It Runs in the Family: Occupational Choice and the Allocation of Talent*

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Abstract

Children tend to choose the same occupations as their parents. We examine the implications of this tendency for talent allocation and intergenerational mobility. Using Swedish data on skills and personality traits, we estimate a general equilibrium Roy model with unequal occupational access depending on parental background. Equalizing access halves occupational following and increases intergenerational earnings mobility by a third, benefiting low-income sons most. Exploiting long-run declines in fathers' occupations, we find that reduced following improves sons' skill-matching and raises earnings, aligning with our model. Our results suggest that facilitating more occupational mobility would increase intergenerational income mobility without reducing output.

JEL Codes: E24, J24, J62.

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1 Introduction

It is a well-documented empirical fact that incomes of children tend to correlate strongly with the incomes of their parents (Solon, 1999; Black and Devereux, 2011). This persistence may be attributed to various factors. One important contributing factor is the fact that children frequently pursue the same occupations as their parents.[1] Although this strong tendency for intergenerational continuity—or inheritance—of occupations has long been recognized (Rogoff, 1953; Blau and Duncan, 1967; Long and Ferrie, 2013), there is no consensus on the reasons behind it. On the one hand, it may reflect occupational sorting based on skills: parents and children share the same productive skills and, hence, select into the same occupations based on their comparative advantages. On the other hand, intergenerational persistence in occupations may reflect unequal opportunities: parental background may facilitate access or impose barriers to entering certain occupations, which are independent of the child's abilities. In both cases, the earnings of parents and children will be correlated, in part due to common occupational choices.

The two explanations have fundamentally different implications for productive efficiency and intergenerational mobility in the economy. Under selection on skills, intergenerational persistence in occupations and incomes is the result of efficient sorting. Low levels of occupational mobility reflect the efficient allocation of talent, implying that efficiency and intergenerational mobility are inversely related (Galor and Tsiddon, 1997; Jovanovic, 2014). In contrast, under inequality in opportunities, lack of mobility is a symptom of inefficiency as it reflects misallocation of talent (Bell et al., 2019; Hsieh et al., 2019). This implies that efficiency and intergenerational mobility move together.

In this paper we examine whether and to what extent occupational following reflects misallocation of talent. We use unique data on the skills, personality traits, and labor market outcomes for the population of Swedish men to estimate a structural general equilibrium model of occupational choice. The model enables us to perform a key experiment: a counterfactual where all children, regardless of parental background, have equal access to occupations and only sort into different occupations depending on skills. Our key result is that under equal opportunities occupational following drops by half and earnings mobility increases by a third. To validate the model's predictions, we exploit long-run employment changes in fathers' occupations as exogenous variations in sons' opportunities to follow their fathers. Consistent with our model's predictions, we find that occupational decline leads to reduced occupational following among sons, better skill-match in the occupations

[1] In the US, sons of medical doctors and lawyers, for example, are, respectively, 24 and 18 times as likely to become doctors and lawyers themselves, than if occupations of sons were chosen independently from those of their fathers (Dal Bó et al., 2009). The same holds true for a range of occupations (Laband and Lentz, 1985).

they pursue, and higher earnings.

We begin our analysis by documenting important patterns in the occupational choices of Swedish children. First, we show that children are disproportionately more likely to choose the same three-digit occupations as their parents, compared to children from different backgrounds.[2] There is strong tendency for occupational following among both sons and daughters, while sons are substantially more likely to follow their fathers than their mothers, and vice versa for daughters. We estimate that, for example, sons of doctors and lawyers are, respectively, 12 and 18 times more likely to become doctors and lawyers themselves compared to a benchmark where the occupations of children are independent of those of their parents. These occupations are not outliers: on average, sons are 18 times more likely to enter the same occupation as their father, compared to children from different fathers. Second, we find that children who do not follow their parents into the same narrow occupation often stay close to it, i.e., within the same broad occupational classification.

We use a structural general equilibrium Roy (1951) model to study the impact of parental background on occupational choice, intergenerational earnings mobility, and efficiency in the economy. In the model, individuals choose the occupation that provides them with the highest utility. Each occupation offers different prospective earnings, which we predict using their skills, but entry is subject to utility costs. In addition, we introduce a force that may cause children to choose the same occupation as their parents even when that occupation does not yield the highest returns on their skills. We model this force as a 'discount' on the entry costs. The discount captures a range of factors that can make children more likely to enter their parent's occupation compared to other children with the same skill set but a different background. This includes several factors that likely vary in importance across occupations, including unequal access to information, networks, or nepotism (rent or wealth transfers). Given individuals' skills, we estimate the entry costs and discounts to match their observed occupational choices. We find these discounts to be large. Sons who pursue their father's occupation receive a reduction in the entry cost equivalent to 81,000 SEK (USD 7,500) when evaluated for the median occupation, relative to sons without a father in that occupation. This is equivalent to 27 percent of prime-age earnings. With the estimated costs and discounts, the model replicates the observed occupational densities and propensities of children to follow their parents across occupations.

The crucial ingredients for the model are measures of individuals' skill-based productivities across occupations. To measure these, we harness unique data on a range of cognitive skills (inductive, verbal, spatial, and technical ability) and personality traits (social

[2] Our main analysis is based on a classification of 91 occupations that is consistent from 1960 until today.

maturity, intensity, psychological energy, and emotional stability) of men at age 18. Using these data, we measure occupational skill requirements and quantify how well workers match with all occupations based on their abilities. Our approach builds conceptually on the 'task framework', according to which occupations differ in tasks and in how productive different skills are in performing these tasks (Acemoglu and Autor, 2011). We rely on the assumption that individuals sort into occupations that fit their heterogeneous skills—a result documented in prior work (e.g. Fredriksson, Hensvik, and Skans, 2018; Autor and Handel, 2013) and a pattern that we document in our data. This implies that we can use the skills of incumbent workers to measure the skill requirements and returns for each occupation. We train a machine-learning algorithm on the skills of incumbents in each occupation—excluding followers—and predict potential earnings ('Roy productivity') and entry probability (skill fit) for every potential entrant based on his skill set.

We use the model to construct a counterfactual experiment that equalises entry-costs for children, so that heterogeneous occupational choices are driven only by skill differences. Our central finding is that there is substantial misallocation of talent in the economy. In the counterfactual, occupational following drops by 65%, from 8.4 percent to 3 percent. While at baseline the propensity for occupational following is near uniform across the fathers' income distribution, the drop in following is substantially larger among sons of lower income fathers. This is due to more misallocation among sons of blue-collar workers than of white-collar workers.

