(LI) ASHE sample
Sons						
Parental Variable	0.245***	0.196***	0.189**	0.185**	0.183**	0.240**
	(0.075)	(0.068)	(0.075)	(0.087)	(0.084)	(0.094)
(Parental Variable)(Age-30)	0.017**	0.011*	0.017**	0.011	0.011	0.016*
	(0.008)	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)
Observations	2582	2582	2582	2582	2582	1153
Adjusted R^2	0.5727	0.3433	0.1643	0.1190	0.1150	0.4005
Daughters						
Parental Variable	0.248**	0.350***	0.254	0.106	0.022	0.446***
	(0.104)	(0.128)	(0.160)	(0.133)	(0.114)	(0.124)
(Parental Variable)(Age-30)	0.015	0.017	0.013	0.002	-0.008	0.024**
	(0.010)	(0.012)	(0.015)	(0.013)	(0.011)	(0.011)
Observations	2259	2259	2259	2259	2259	1017
Adjusted R^2	0.6088	0.4797	0.2664	0.1987	0.1970	0.5532

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Bootstrap standard errors in parenthesis. Controls include ages, year of birth, interaction between parental variables and age. The elasticity refers to a thirty year old individual. The variable on which the elasticity is computed differs according to the model: in the 1st column it is the ln of LI; in the 2nd the ln of the mean LI by year and by occupation computed on ASHE; in the 3rd on ln of the mean LI by occupation computed on all the available observations from BHPS; in the 4th, the ln of the Hope-Goldthorpe prestige score; in the 5th on the mean HG score by occupation computes on BHPS; in the 6th it is the same variable as the 2nd col but on the reference sample.

Table B.7: Intergenerational elasticities of occupational income on mothers and fathers

	(1) Father and mother		(2) Father and mother in MS		(3) Father		(4) Mother	
Sons								
F ln LI	0.187***	[0.061]	0.327***	[0.111]	0.290***	[0.092]		
M ln LI	0.093	[0.060]	-0.056	[0.082]			0.065	[0.067]
(F LI)(Age-30)	0.010*	[0.006]	0.024**	[0.010]	0.022***	[0.008]		
(M LI)(Age-30)	0.008	[0.005]	-0.004	[0.007]			0.005	[0.006]
Observations	3434		1153		1153		1153	
Adjusted R^2	0.3656		0.4055		0.4048		0.3882	
Daughters								
F ln LI	0.384***	[0.078]	0.526***	[0.113]	0.453***	[0.099]		
M ln LI	-0.010	[0.099]	-0.087	[0.122]			0.107	[0.113]
(F LI)(Age-30)	0.027***	[0.007]	0.040***	[0.010]	0.031***	[0.008]		
(M LI)(Age-30)	-0.008	[0.009]	-0.018	[0.011]			-0.000	[0.010]
Observations	2959		1017		1017		1017	
Adjusted R^2	0.4866		0.5617		0.5562		0.5355	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father, M for mother, LI for labour income. Controls include ages and respondent's year of birth

Table B.8: Additional checks for intergenerational elasticities

	Sons				Daughters			
	Only mother in HH		Older 25		Only mother in HH		Older 25	
M ln LI	0.244***	[0.064]	0.148**	[0.068]	0.244***	[0.090]	0.014	[0.101]
(M LI)(N. age)	0.013**	[0.005]	0.014	[0.012]	0.014*	[0.007]	-0.048**	[0.024]
Observations	1713		341		1549		341	
Adjusted R^2	0.4524		0.4420		0.4719		0.4459	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father, M for mother, LI for labour income. Controls include ages and respondent's year of birth. Model 1 - 3 consider all observations that can only be matched with the mother (the individual has not lived with the father). Models 2 - 4 consider a subsample of individuals who are matched with both parents and who are older than 25.

Table B.9: Children and fathers: probability differential of transition

	1st		2nd		3rd		4th		5th	
Sons										
1st	0.002	(0.002)	0.014	(0.012)	0.042*	(0.025)	-0.028	(0.039)	-0.031	(0.034)
2nd	-0.000	(0.001)	0.002	(0.004)	0.062**	(0.028)	-0.038	(0.035)	-0.025	(0.028)
3rd	0		0		0		0		0	
4th	-0.000	(0.001)	-0.005	(0.005)	-0.025	(0.020)	-0.069	(0.047)	0.098**	(0.041)
5th	-0.001	(0.001)	-0.006	(0.006)	-0.037	(0.022)	-0.093*	(0.056)	0.136***	(0.049)
Daughters										
1st	0.002	(0.001)	0.012	(0.010)	0.039	(0.024)	-0.019	(0.041)	-0.034	(0.036)
2nd	-0.000	(0.001)	0.001	(0.003)	0.056**	(0.028)	-0.030	(0.036)	-0.027	(0.030)
3rd	0		0		0		0		0	
4th	-0.000	(0.001)	-0.004	(0.004)	-0.022	(0.018)	-0.078*	(0.043)	0.105***	(0.038)
5th	-0.000	(0.001)	-0.005	(0.005)	-0.033	(0.021)	-0.106**	(0.049)	0.144***	(0.043)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Bootstrap standard errors in parenthesis

B.3.2 Homophily

B.3.2.1 The respondents and their network

This section explores the characteristics of over 48,000 observations of respondents (and of their three closest friends) from 16 to 65 years old. Overall, the respondents and their friends have similar demographic characteristics, for example in terms of age and gender.[15] Males have fewer female friends and females have fewer male friends, the percentage of same-sex friends ranging from 75% to 91%.

The respondents have known their best friends for over 10 years in almost 90% of the cases and most friends live relatively close. In fact, on average only around 15% of them live more than 50 miles away.

Appendix Table B.10 suggests that friends also share some socio-economic characteristics. As expected, most friends are employed independently of the respondent's economic activity. Nonetheless, the likelihood is higher when the respondent is also employed. Similarly, in over 38% of cases, friends of retired respondents are also retired. If common retirement patterns may be related to age, age may not be the main driver of common unemployment spells. In the sample, the percentage of unemployed friends increases from 2% to 10% (15% for the third closest friend) if the respondent is unemployed as well.

[15]There are more similarities with the best friend than with the second and third closest friends.

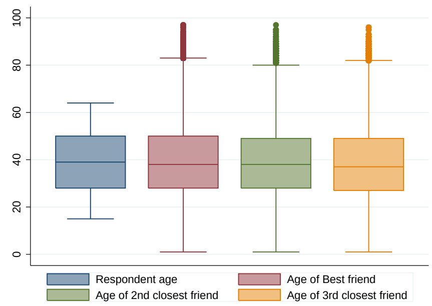

Figure B.3: Age of the respondent's three closest friends

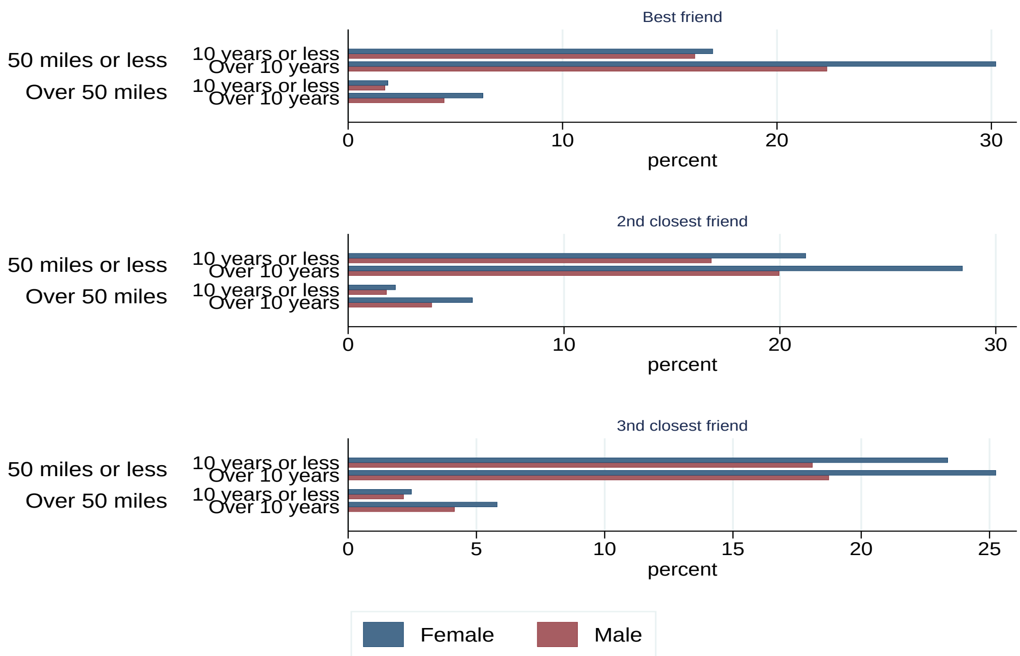

Figure B.4: Distance between the respondent and his friends and time since they know each other, by friend and friend's sex

Table B.10: Cross-tabulation of the friend's employment status conditional on the respondent's

Best Friend					
	Employed	Unemployed	Housework	Retired	At school
Employed	0.88	0.03	0.01	0.07	0.01
Unemployed	0.78	0.1	0.01	0.05	0.05
Housework	0.73	0	0.18	0	0.09
Retired	0.44	0.04	0	0.52	0
At school	0.45	0.04	0	0	0.5
Second closest friend					
	Employed	Unemployed	Housework	Retired	At school
Employed	0.85	0.04	0.02	0.07	0.02
Unemployed	0.68	0.13	0.03	0.06	0.1
Housework	0.82	0.09	0	0.09	0
Retired	0.67	0.03	0.01	0.28	0
At school	0.34	0.04	0	0	0.61
Third closest friend					
	Employed	Unemployed	Housework	Retired	At school
Employed	0.85	0.04	0.02	0.06	0.03
Unemployed	0.65	0.15	0.05	0.06	0.09
Housework	0.73	0	0.09	0	0.18
Retired	0.54	0	0.04	0.38	0.04
At school	0.37	0.04	0	0	0.58

Table B.11: Pearson's correlation coefficients

	ln LI	ln F LI	ln M LI	ln friend LI	ln F friend LI	ln M friend LI
ln LI	1					
ln F LI	0.0807	1				
ln M LI	0.0963	0.3003	1			
ln friend LI	0.5055	0.0579	0.1204	1		
ln F friend LI	0.0876	0.3781	0.2727	0.0564	1	
ln M friend LI	0.1052	0.247	0.4309	0.1143	0.2378	1

Table B.12: Transition matrix between occupational income of the respondent (rows) and of their friends(columns).

	1	2	3	4	5	6	7	8	9	10	Total
1	**0.39**	0.18	0.24	0.09	0.05	0.04	0.01	0	0	0	1,723
2	0.05	**0.36**	0.26	0.17	0.07	0.06	0.02	0.01	0	0	5,418
3	0.03	0.11	**0.42**	0.21	0.09	0.08	0.04	0	0	0	12,273
4	0.01	0.08	0.22	**0.38**	0.12	0.11	0.06	0.01	0	0	11,272
5	0.02	0.07	0.18	0.21	**0.27**	0.15	0.08	0.02	0	0	6,231
6	0.01	0.05	0.16	0.18	0.14	**0.32**	0.11	0.02	0.01	0	6,728
7	0	0.02	0.13	0.18	0.13	0.2	**0.28**	0.03	0.01	0	3,777
8	0.01	0.03	0.09	0.15	0.12	0.22	0.19	0.17	0.01	0.01	749
9	0	0.03	0.08	0.11	0.09	0.21	0.19	0.06	**0.21**	0	188
10	0	0.04	0.04	0.32	0.16	0.2	0.12	0.12	0	0	48
Total	1,708	5,522	12,179	11,370	6,211	6,961	3,537	658	236	25	48,407

Notes: The matrix is derived by dividing the interval between the minimum and the maximum value of log income into ten categories of equal width in terms of income, circa 0.24 log-unit.

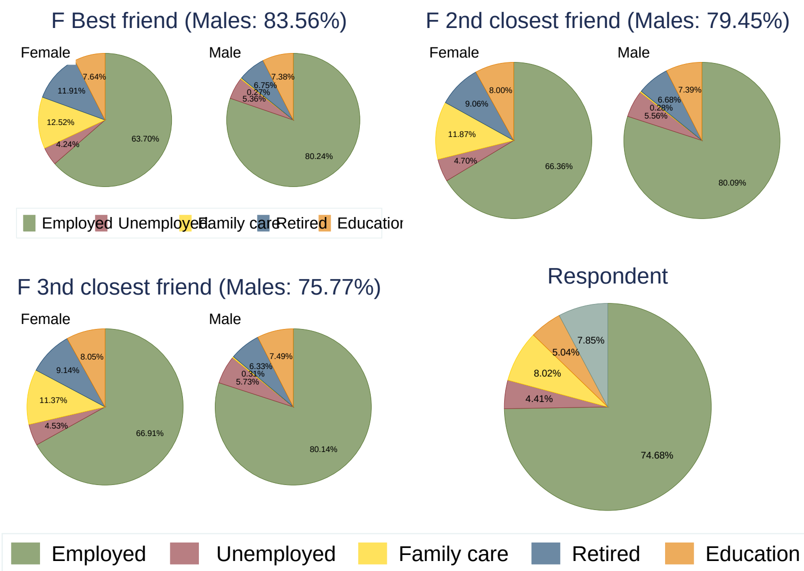

Figure B.5: Employment status of the respondent and of his three closest friends, by friend's sex

B.3.2.2 The parents and their network

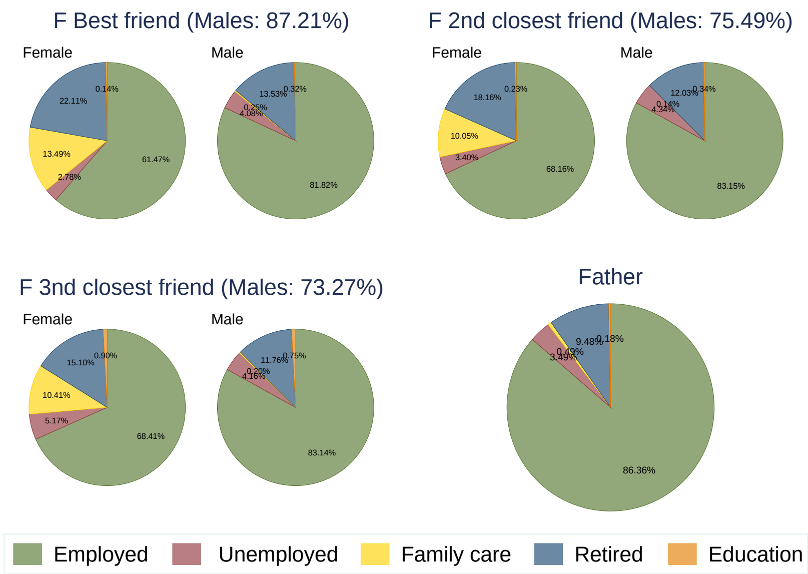

Figure B.6: Employment status of the father and of his three closest friends, by friend’s sex