Increased occupational mobility increases intergenerational earnings mobility by almost 30 percent, measured either by the probability of sons of fathers in the bottom earnings quintile moving to the top quintile, or the change in the correlation in the earnings rank of sons and fathers. This reflects both relative and absolute earnings changes. Among sons of the lowest earning fathers, real earnings rise by 2.8 percent while their earnings percentile rank increases by 4.1 ranks. In contrast, the real earnings of sons of the highest earning fathers decline by 3 percent and their relative earnings by 4.6 ranks. Our results allow us to decompose the observed intergenerational earnings persistence into its contributing factors. Relative to the perfect mobility benchmark, when earnings of sons are independent from those of their fathers, we find that 26 percent of the observed intergenerational earnings persistence is accounted for by the influence of father's occupational background.

Our results highlight the importance of general equilibrium effects of reallocation. In partial equilibrium, reallocation of workers across occupations increases annual aggregate income in the counterfactual economy by about 2 percent. However, the net flow of misallocated workers from blue-collar to white-collar occupations is sufficiently large to reduce wages in the white-collar occupations they enter. This force brings real aggregate earnings in general equilibrium to almost the same level as in the baseline economy. In sum, we estimate that equal opportunities for occupational entry leads to a sizable increase in intergenerational earnings mobility while leaving aggregate real earnings almost unchanged.

We estimate entry costs and heterogeneous entry cost discounts necessary to rationalize the differences between observed occupational choices and those predicted by individuals' skills. However, as these discounts are not microfounded, they may capture both barriers to entry and exit, and also inherited preferences. This influences the welfare implications of our results. In the last part of the paper, we introduce quasi-experimental evidence to support the interpretation of the entry cost discounts and validate our model results. We exploit structural occupational decline in fathers' occupations as exogenous variation in sons' opportunities to pursue their fathers' occupations. We hypothesize that a decline in employment in the father's occupation affects some of the factors that are captured by the entry cost discounts in our model, such as father's network or provision of information about the occupation, but is unrelated to sons' inherited preferences for entering their fathers' occupations. In support of this hypothesis, we estimate a strong first stage: a decline in a father's occupation makes it less likely that their son will follow them. In turn, sons who do not follow their fathers receive higher prime-age earnings. These results are driven by sons of low-income fathers and sons with a skill mismatch to their father's occupation. We estimate the same relationship using model-generated data: for sons of low- to medium-income fathers, increased propensity to follow due to a change in discounts leads to a stark earnings decline. Among sons of the highest income fathers, however, following leads to earnings beyond what their skills would predict. This lends support to the interpretation that the discounts we estimate reflect, at least to a large extent, heterogeneous occupational entry and exit barriers.

Our paper integrates and contributes to two strands of literature. First, a voluminous literature in economics and sociology documents strong persistence in occupations (e.g., Rogoff, 1953; Blau and Duncan, 1967; Laband and Lentz, 1985; Long and Ferrie, 2013) and incomes (Solon, 1999; Black and Devereux, 2011). An extensive, related literature studies the determinants of the career choice of children and their tendency to follow their parents, documenting the influence of parental networks (Kramarz and Skans, 2014; Dal Bó et al., 2009; Staiger, 2023), provision of information (Lentz and Laband, 1989; Laband and Lentz, 1983; Lentz and Laband, 1990; Laband and Lentz, 1992), or transfers of wealth or rent (nepotism) (Mocetti, 2016; Mocetti et al., 2022; Aina and Nicoletti, 2018). In addition, prior work has exploited quasi-experimental variation in children's exposure to occupations, e.g. through occupations of parents or neighbors (Bell, Chetty, Jaravel, Petkova, and Van Reenen, 2019) or parents' fields of study (Altmejd, 2023; Dahl et al., 2020). One interpretation of the findings is that exposure to occupations influences the child's 'consideration set' of occupations, similar to how advertising affects consumer behavior (e.g. Hauser, 2014). Using our structural model, we quantify the implications that this range of forces has on occupational choice and, in turn, on output and intergenerational mobility.

Second, a growing literature documents the effects of the misallocation of talent across occupations and space (e.g. Murphy, Shleifer, and Vishny, 1991; Nakamura, Sigurdsson, and Steinsson, 2021; Chetty, Hendren, and Katz, 2016; Munshi and Rosenzweig, 2016; Bryan and Morten, 2019; Aghion, Akcigit, Hyytinen, and Toivanen, 2017). Closer to our work are recent papers that study the aggregate effects of misallocation of talent resulting from barriers to labor market participation and occupational entry based on gender and race (Hsieh, Hurst, Jones, and Klenow, 2019), and parental background (Lo Bello and Morchio, 2021; Celik, 2023). This work has relied on assumptions about the distribution of innate talent in the population or the process through which the skills of parents and children are related. We proceed differently and use individual-level data on skills and labor market outcomes to measure occupation-specific skill returns and requirements. This enables us to quantify the effect of talent misallocation on individuals and the economy, and to decompose the drivers of observed intergenerational occupation persistence into individuals' abilities and their background.[3]

In contrast to prior studies, in particular Hsieh, Hurst, Jones, and Klenow (2019), we estimate limited output gains from reallocation. Several reasons may explain this. First, our analysis is restricted to individuals in the labor force. Any gains from labor force participation of talented individuals are excluded. Second, our analysis excludes groups, such as women and immigrants, which likely face higher barriers to occupational entry than native men, e.g., through labor market discrimination (Goldin, 2014) and social norms (Bertrand, 2011). Third, the Swedish welfare state provides tuition-free education and social security to its public, which may reduce misallocation at baseline. As a result, our estimates likely reflect a lower bound on the potential efficiency and equity gains in settings where mobility and equality of opportunities are lower.

In the next section we describe our data. In Section 3 we document patterns of occupational choice and intergenerational persistence in occupations. In Section 4 we present a simple Roy model with entry costs and discounts to highlight the mechanisms through which parental background can affect occupational choices and intergenerational earnings

[3] These results contribute to a literature documenting the intergenerational correlation in abilities (e.g. Grönqvist, Öckert, and Vlachos, 2017; Björklund and Jäntti, 2012; Collado, Ortuño-Ortín, and Stuhler, 2023) and the role of abilities as a determinant of occupational choice, e.g., to become an entrepreneur (Lindquist, Sol, and Van Praag, 2015; Nicolaou, Shane, Cherkas, Hunkin, and Spector, 2008).

mobility. In Section 5, we develop our structural general equilibrium model and describe how we measure individual skill fit to occupations. We present the results from model estimation in Section 6. Section 7 contains the results from our counterfactual experiment. In Section 8 we present supporting quasi-experimental evidence. Section 9 is the conclusion. Additional background material is relegated to an online appendix.