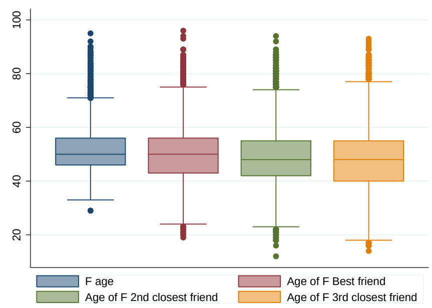

Figure B.7: Age of the father’s three closest friends

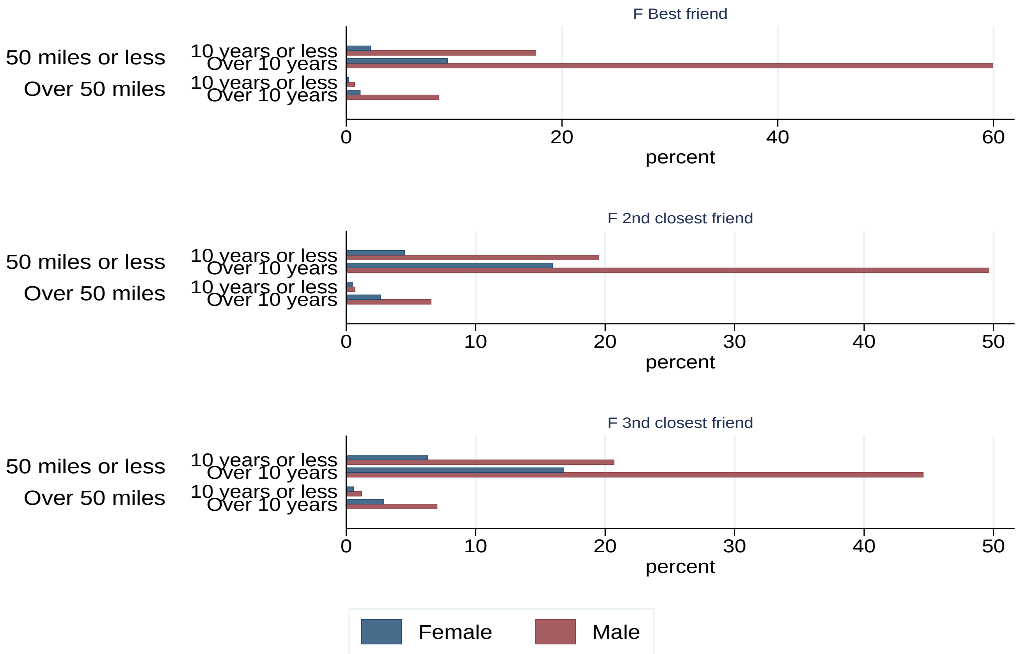

Figure B.8: Distance between the father and his friends and time since they know each other, by friend and friend's sex

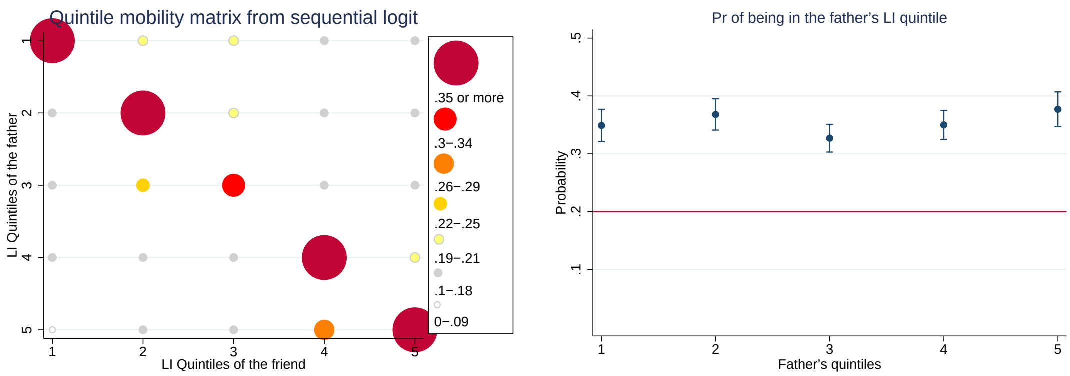

Figure B.9: Logit mobility matrix for fathers and friends

Logit mobility matrix (left); Probability of being on the main diagonal of the matrix with standard errors. The horizontal line at 0.2 indicates perfect mobility (right)

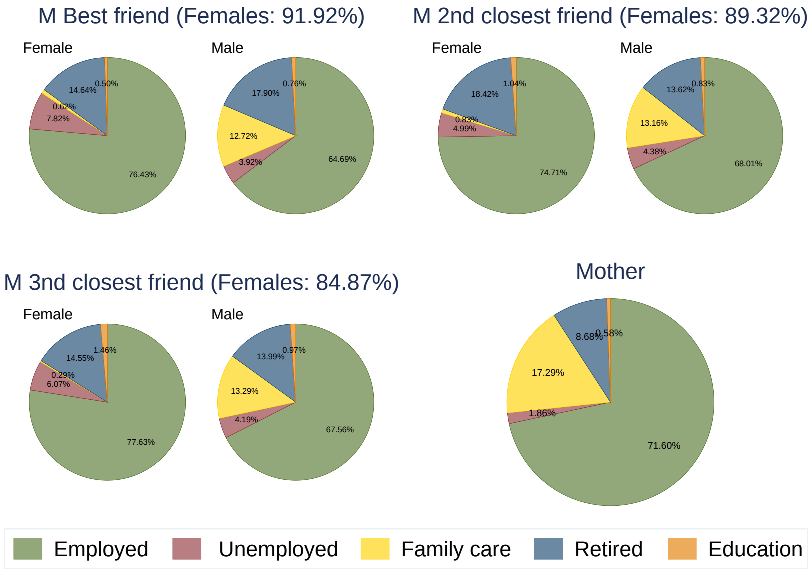

Figure B.10: Employment status of the mother and of her three closest friends, by friend's sex

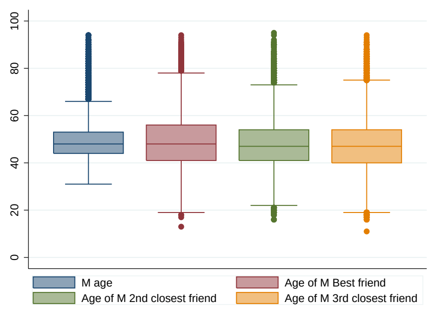

Figure B.11: Age of the mother's three closest friends

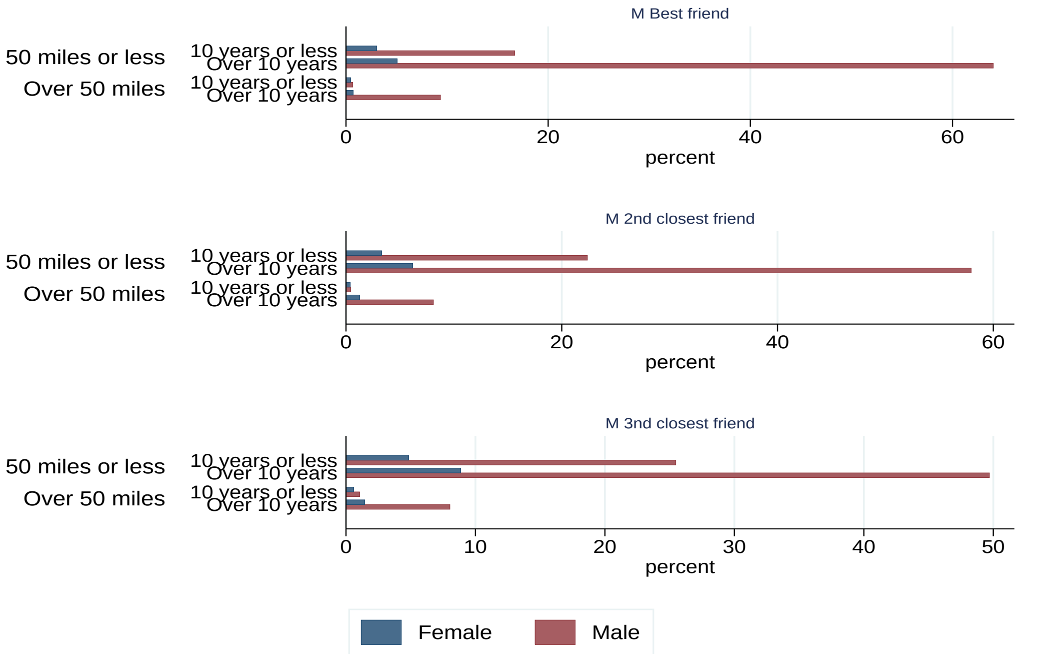

Figure B.12: Distance between the mother and her friends and time since they know each other, by friend and friend's sex

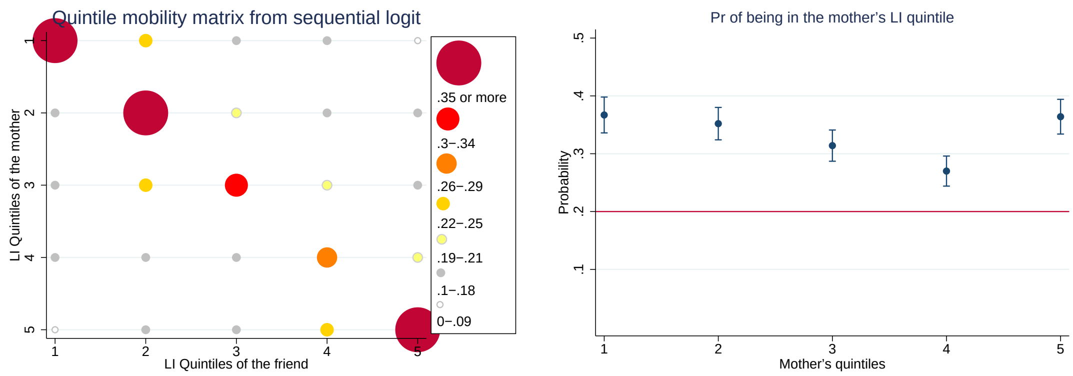

Figure B.13: Logit mobility matrix for mothers and friends

Logit mobility matrix (left); Probability of being on the main diagonal of the matrix with standard errors. The horizontal line at 0.2 indicates perfect mobility (right)

B.3.3 Social networks and education

Table B.13: Summary statistics for the 905 observations of the ordered logit

Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
Primary ed	0.07	0.25	Female F friend	0.11	0.32
Low second. ed.	0.33	0.47	Female M friend	0.94	0.23
Higher sec/vocational ed.	0.36	0.48	M friend LI	343.76	136.11
Degree or higher	0.24	0.43	F friend LI	476.10	191.88
Age	25.09	3.45	ln M friend LI	5.77	0.36
Year of birth	1976.04	5.64	ln F friend LI	6.10	0.35
Daughter	0.40	0.49			

Table B.14: Ordered logit for educational outcome

Education	Odds Ratio	Bootstrap SE	z	P>z
ln F LI	2.30	0.60	3.2	0.001
ln M LI	1.62	0.47	1.68	0.093
ln F friend LI	1.22	0.30	0.79	0.43
ln M friend LI	2.82	0.67	4.38	0
Female F friend	0.62	0.16	-1.85	0.064
Female M friend	1.50	0.50	1.22	0.224
Female	1.59	0.30	2.48	0.013
/cut1	-63.20	35.82		
/cut2	-60.77	35.82		
/cut3	-58.97	35.81		
Observations	905			

B.3.4 The intergenerational equation and the role of the social network

Table B.15: Intergenerational elasticities at different levels of normalized age for sons

	Age-mean		Age-25		Age-35		Age-45	
Sons								
F ln LI	0.086**	(0.041)	0.171**	(0.067)	0.380**	(0.169)	0.588**	(0.279)
M ln LI	-0.074**	(0.038)	-0.073	(0.060)	-0.071	(0.151)	-0.069	(0.249)
F friend ln LI	0.086**	(0.035)	0.129***	(0.048)	0.235**	(0.114)	0.341*	(0.188)
Female F friend ln LI	-0.035	(0.085)	-0.035	(0.085)	-0.035	(0.085)	-0.035	(0.085)
M friend ln LI	0.177*	(0.098)	0.185*	(0.102)	0.207	(0.145)	0.229	(0.210)
Female M friend ln LI	-0.156	(0.100)	-0.156	(0.100)	-0.156	(0.100)	-0.156	(0.100)
Friend LI	0.295***	(0.048)	0.194***	(0.057)	-0.053	(0.133)	-0.301	(0.222)
Female friend ln LI	-0.136*	(0.069)	-0.136*	(0.069)	-0.136*	(0.069)	-0.136*	(0.069)
(M LI)(N. age)	0.000	(0.010)	0.000	(0.010)	0.000	(0.010)	0.000	(0.010)
(F LI)(N. age)	0.021*	(0.011)	0.021*	(0.011)	0.021*	(0.011)	0.021*	(0.011)
(F friend LI)(N. age)	0.011	(0.008)	0.011	(0.008)	0.011	(0.008)	0.011	(0.008)
(M friend LI)(N. age)	0.002	(0.008)	0.002	(0.008)	0.002	(0.008)	0.002	(0.008)
(Friend LI)(N. age)	-0.025***	(0.009)	-0.025***	(0.009)	-0.025***	(0.009)	-0.025***	(0.009)
Observations	861		861		861		861	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father, M for mother, LI for labour income. Controls include ages and respondent's year of birth, friend's gender, interaction between age and LI. For each column the age is normalized at a different value

Table B.16: Intergenerational elasticities with controls for education and region of residence