2 Data

2.1 Labor Market Outcomes

We use several data sets in our analysis, covering the Swedish population back to 1960. Data on earnings and other labor market outcomes are obtained from tax records. Demographic information, including data linking parents and children, is obtained from administrative records.[4]

The core of our analysis is intergenerational relationships between the occupations of parents and children. For the period from 1960 to 1990, we measure occupation using data from the Swedish Census (*Folk-och bostadsräkningen*), conducted by Statistics Sweden at five year intervals. The census records both occupation and industry of the working age population. Starting in 1996, we use data from the wage statistics register (*Lönestrukturstatistiken*), which gathers data from employers about their employees every year. From this source, we have information on the occupations of all workers in the public sector every year and a random sample of half of all workers in the private sector. Occupations are classified according to a Swedish version (SSYK-96) of the International Standard Classification of Occupations (ISCO) codes. Using cross-walks between versions of the classifications that we obtain from Statistics Sweden, we have a consistent classification of 113 3-digit ISCO-88 level occupations for the period 1960-2013.[5] Appendix A.1 provides details on the occupation classification and our cross-walks.

Because we focus on the persistence of occupations and income across generations, we measure these when individuals are of prime age. For children, we define the prime-age occupation as the modal occupation between the ages of 30 and 40. If two occupations tie according to this criterion, we define the prime age occupation to be the one observed at the end of the age span. Income at prime age is then defined as total yearly labor earnings while working in the prime age occupation. For parents, prime age occupation and income

[4] All of this data is compiled by Statistics Sweden and was made available to us through the servers of the Institute for Evaluation of Labor Market and Education Policies (IFAU).

[5] In 2013 the occupation classification scheme changed substantially. In order to maintain a consistent classification for parents and children, we end our sample period there.

are defined in the same manner, but at ages 45 to 55, to increase the number of parent-child observations. We restrict our sample to occupations with at least 1,000 men in order to avoid small cells, especially when measuring workers' skill-matches and predicted earnings in occupations, as we describe below. Our final data set includes 696,016 father-son pairs in 91 different occupations.

2.2 Skills

We use a detailed measure of individuals' skills, utilizing scores from tests administered at military enlistment. These scores are available from the Swedish Military Archives from 1969. During our sample period, almost all men went through a draft at age 18 or 19. The draft process has standardized tests that measure cognitive skills along four dimensions and a structured evaluation by a trained psychologist, using behavioral questions that evaluate individuals' personality traits (non-cognitive skills) along four dimensions. The cognitive skills are (1) *Logic-inductive ability* (fluid intelligence), (2) *Verbal comprehension* (crystallized intelligence), (3) *Spatial ability*, and (4) *Technical understanding*. The non-cognitive skills or personality traits are: (5) *Social maturity* (extroversion, having friends, taking responsibility), (6) *Intensity* (the capacity to activate oneself without external pressure, the intensity and frequency of free-time activities) (7) *Psychological energy* (perseverance, ability to fulfil plans, to remain focused), (8) *Emotional stability* (ability to control and channel nervousness, tolerance of stress, and disposition to anxiety). For further information about these measures, see Carlsted and Mårdberg (1993) and Mood et al. (2012). Previous work has documented that the cognitive and non-cognitive test scores are correlated, but contain independent information about individuals' abilities and traits (Fredriksson et al., 2018).

3 Intergenerational Occupational Persistence

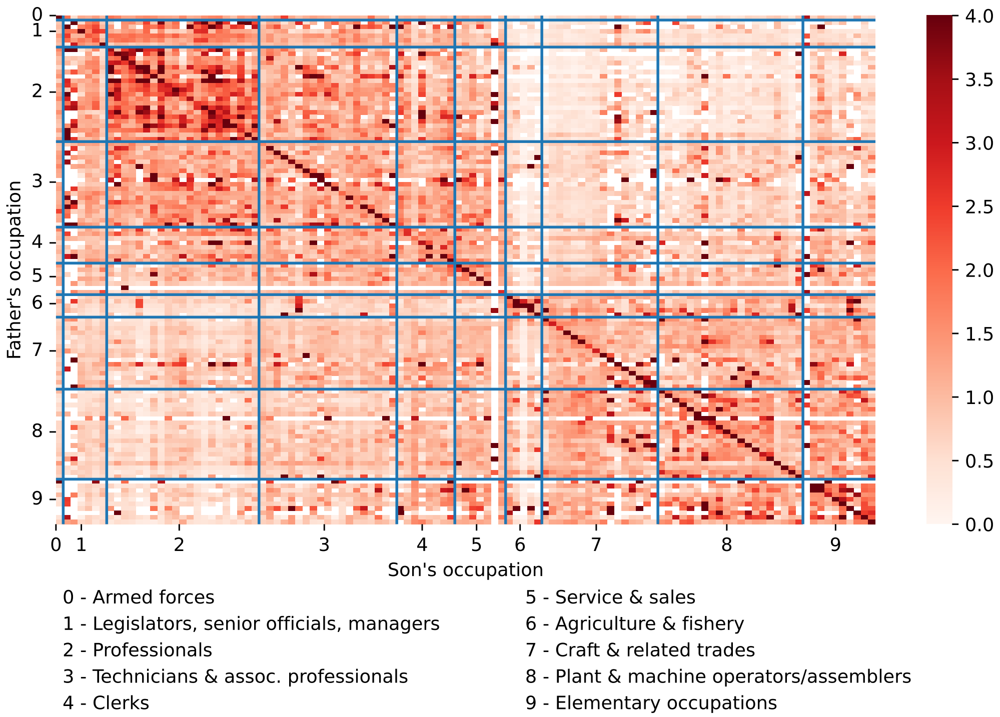
In this section we document the systematic tendency of children to enter the same occupation as their parents. We follow Rogoff (1953) and compute what we refer to as the *occupational mobility bias*, defined as:[6]

$$OMB_{f,k} = \frac{share_{f,k}}{share_k}$$

where f and k index the parent's and child's occupations, respectively. The occupational mobility bias is the share of children with a parent in occupation f who are observed in oc-

[6] As discussed in Blau and Duncan (1967), in the sociology literature this ratio has been referred to as the "index of association" or the "social distance mobility ratio".

Figure 1: Mobility Bias Across Occupations



Note: This figure shows the mobility bias estimates across different occupations. The y-axis displays the father's occupation, the x-axis displays the son's occupation. On the x-axis, occupations are ordered according to their 3-digit code in the SSYK-96 classification system. The vertical and horizontal lines partition the space into 1-digit occupational categories. For the computation of the mobility bias, see the text. The sample period is 1960-2013.

cupation k, $share_{f,k}$, relative to the fraction of children in occupation k, $share_k$. Intuitively, if occupations were assigned to children at random, then the occupational mobility bias would be equal to one, but larger than one if more children are found in occupation k with their parents in occupation f than would be expected under random assignment.[7]