	(1)		(2)		(3)		(4)		(5)		(6)	
Sons												
F ln LI	0.242**	(0.095)			0.286**	(0.111)	0.280**	(0.116)	0.259**	(0.119)	0.256**	(0.119)
M ln LI			0.049	(0.082)	-0.080	(0.102)	-0.073	(0.106)	-0.071	(0.100)	-0.070	(0.100)
F friend ln LI	0.118*	(0.067)			0.161**	(0.074)	0.160**	(0.079)	0.161*	(0.086)	0.155*	(0.089)
Female F friend ln LI	-0.086	(0.074)			-0.080	(0.075)	-0.071	(0.080)	-0.048	(0.091)	-0.037	(0.095)
M friend ln LI			0.167	(0.120)	0.109	(0.125)	0.114	(0.125)	0.219*	(0.123)	0.226*	(0.125)
Female M friend ln LI			-0.178*	(0.107)	-0.157	(0.113)	-0.146	(0.115)	-0.180*	(0.100)	-0.182*	(0.104)
Friend LI									0.307***	(0.052)	0.295***	(0.053)
Female friend ln LI									-0.133*	(0.072)	-0.134*	(0.072)
(F LI)(N. age)	0.020**	(0.009)			0.023**	(0.010)	0.022**	(0.010)	0.019*	(0.012)	0.019	(0.012)
(F friend LI)(N. age)	0.004	(0.006)			0.008	(0.007)	0.008	(0.007)	0.009	(0.009)	0.009	(0.009)
(M LI)(N. age)			0.006	(0.008)	-0.005	(0.009)	-0.007	(0.009)	0.002	(0.010)	-0.001	(0.010)
(F friend LI)(N. age)			0.000	(0.007)	-0.003	(0.007)	-0.002	(0.006)	0.003	(0.008)	0.003	(0.009)
(Friend LI)(N. age)									-0.025**	(0.010)	-0.023**	(0.010)
Observations	1153		1153		1153		1153		861		861	
Daughters												
F ln LI	0.253**	(0.101)			0.314***	(0.110)	0.311***	(0.103)	0.203	(0.137)	0.209	(0.141)
M ln LI			-0.119	(0.100)	-0.239**	(0.112)	-0.223**	(0.110)	-0.269*	(0.142)	-0.264*	(0.139)
F friend ln LI	0.276**	(0.113)			0.242**	(0.115)	0.229**	(0.114)	0.129	(0.121)	0.121	(0.123)
Female F friend ln LI	0.058	(0.082)			0.061	(0.087)	0.060	(0.085)	-0.011	(0.081)	-0.005	(0.084)
M friend ln LI			0.393***	(0.150)	0.278*	(0.145)	0.297**	(0.146)	0.265*	(0.160)	0.284*	(0.159)
Female M friend ln LI			-0.039	(0.107)	-0.016	(0.101)	-0.022	(0.103)	-0.052	(0.115)	-0.068	(0.114)
Friend LI									0.166***	(0.057)	0.167***	(0.061)
Female friend ln LI									0.033	(0.070)	0.030	(0.071)
(F LI)(N. age)	0.014	(0.009)			0.021**	(0.010)	0.020**	(0.009)	0.009	(0.012)	0.010	(0.012)
(F friend LI)(N. age)	0.021**	(0.010)			0.020*	(0.010)	0.019*	(0.010)	0.010	(0.011)	0.009	(0.011)
(M LI)(N. age)			-0.021**	(0.009)	-0.030***	(0.010)	-0.028***	(0.010)	-0.034**	(0.014)	-0.034**	(0.013)
(F friend LI)(N. age)			0.031***	(0.010)	0.023**	(0.010)	0.025***	(0.009)	0.021*	(0.012)	0.022*	(0.012)
(Friend LI)(N. age)									0.020*	(0.011)	0.019*	(0.011)
Observations	1017		1017		1017		1017		761		761	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father, M for mother, LI for labour income. Controls for all models include ages and respondent's year of birth, friend's gender, education and region of residence. Models: (1) Father and his friend (2) Mother and her friend (3) Both parents and friends (4) Both parents and friends with parental education as an additional control (5) Both parents and all friends (6) Both parents and all friends with parental education as an additional control. The coefficient of the latter is for a twenty-two-year old respondent

Table B.17: Inter and intra- generational elasticities with the parental friends and own friends

	(1)	(2)	(3)	(4)	(5)	(6)
Sons						
F friend ln LI	0.269***			0.224***		
	(0.059)			(0.049)		
Female F friend ln LI	-0.037			0.034		
	(0.071)			(0.054)		
M friend ln LI		0.219*			0.175***	
		(0.119)			(0.067)	
Female M friend ln LI		-0.176*			-0.069	
		(0.104)			(0.060)	
Friend LI			0.196**			0.400***
			(0.078)			(0.010)
Female friend ln LI			-0.171***			-0.068***
			(0.064)			(0.017)
Observations	1153	1153	861	1785	2282	22751
Adjusted R^2	0.1965	0.1793	0.2243	0.1958	0.1773	0.2418
Daughters						
F friend ln LI	0.362***			0.278***		
	(0.070)			(0.057)		
Female F friend ln LI	0.044			0.009		
	(0.076)			(0.057)		
M friend ln LI		0.313**			0.139*	
		(0.127)			(0.073)	
Female M friend ln LI		0.056			0.144**	
		(0.106)			(0.065)	
(Friend LI)			0.323***			0.349***
			(0.099)			(0.018)
Female friend ln LI			-0.014			0.070***
			(0.057)			(0.018)
Observations	1017	1017	761	1532	2019	25656
Adjusted R^2	0.3408	0.3387	0.3855	0.3451	0.3309	0.2858

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Bootstrap standard errors in parenthesis. F stands for father, M for mother, LI for labour income. Controls include ages and respondent's year of birth. Main regressor by model: (1) F Friend (2) M Friend (3) Friend (4) F Friend (5) M Friend (6) Friend

Appendix C

“Job polarization and household income”

Table C.1: Summary statistics

	Males			Females		
Variable	N	Mean	s.d.	N	Mean	s.d.
Age	28406	41.75	10.15	30835	41.57	10.14
Year of birth	28406	1957.79	10.33	30835	1957.97	10.16
Cog. non-rout	28406	0.40	0.49	30835	0.27	0.47
Man rout	28406	0.28	0.45	30835	0.04	0.20
Cog. rout	28406	0.09	0.32	30835	0.26	0.46
Man non-rout	28406	0.09	0.31	30835	0.16	0.39
OLF	28406	0.14	0.25	30835	0.27	0.35
Unemployed	28406	0.03	0.16	30835	0.02	0.12
Partner	28406	0.83	0.38	30835	0.78	0.41
HH size	28406	2.97	1.25	30835	2.95	1.20
N kids	28406	0.77	1.02	30835	0.79	1.01
Earnings	26421	2398.61	1578.06	26399	1362.75	1141.53
HH net income	26809	632.28	343.89	29726	608.72	361.10
N waves	28406	12.30	4.17	30835	11.69	4.08

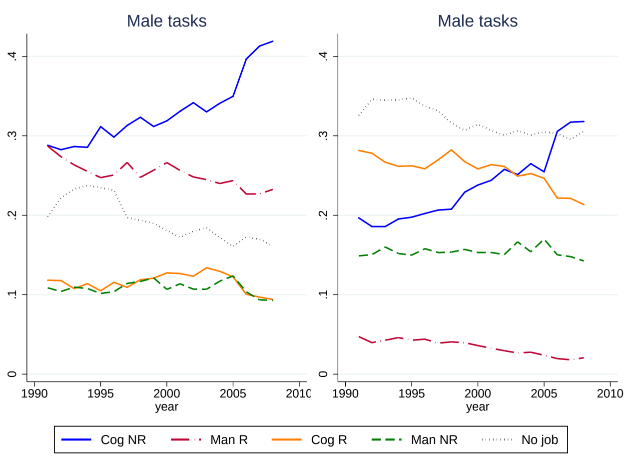

Figure C.1: Employment patterns of the BHPS original sample

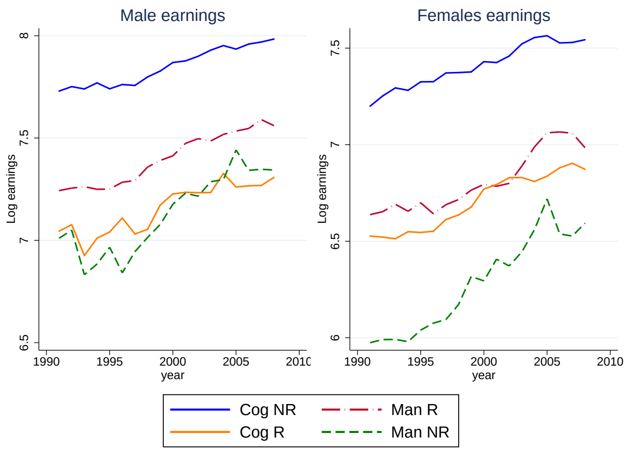

Figure C.2: Mean log earnings of the BHPS original sample

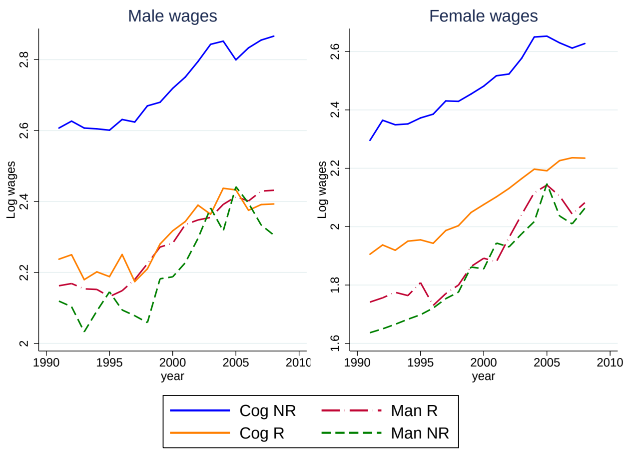

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Figure C.3: Mean log wages on 16 to 64 y-olds

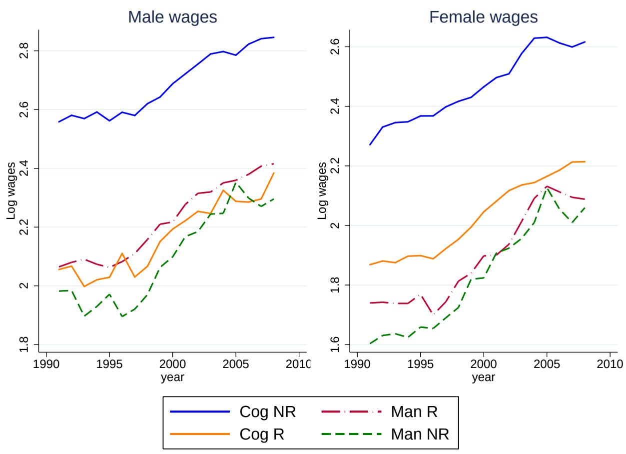

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Figure C.4: Mean log wages of the BHPS original sample.

Table C.2: Wage change differential by initial occupation à la Cortes

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
NR Cog	0.011***	0.015***	0.023***	0.020**	0.026**	0.036***	0.037**	0.049***	0.043**	0.063***
	(0.003)	(0.005)	(0.007)	(0.009)	(0.011)	(0.013)	(0.015)	(0.018)	(0.020)	(0.023)
R Cog	0.007	0.016*	0.015	0.017	0.031*	0.036*	0.025	0.040	0.041	0.041
	(0.005)	(0.008)	(0.011)	(0.014)	(0.016)	(0.020)	(0.023)	(0.027)	(0.031)	(0.036)
NR Man	0.012**	0.008	0.002	-0.008	-0.009	0.011	0.010	0.016	0.011	0.028
	(0.005)	(0.008)	(0.011)	(0.013)	(0.016)	(0.018)	(0.022)	(0.025)	(0.028)	(0.032)
Constant	0.019*	0.010	0.027**	0.019	0.065***	0.060***	0.087***	0.119***	0.154***	0.185***
	(0.010)	(0.011)	(0.012)	(0.013)	(0.017)	(0.015)	(0.017)	(0.018)	(0.018)	(0.020)
Observations	15537	13668	12021	10469	9052	7703	6498	5428	4488	3642
Adjusted R^2	0.002	0.005	0.008	0.011	0.012	0.014	0.013	0.010	0.008	0.007

Clustered standard errors in parenthesis. Controls include year fixed effects

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.1 Changes in earnings on two subsamples according to age

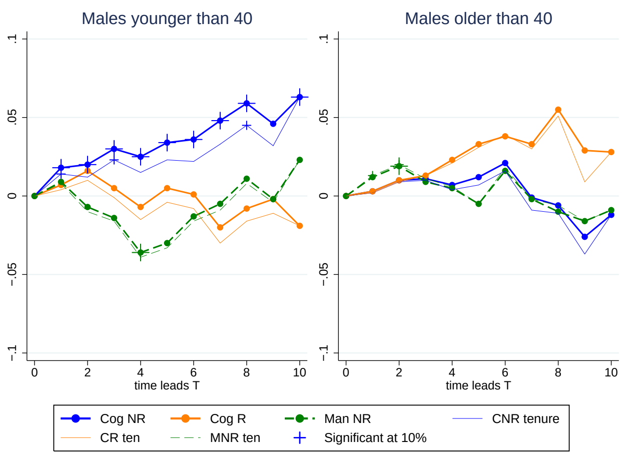

Figure C.5: Changes in male wageson two age subsamples
Picture shows changes in wages by initial occupation on men younger than 40 and men who are at least 40. The thinner lines replicate the same results when job tenure as an additional control variable.

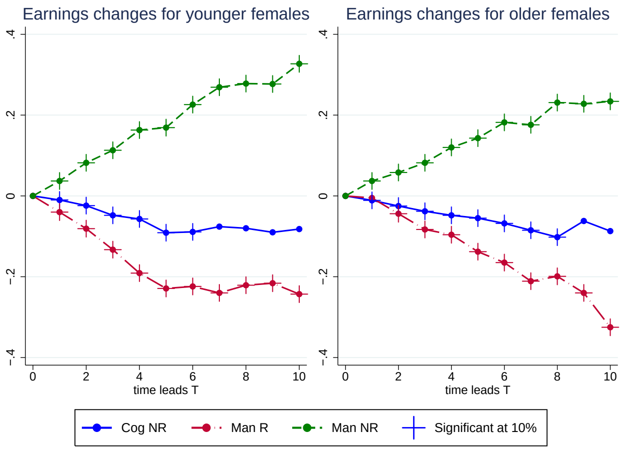

Figure C.6: Changes in female earnings on two age subsamples
Picture shows changes in earnings by initial occupation on women younger than 40 and women who are at least 40.