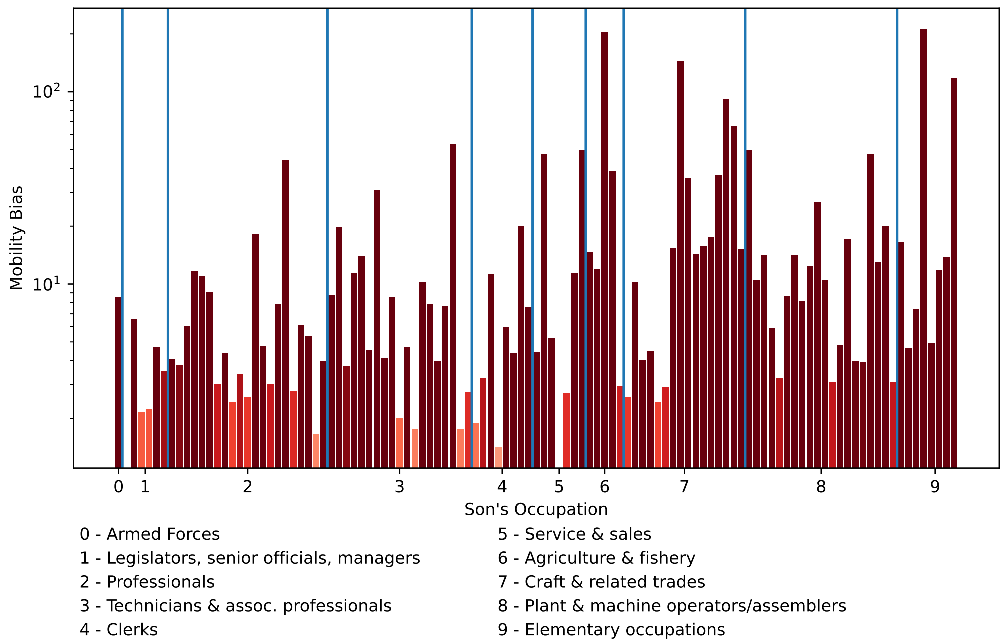
Figure 1 documents the occupational mobility bias across all combinations of fathers' and sons' occupations.[8] The y-axis represents the father's occupation, while the x-axis represents the son's occupation. Each row or column in the matrix is a specific three-digit occupational code in the Swedish SSYK-96 system, the vertical and horizontal lines partition the space into one-digit occupational categories.[9] The figure depicts three key patterns.

[7] Dal Bó et al. (2009) compute the probability of observing a father in occupation f conditional on a child being in occupation k and compare it to the unconditional probability of observing a father in occupation f. They refer to this measure as *dynastic bias*. By Bayes' rule, this is mathematically equivalent to our OMB measure.

[8] For a list of occupational codes and descriptions, see Table A.2 in Appendix E.

[9] Our exposition is focused on fathers and sons, as our main analysis is focused on their occupational choices, leveraging detailed data on men's skills. For completeness, however, we present the occupational mobility matrix for other combinations of parents and children in Appendix Figures A.12, A.13, and A.14.

Figure 2: Occupational Following



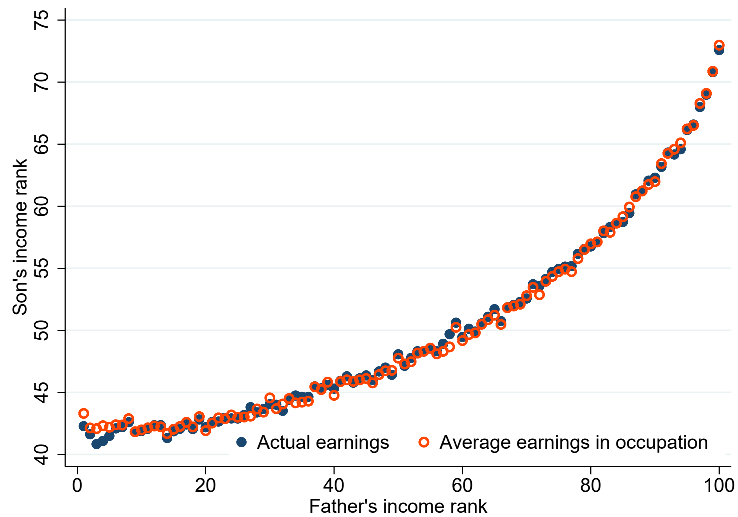
Note: This figure shows a bar graph of mobility bias for children following their parents into the same occupation, i.e., $f = k$. The values are equivalent to those on the diagonal of Figure 1. The y-axis is in log scale. On the x-axis, occupations are ordered according to their 3-digit code in the SSYK-96 classification system, the horizontal lines mark the borders of 1-digit occupational groups. Sample period: 1985-2013.

The first and most prominent pattern is the clearly visible diagonal, reflecting the systematic tendency of sons to enter the same occupation as their fathers. Along the diagonal, the occupational mobility bias is far in excess of unity. The weighted (unweighted) average of the bias along the diagonal is 8.53 (18.23), meaning that sons are on average six times more likely to enter the same occupation as their father than to enter another occupation at random.[10] To highlight the magnitudes along the diagonal, as well as the heterogeneity, Figure 2 presents the mobility bias only along the diagonal of the matrix (note that the y-axis displays the bias in log-scale). While the bias is highly heterogeneous across occupations, it is almost always greater than one, across all occupations irrespective of skill requirements or earnings levels. We register the highest mobility bias among sons who choose agricultural professions, with values exceeding 100. The only profession for which the mobility bias is smaller than one can be found among clerks. These findings are in line with previous studies that have documented substantial occupational mobility bias, e.g., in the US labor market (Rogoff, 1953; Blau and Duncan, 1967; Dal Bó et al., 2009).

The second key pattern is that there are clusters of occupational persistence around the diagonal. Especially among *professionals*, which include high-paying white-collar oc-

[10]Below, due to various sample selection criteria, we restrict attention to 91 occupations. For these, the weighted (unweighted) average of the bias along the diagonal is 7.93 (9.38)

Figure 3: Association between Sons' and Fathers' Incomes



Note: The figure shows the relationship between sons' and fathers' income ranks. Fathers are placed into 100 percentile bins. For each such bin, we calculate the average income rank of sons, which is then plotted on the y-axis. Fathers and sons are ranked within cohort-year cells. Blue dots are based on observed earnings for the sons. Orange circles plot average income ranks, conditional on the income rank of fathers, when we measure income as the average income in the son's occupation, instead of using each individual's actual earnings. The sample period is 1985-2013.

cupations such as lawyers, medical doctors and pharmacists, there is high mobility bias outside of, but close to, the diagonal. This implies that, while the sons of doctors are very likely to become doctors themselves, they are also more likely to stay within the broader occupational category than they would under random assignment.

The third key pattern is that the occupational mobility matrix splits occupations into quadrants along white-collar vs. blue-collar axes. The north-west and the south-east quadrants show noticeably higher levels of occupational mobility bias; the north-east and south-west corners show noticeably less. Occupations with one digit codes from one to five can mostly be characterised as white-collar, e.g. police officers, lawyers, doctors and teachers, while the occupations with one digit codes from six to nine are blue-collar occupations, e.g. fishermen, painters and machine-operators. Sons are highly likely to stay within these two broad occupation categories - more than random assignment would imply - and there is little movement across the two, as signified by bias below unity.