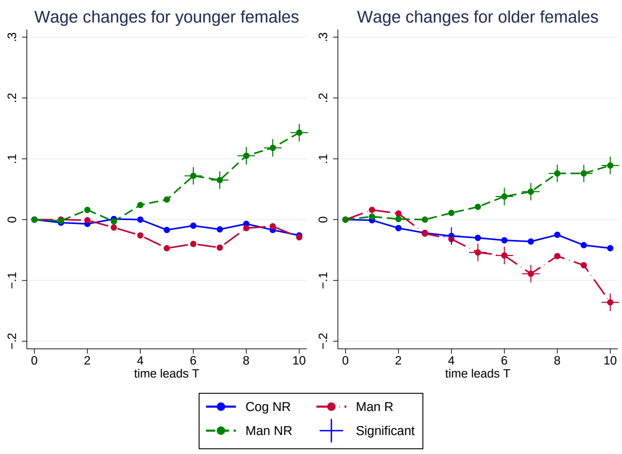

Figure C.7: Changes in female wages on two age subsamples
Picture shows changes in wages by initial occupation on women younger than 40 and women who are at least 40.

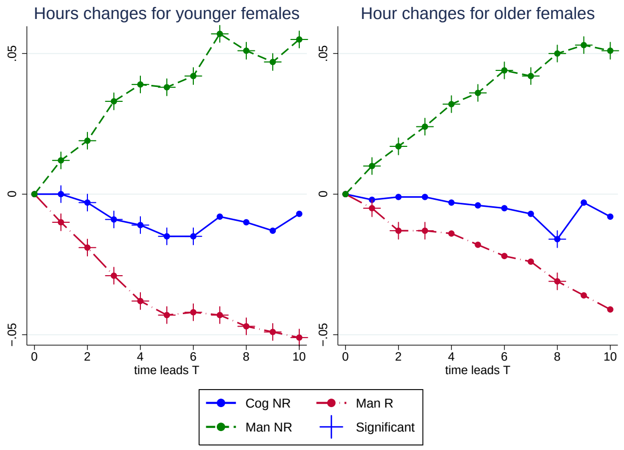

Figure C.8: Changes in female worked hours on two subsamples
Picture shows changes in worked hours by initial occupation on women younger than 40 and women who are at least 40.

C.2 Changes in household income by initial occupation of couples

We repeat the exercise in the main section with a slight difference. We only consider couples to examine the evolution of income based on the initial occupation. We estimate eq. C.1:

$$\Delta \ln y_{i(t+T,t)} = \lambda task_{it} + \gamma spousetask_{it} + \delta X_{it} + \varepsilon_{it} \; for \; T = 1,2,..10 \tag{C.1}$$

where y is the total household net equivalised income; $task$ and $spousetask$ are the the husband's and wife's occupation at t, respectively. X is the matrix of control variables for socio and demographic characteristics of husbands and wives. It includes the same variables as in eq. 4.4.

Fig. C.9 reports the λ and γ coefficients in the left and in the right panel, respectively. The coefficients are to be interpreted as income change differentials for households in which the husband (wife) started in a given occupation at t with respect to households with a manual routine male worker (cognitive routine female), all other things being equal.[1]

The left panel indicates that the average income growth in households where the husbands are in cognitive non-routine jobs at t is almost identical to families where the heads started as manual routine workers.

The right panel highlights patterns that are very similar to the results in the main analysis, concerning changes in earnings and wages for women. In particular, households with women who were manual non-routine workers as initial occupation experience a higher income growth over the years than households with women in cognitive routine jobs. The latter, in turn see their income grow more than households where the wives are in a cognitive non-routine or in a manual routine job.

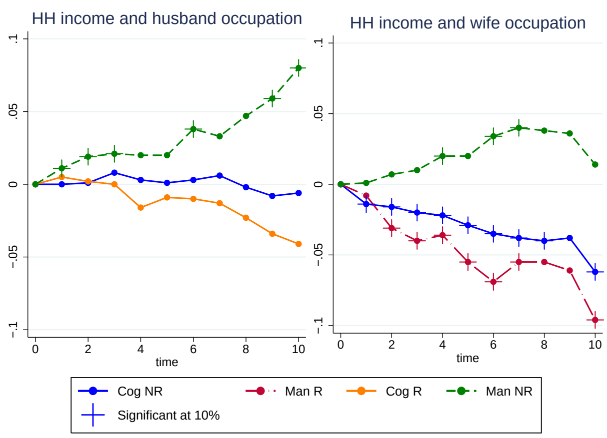

Figure C.9: Changes in the household total net equivalised income by the initial occupation of husband and wife.
The left panel illustrates the λ coefficients of eq. C.1. The right panel illustrates the γ coefficients of the same eq.

[1]Like before, manual routine is the base category for *task* in eq. C.9. Cognitive routine is the base category for *task spouse*.

C.3 Occupational wage premia

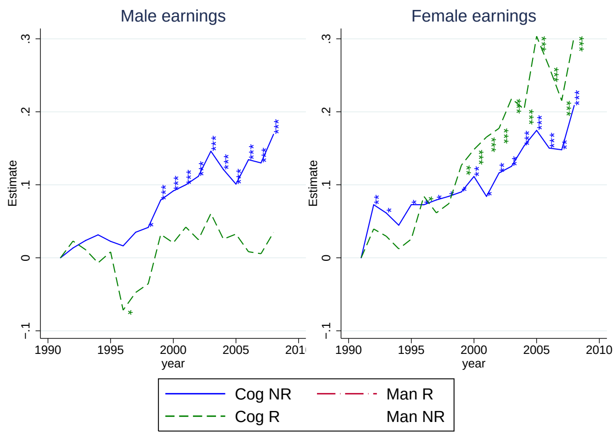

Figure C.10: Occupation-year fixed effects for earnings on the main sample

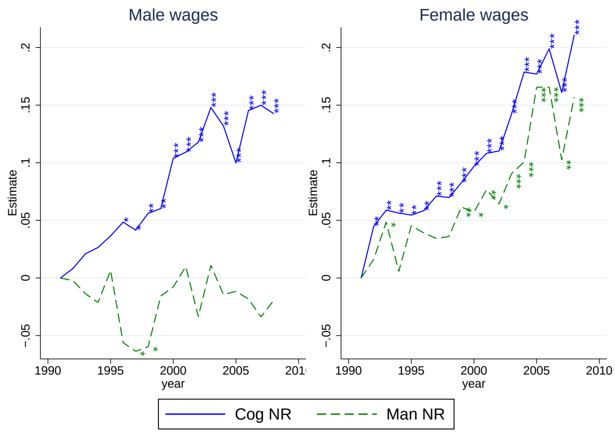

Figure C.11: Occupation-year fixed effects for16 to 64 y-olds

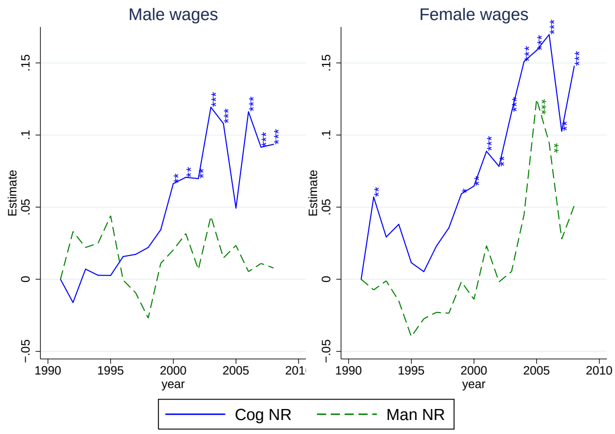

Figure C.12: Occupation-year fixed effects for workers with non-missing information about their wages in at least 11 waves