This intergenerational persistence in occupations has important implications for intergenerational earnings mobility. Figure 3 plots the relationship between the fathers' and the sons' prime-age income ranks constructed within cohort-year cells.[11] To show the im-

[11]Figure 3 plots ranks of full-time earnings in prime-age occupations, measured as the modal occupation at ages 30-40 for sons and as the modal occupation at ages 45-55 for fathers. The rank-rank slope is 0.261. This measure differs somewhat from the literature, both in steepness and shape. The literature tends to measure

portance of intergenerational occupational persistence for intergenerational earnings persistence, we assign every son in our sample the average earnings of his occupation. Thus, we net out the impact of son's relative position within an occupation for earnings mobility and isolate only what is contributed by across-occupation earnings differences. The orange circles in Figure 3 display the result of this exercise. The relationship is almost identical to that using actual earnings, including both within and across occupation earnings differences. Hence we conclude that the relationship between the fathers' and sons' income ranks is strongly influenced by occupational choices. Consequently, we argue that understanding the intergenerational persistence of occupational choices will help to shed light on the mechanisms that underlie the observed intergenerational persistence in earnings.

4 A Basic Model of Occupational Choice

To study how skills and family background influence occupational choices and labor market outcomes, we build a Roy (1951) model that incorporates these factors. We build on and extend Roy models presented in Ohnsorge and Trefler (2007), Adão (2015), Nakamura, Sigurdsson, and Steinsson (2021), and, in particular, Mayer (2008). In the standard model, individuals are endowed with heterogeneous skills and choose between occupations where the productivity of skills and hence returns differ. Importantly, we add two features to this setup. First, a child's skills partly depend on their parent's skills, leading to intergenerational correlation in occupation-specific productivities across generations. Second, entering an occupation is costly and this cost may depend on the parent's occupation. In this section, we present a simple partial equilibrium model to illustrate the mechanisms at play. In the subsequent section, we relax several of our simplifying assumptions and extend the model to a multi-occupation general equilibrium model that fits the Swedish economy.

In this simple model, there are two occupations—hunting and fishing—that an individual from family i and generation g can choose between.[12] We use the generic index n to denote the occupations and denote fishing by F and hunting by H. Individuals live for two periods. In the first period, individuals from generation g are born as children of parents from generation $g-1$ and choose an occupation based on their endowed skills. In their second period they are parents and inelastically supply one unit of labor to market work in

income as total taxable earnings, including zeros (Chetty et al., 2014). For comparison, Appendix Figure A.7 plots the rank-rank association for our sample, measuring income as total taxable earnings. This leads to a near-linear relationship with a slope of 0.19. This is a substantially flatter slope than documented for the US (0.341) (Chetty et al., 2014) but closer to, although steeper than, that documented for Denmark (0.180) (Boserup et al., 2013) and Canada (0.174) Corak and Heisz (1999).

[12] We use g to denote both time and a generation, which consists of all individuals born in the same period, i.e., a birth cohort.

their chosen occupation. This implies that in a given period only one generation is active in the labor market.

Occupations require an occupation-specific skill for workers to be productive.[13] Individuals are endowed with a bivariate skill vector $(Z_H^g(i), Z_F^g(i))$, where $Z_n^g(i)$ is the productivity of the individual from family i of generation g in occupation n. Each generation consists of a unit mass of individuals distributed across $\mathcal{Z}_F \times \mathcal{Z}_H$. We posit the distribution of Z_F^g in the population to be $F(Z_F)$ and the conditional distribution of Z_F^g to be $\{Z_F^g(i)|Z_H^g(i) = z\} \sim H(Z_F^g(i)|z)$.

We denote logarithms with a lower-case letter, i.e., $z_n^g(i) \equiv \log(Z_n^g(i))$. Children imperfectly inherit skills from their parents according to the following process:

$$z_n^g(i) = \tau z_n^{g-1}(i) + (1-\tau)\varepsilon_n^g(i), \tag{1}$$

where τ governs the heritability of skills. As $\tau \to 0$, children's abilities become independent of their parents' abilities, whereas $\tau \to 1$ implies that skills do not change from a parent to a child. The joint distribution of the skill innovations ε_n^g is assumed to be bivariate normal with mean $\mu_n = 0$ and variance $\sigma_n^2 = 1$. The correlation between the two skills is ρ. This leads to an ergodic distribution with mean $\bar{\mu}_n = 0$ and variance $\bar{\sigma}_n(\tau)$.

We assume, for simplicity, that labor is the only factor of production and firms produce using linear production functions:

$$Y_F = A_F L_F \quad \text{and} \quad Y_H = A_H L_H, \tag{2}$$

where

$$L_F = \int_{i\in\Gamma^F} Z_F^g(i)^{\beta_F} di, \quad L_H = \int_{i\in\Gamma^H} Z_H^g(i)^{\beta_H} di \tag{3}$$

Γ^n denotes the set of workers employed in occupation n, A_n represents aggregate productivity in sector n, and β_n represents the marginal return to productivity in sector n.[14] The labor markets for both occupations are perfectly competitive and firms operating in those markets take the prices of fish, P_F, and rabbits, P_H, as given. Here, we assume that prices are fixed, an assumption we relax when estimating the extended general-equilibrium model in the subsequent section. These assumptions imply that the wages per efficiency unit of

[13] We use the terms skills and abilities interchangeably to describe a fixed characteristic of a worker which governs their productivity within an occupation.

[14] Our choice to model the marginal product of efficiency units using β_n follows Ohnsorge and Trefler (2007). Another common, and isomorphic, formulation is to assume that the variances of the intergenerational productivity innovations, ε_n^g differ across occupations (e.g., Sattinger, 1993).

labor in fishing and hunting, respectively, are given by

$$W_F = P_F A_F \quad \text{and} \quad W_H = P_H A_H \tag{4}$$

Earnings of worker i in occupation n is $Y_n(i) = W_n Z_n(i)^{\beta_n}$ and thus depends on the occupation's wage rate W_n, the number of efficiency units of labor the worker can supply $Z_n(i)$, and the marginal return to skills in the occupation, β_n. The logarithm of labor income is therefore given by

$$y_F^g(i) = w_F + \beta_F z_F^g(i) \quad \text{or} \tag{5a}$$

$$y_H^g(i) = w_H + \beta_H z_H^g(i), \tag{5b}$$

depending on whether the worker is a fisherman or a hunter, respectively.

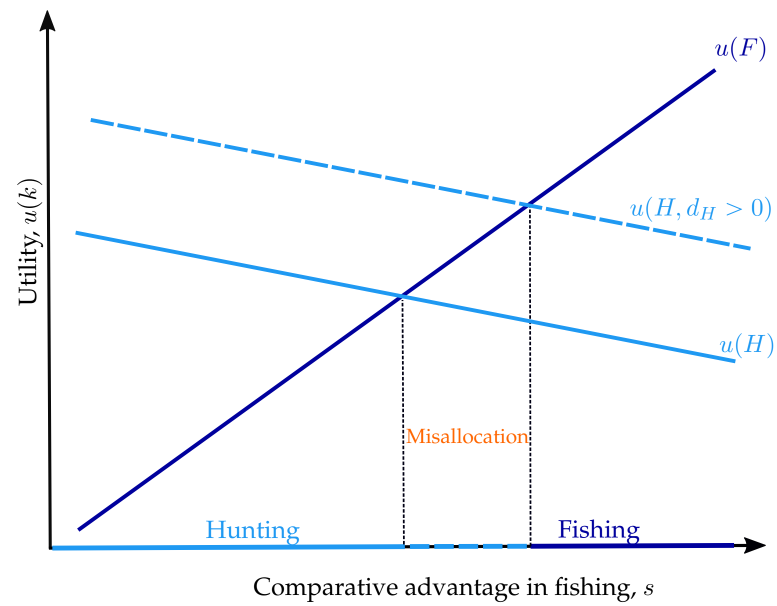
Lastly, as children, individuals choose an occupation $k \in \{F, H\}$ that maximizes their utility in adulthood. Utility is log-linear and depends on three factors: earnings, y_n, an entry cost, m_n, and an entry-cost discount, d_n. Entry costs are occupation-specific, meaning that any entrant has to incur them. Workers who follow their parents into the same occupation, however, secure a discount on the entry costs. Intuitively, this discount captures multiple forces: parents may facilitate better information about and access to necessary education (Lentz and Laband, 1989), provide a network or contacts in the occupation (Kramarz and Skans, 2014; Dal Bó et al., 2009), or transfer rents or wealth to their children (Mocetti, 2016; Mocetti et al., 2022; Aina and Nicoletti, 2018). Hence, utility is

$$u(i, g, n) = y_n^g(i) - m_n + d_n \mathbb{I}_{i^{g-1}, n = i^{g-1}, k}, \tag{6}$$

where $\mathbb{I}_{i^{g-1}, n = i^{g-1}, k}$ is an indicator function for having a parent in occupation n. The entry-cost discount acts as a pull factor for children with a parent in occupation n. If the discount is large, more children with parents in occupation n will follow them into that occupation, all else equal. For simplicity, we assume that parental discounts are zero for all generations $g < \underline{g}$. Below, we analyse how entry discounts in the model affect mobility between generations $\underline{g} - 1$ and $\underline{g}$.

Figure 4 outlines the main mechanism in the model. It plots individuals' utilities in fishing (dark blue) and hunting (light blue) depending on their relative productivity in fishing compared to hunting, $s \equiv \beta_F z_F - \beta_H z_H$. It is useful to think of this as determining an individual's *comparative advantage* in fishing, with the shorthand s referring to sorting. Similarly, $a \equiv \beta_H z_H$ measures a worker's *absolute advantage*. By rewriting equations (5a) and (5b) in terms of s and a, one can see that a change in a shifts y_F and y_H—and therefore

Figure 4: Occupational Sorting by Comparative Advantage



Note: The figure illustrates sorting into occupations based on comparative advantage and the effect of parental background on occupational choice. For simplicity, the figure illustrates the case where only sons of hunters receive a discount on the entry cost into hunting. This leads to increased entry of hunting sons into hunting, despite them having a comparative advantage in fishing, i.e. misallocation of talent. The case of discount on the entry cost into fishing is analogous.

$u(F)$ and $u(H)$—by the same amount, while a change in s only shifts y_F.

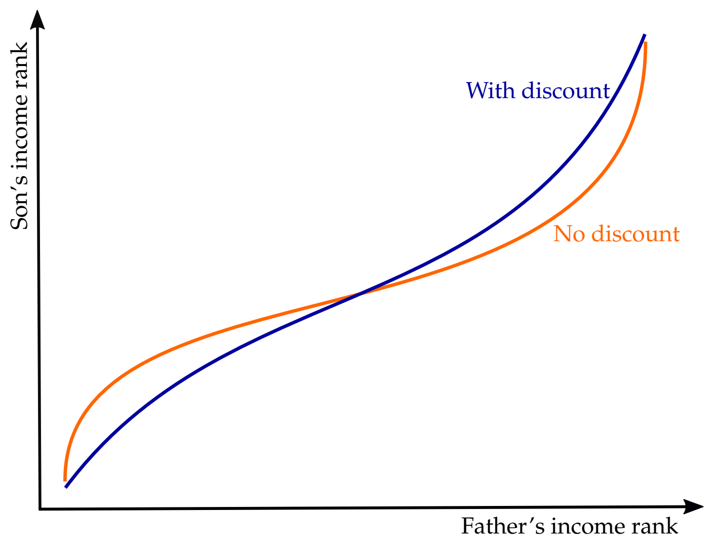
Individuals with a large s are relatively more skilled as fishermen than hunters, i.e., have a comparative advantage in fishing, and choose to become fishermen. Given s, individuals who have a high a are highly productive in both occupations, i.e., have an absolute advantage in both fishing and hunting.[15] Furthermore, under the assumption that $\rho > 0$ (ρ is the correlation between skill realizations z_F and z_H), those that become fishermen also tend to be skilled hunters, i.e., have a high absolute advantage in both occupations. Those that choose to become hunters, however, tend to have a low absolute advantage in both occupations, but a comparative advantage in hunting. Under $\rho < 0$ the reverse is true. In this section we assume $\rho > 0$, in line with the cross-sectional correlation in skills in the Swedish data. This assumption simplifies the discussion that follows, on the model's implications for intergenerational mobility. When extending this model and bringing it to data, we do not, however, need to make assumptions about skills or their correlation, as these are measured in the data.

Occupational choice in this model is directly influenced by parents' occupational choices. Figure 4 displays this influence on the occupational choices of children of hunters.[16] Hav-

[15]This can be seen from the definition of s: for a given s, a high $Z_H^{\beta_H}$ implies high $Z_F^{\beta_F}$.

[16]The case where children of fishermen receive a discount into fishing, not depicted, is analogous and

Figure 5: Intergenerational Income Mobility



Note: The figure presents the relationship between the income rank of children and their fathers in the case with discounts on entry costs into fathers' occupations (blue) and in the case of selection only on comparative advantage (orange).

ing hunter parents shifts the line reflecting utility in hunting upwards, inducing more children to follow their parents into hunting. Absent parental discounts, however, these workers would have selected into fishing based on their comparative advantage. Therefore, parental discounts misallocate talent and distort efficiency.