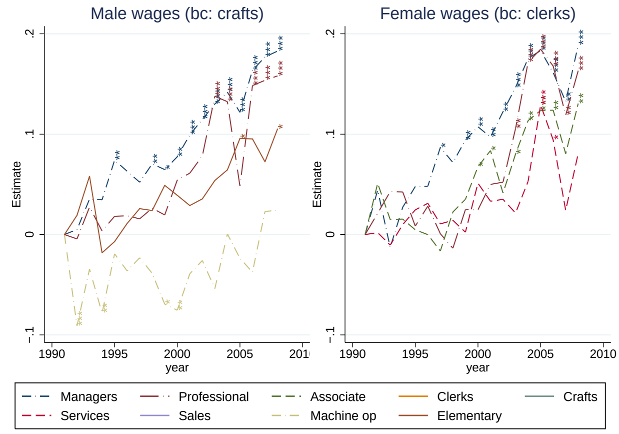

Figure C.13: Occupation-year fixed effects for by occupation
The base occupation is crafts for males and clerks for females

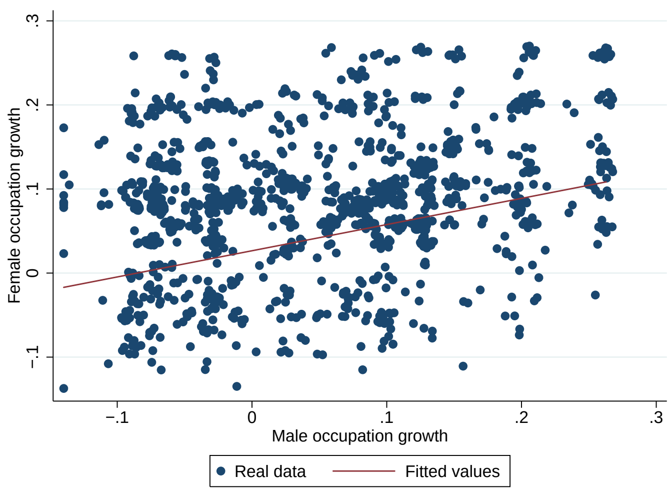

Figure C.14: Correlations of occupations of husbands and wives (Source: LFS)

Table C.3: Men: Changes in wage premia for cognitive non routine workers with respect to changes for manual routine for alternative specifications

	1		2		3	
1992 CNR	0.021	(0.02)	0.019	(0.02)	0.021	(0.02)
1993 CNR	0.024	(0.02)	0.020	(0.02)	0.025	(0.02)
1994 CNR	0.037	(0.02)	0.033	(0.02)	0.038*	(0.02)
1995 CNR	0.033	(0.02)	0.025	(0.02)	0.033	(0.02)
1996 CNR	0.044*	(0.03)	0.036	(0.03)	0.046*	(0.03)
1997 CNR	0.039*	(0.02)	0.031	(0.02)	0.040*	(0.02)
1998 CNR	0.047*	(0.02)	0.035	(0.03)	0.047*	(0.02)
1999 CNR	0.053**	(0.03)	0.041	(0.03)	0.053*	(0.03)
2000 CNR	0.093***	(0.03)	0.079***	(0.03)	0.093***	(0.03)
2001 CNR	0.099***	(0.03)	0.084***	(0.03)	0.099***	(0.03)
2002 CNR	0.106***	(0.03)	0.092***	(0.03)	0.109***	(0.03)
2003 CNR	0.139***	(0.03)	0.124***	(0.03)	0.142***	(0.03)
2004 CNR	0.117***	(0.03)	0.102***	(0.03)	0.120***	(0.03)
2005 CNR	0.086***	(0.03)	0.070**	(0.03)	0.089***	(0.03)
2006 CNR	0.142***	(0.03)	0.125***	(0.03)	0.146***	(0.03)
2007 CNR	0.143***	(0.03)	0.126***	(0.03)	0.148***	(0.03)
2008 CNR	0.142***	(0.03)	0.122***	(0.03)	0.144***	(0.03)
Observations	25345		25345		25345	
Adjusted R^2	0.230		0.230		0.228	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Clustered standard errors in parenthesis. For all models, controls include region, age and its squared, marital status, year fixed effects. In 1, we add trade union membership; in 2, we add education and job tenure and the interaction between age and education and education and occupation; in 3, the model in 1 is augmented with an interaction between job tenure and occupation. CNR stands for Cog Non routine. To make the table more readable, only the statistically significant coefficients are reported.

Table C.4: Women: Changes in wage premia for non routine workers with respect to changes for cognitive routine for alternative specifications

	1		2		3	
1992 CNR	0.044*	(0.02)	0.040*	(0.02)	0.042*	(0.02)
1992 MNR	0.022	(0.02)	0.020	(0.03)	0.022	(0.03)
1993 CNR	0.042*	(0.02)	0.036	(0.03)	0.042*	(0.03)
1993 MNR	0.031	(0.03)	0.027	(0.03)	0.033	(0.03)
1994 CNR	0.042	(0.03)	0.034	(0.03)	0.043*	(0.03)
1994 MNR	0.005	(0.03)	-0.000	(0.03)	0.008	(0.03)
1996 CNR	0.043*	(0.03)	0.033	(0.03)	0.047*	(0.03)
1996 MNR	0.022	(0.03)	0.019	(0.03)	0.033	(0.03)
1998 CNR	0.050*	(0.03)	0.037	(0.03)	0.056**	(0.03)
2000 CNR	0.092***	(0.03)	0.075**	(0.03)	0.097***	(0.03)
2000 MNR	0.038	(0.03)	0.033	(0.03)	0.057*	(0.03)
2002 CNR	0.103***	(0.03)	0.088***	(0.03)	0.116***	(0.03)
2002 MNR	0.041	(0.04)	0.037	(0.04)	0.069*	(0.04)
2004 CNR	0.172***	(0.03)	0.156***	(0.04)	0.186***	(0.03)
2004 MNR	0.070**	(0.03)	0.064*	(0.03)	0.100***	(0.04)
2006 CNR	0.186***	(0.03)	0.168***	(0.04)	0.202***	(0.03)
2006 MNR	0.122***	(0.04)	0.119***	(0.04)	0.160***	(0.04)
2008 CNR	0.202***	(0.03)	0.177***	(0.04)	0.216***	(0.04)
2008 MNR	0.118***	(0.04)	0.111***	(0.04)	0.159***	(0.04)
Observations	24885		24885		24885	
Adjusted R^2	0.200		0.196		0.196	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Clustered standard errors in parenthesis. For all models, controls include region, age and its squared, marital status, year fixed effects. In 1, we add trade union membership; in 2, we add education and job tenure and the interaction between age and education and education and occupation; in 3, the model in 1 is augmented with an interaction between job tenure and occupation. CNR stands for Cog Non routine; MNR for Manual non routine. To make the table more readable, only the statistically significant coefficients are reported, and only for alternate years.