Importantly, this model also allows us to study how parental influence on occupational choices can affect intergenerational mobility. In the model, as in the data, we measure intergenerational mobility by the relationship between the earnings rank of sons relative to other sons in generation g and the earnings rank of fathers within generation $g-1$. Before investigating this relationship, we make three more assumptions in the model which anticipate regularities we document in the full model. First, we assume, without loss of generality, that $\beta_F > \beta_H$. This echos the assumption in Roy (1951), namely that "*rabbits are plentiful and stupid*" but the "*trout, on the other hand, are particularly wily and fight hard*". The relative magnitude of the two coefficients controls the relative slopes of utility function in Figure 4. Second, we assume that $w_F > w_H$. This enables the model to generate a high-paying (fishing) and low-paying (hunting) occupation; strong differences in average earnings are a prominent feature of the real world, hence we view this assumption as useful. Finally, we also assume that entry costs are larger in the fishing occupation, $m_F > m_H$. These entry costs thus partly cancel out the higher average earnings in fishing. Without this assumption, if w_F is very large, only individuals with very high values of z_H will choose

would be represented with an upward shift of the dark blue line and an increase in the share of fishermen.

hunting. In this case, discounts will have only small effects as there is only a small mass of individuals with z_H high enough. The entry cost assumption centers the crossing point in Figure 4, where the skill distribution is densest.

Figure 5 plots the rank-rank relationship in the model. The figure presents the rank-rank relationship for two cases: with and without discounts on entry costs based on parental background. The discounts lead some children of fishermen to choose fishing and some children of hunters to choose hunting, despite their comparative advantage being in the other occupation. For children of fishermen, the discounts allow them to enter the higher-paying occupation, leading them to earn higher incomes than otherwise. For children of hunters, the discounts keep them in the lower-paying occupation, leading them to earn lower incomes than otherwise. Together the discounts decrease intergenerational income mobility, depicted as steepening the slope of the rank-rank relationship.

To summarize, the model provides two testable predictions. If parental influence on children's occupational choices increases the intergenerational persistence in occupations, this reduces intergenerational income mobility. Second, parental influence distorts the efficient allocation of talent in the economy. The size of these effects will depend on the importance of parental influence relative to selection on skills in explaining the observed intergenerational occupation persistence.

5 General Equilibrium Model of Occupational Choice

We now extend the basic model from the previous section to a structural model that we can estimate using administrative data and use to perform counterfactual experiments. A central component of the model is a measure of how productive individuals are in different occupations, depending on their skills. We measure this by predicting the potential earnings of every individual in every occupation he could choose. Before we outline the model structure, we describe this procedure.

5.1 Skill-Based Predictions of Potential Earnings and Occupational Fit

Conceptually, our approach to measuring occupational skill requirements and how well individuals fit with occupations based on their skills builds on the "task framework" (Autor et al., 2003; Gibbons and Waldman, 2004; Acemoglu and Autor, 2011).[17] According to this framework, occupations differ in tasks as well as skills required to perform these tasks. As individuals are heterogeneous in their skills, they differ in how productive they are in

[17]Our approach is also consistent with the model in Lazear (2009), where skills are general but different jobs attach different weights to them.

different occupations. This leads to the presumption that occupations differ in returns to skills, which is in line with results from prior work documenting heterogeneous returns to skills, e.g., higher returns to cognitive skills in occupations where such skills are a complement to technology (Acemoglu and Autor, 2011) and high returns to non-cognitive skills in occupations requiring significant interpersonal interactions (Deming, 2017; Edin et al., 2022). By extension, this implies that the skills of incumbent workers can be used to measure the skill returns and requirements in each occupation. The nature of this approach, i.e. to use incumbents' skills to characterize skill requirements, is similar to Fredriksson et al. (2018) who study job-skill mismatch.

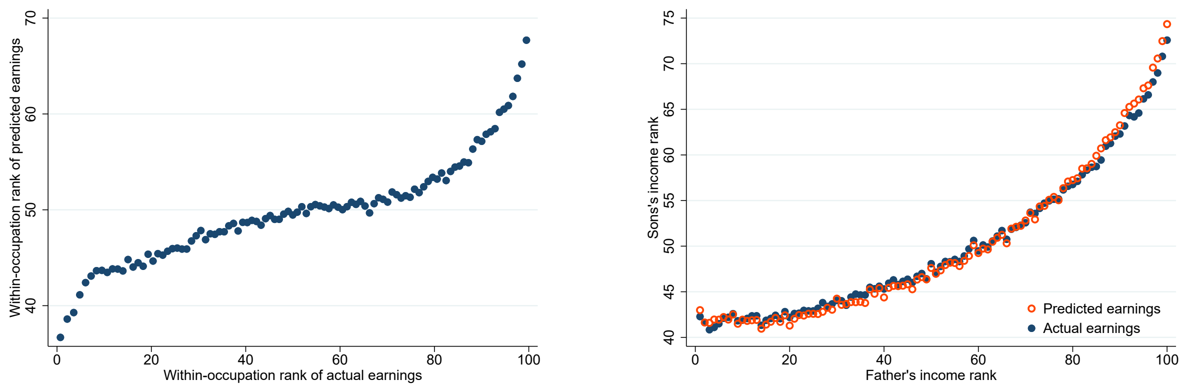
Our empirical approach to measuring skill-based potential earnings is to first train a machine-learning algorithm using the combination of skills and earnings of incumbents in each occupation and then predict potential earnings for all individual-occupation pairs. This procedure approximates an individual's 'Roy productivity' in each occupation. We also use a similar algorithm which predicts entry probabilities across occupations for each individual, which we use as a measure of occupational fit, i.e., match quality. Under the assumption that earnings reflect productivity, we base our predictions of entry probability—or occupational fit—on the skills of the most productive workers in each occupation, measured as workers in the highest quintile of the within-occupation earnings distribution. For earnings we instead use the whole distribution of earnings within an occupation to measure the productivity of different skills and skill compositions, exploiting that earnings are increasing in skills but differently across occupations. In both cases, the training sample for the prediction is based on a sample of incumbents that excludes individuals who follow their fathers into the same occupation. This is to avoid the influences of characteristics other than skills that may influence earnings and entry probability.[18]

For our training and prediction, we use a random forest algorithm (Breiman, 2001), which constructs a multitude of decision trees along splits of skills and predicts an outcome by aggregating over the predictions of the individual trees. The algorithm then minimizes the root mean squared error (RMSE) between predictions and observed realizations for multiple training samples. The usefulness of this method is its flexibility, as skills are likely to be required in various degrees and interactions across different occupations (Lazear, 2009). In this sense, the random forest is superior to, e.g., a simple regression of individual earnings on skills, which would impose linearity on the relationship and not allow for exhaustive possibilities of interactions of skills. In practice, for each occupation, we predict individual residualized earnings in logarithms, that is, residuals from a regression on age, year and occupation fixed effects. For our model estimation and analysis, we convert the

[18]In practice, this restriction has limited quantitative influence on the predictions, as those based on the sample that excludes vs. includes followers have a correlation of 0.98.

Figure 6: Actual and Predicted Earnings

(a) Within-Occupation Rank of Earnings (b) Rank of Sons' and Fathers' Earnings



Note: This figure plots the relationship between predicted and actual earnings, presented in ranks for comparability across occupations. Panel (a) plots the average within-occupation rank of predicted earnings for individuals in a specific bin of actual within-occupation earnings. Panel (b) plots the relationship between sons' actual and predicted earnings and their fathers' earnings. Fathers are placed into 100 percentile bins. For each such bin, we calculate the average earnings rank of sons according to their actual and predicted earnings, which is then plotted on the y-axis. Earnings are predicted by a random-forest algorithm using individual skills as inputs. Occupational followers are excluded from the estimation.

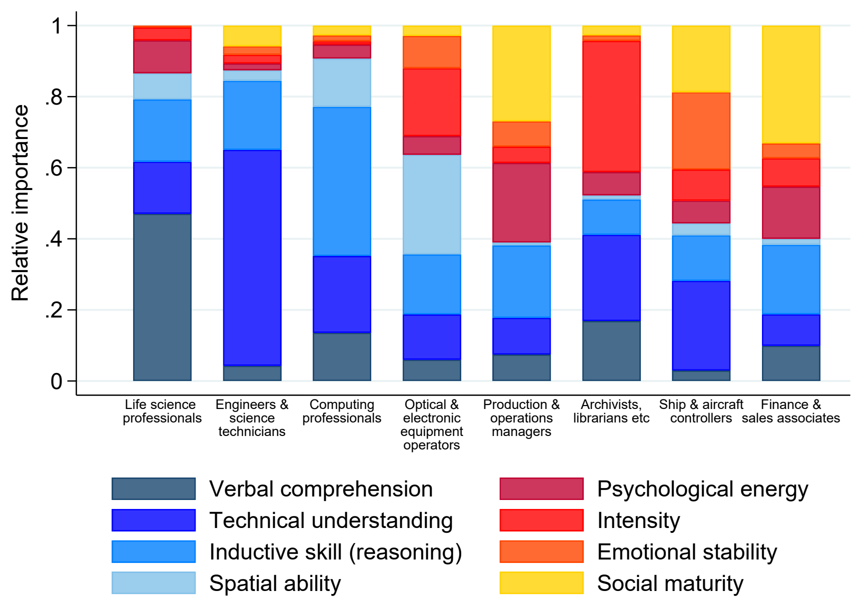
predicted residuals into values in Swedish Kronor (SEK), using the estimated fixed effects, normalizing earnings by time and age. We conduct all following estimations separately for six sub-periods, two for every decade. This way, we avoid comparing individuals in occupations which lie far apart in time. In the face of occupations potentially changing in skill returns over time, this minimizes concerns of measurement error. For comparability of earnings across individuals within occupation, we normalize earnings to earnings at age 40 in a sub-period. Appendix B provides a detailed description of the estimation procedure.

We find that cognitive and non-cognitive skills have substantial predictive power for entry probability and earnings within occupations.[19] Figure 6 shows the relationship between the earnings predictions obtained from our random-forest algorithm and actual earnings of incumbents. Figure 6a is a plot of the within-occupation rank of predicted earnings against the rank of actual earnings, across all occupations. There is a strong positive correlation between the skill-based predictions of earnings and actual earnings.[20] In

[19] Appendix Figure A.15 plots the histogram of predicted probabilities of occupational entry. The figure documents a dominantly higher probability for high-earning incumbents. As these are used as the training sample, this provides a within-sample validation of the prediction. In addition, the figure documents similarly high probability for lower-earning incumbents not in the training sample. This provides an out-of-sample validation of the prediction.

[20] As the figure documents, while we are able to obtain a qualitatively good prediction of earnings, it is quantitatively imperfect, as shown by the considerably smaller range of the predicted earnings than the range of their empirical counterpart. This is expected, as the prediction is solely based on skills, while actual earnings reflect a range of other factors.

Figure 7: Factor Importance



Note: This figure shows the relative importance of our eight skill measures in predicting incomes across occupations. The selected occupations are those in which each of the eight skills contributes the most to the overall prediction of income (see text for details). Occupations are ordered along the x-axis by cognitive (left) and non-cognitive (right) skills. Relative importance measures the contribution of a split along a given skill to the prediction.

addition to this, in Appendix Figure A.8 we plot the histogram of R^2 from the random-forest predictions, by occupation, which average to 0.093. In Figure 6, panel (b) we plot the relationship between predicted and actual earnings of sons to the earnings of their father, presented as ranks within birth cohort and year. The figure documents that when based on predicted earnings, the intergenerational earnings persistence is in line with what we measure based on actual earnings.

As described above, our hypothesis is that skills are differently productive in different occupations. To evaluate this empirically, we document the relative importance of each of the eight skills in predicting earnings in occupations. In Figure 7 we plot a measure of relative importance that is based on the contribution of splits along the dimension of each skill to the overall prediction of income. The figure illustrates eight different occupations, selected and ordered based on the relative importance of each skill. It shows that occupations differ substantially in the relative importance of skills, but also that a variety of skills are productive in each occupation. Looking first at cognitive skills, the skills with the highest relative importance in predicting income are verbal comprehension for life science professionals; technical understanding for engineers; inductive reasoning for computer scientists and programmers, and spatial ability for those that operate optical and electronic equipment. In each of these occupations, a range of other cognitive and non-cognitive skills are also important predictors. Among non-cognitive skills, psychological energy (i.e. focus and perseverance) is most important in predicting earnings of production managers; intensity (i.e. self motivation) for archivists and librarians; emotional stability (i.e. stress tolerance) for captains and pilots, and social maturity (i.e. extroversion) for finance and sales associates, such as real-estate agents.[21]

A general concern regarding our methodology is that the measured skills, and consequently predicted earnings and occupational fit, might partly be a result of upbringing. If so, we may underestimate how much background factors affect outcomes, such as occupational choice and earnings. Importantly, to the extent that our results measure misallocation of talent, this is in terms of talent at the age of 18. Still, we have investigated this concern and concluded that such endogeneity of skills to parental background appears quantitatively limited. We study this in two ways. First, we leverage the fact that for a subset of our sample we have the skills measured in sixth grade, when children are aged 12 or 13. In Appendix A.2, we document that the relationship between sons' skills and both their fathers' skills and fathers' incomes is strongly positive and strikingly similar when measured in the early teens and in the late teens. Second, we exploit the fact that a share of sons in our data have a brother for whom we also have a measure of skills and occupation. If skills are endogenous to parental background, or occupational choice reflects an unobserved skill that is common among brothers, we can difference out this common brother factor. In Appendix A.3, we document that the probability of occupational entry in general, and entry into father's occupation in particular, is increasing in occupational skill-fit. Crucially, this relationship is almost the same when looking within brother pairs, isolating the relationship between the differences in brother skills and the differences in their likelihood of entering a given occupation. This implies that among brothers, differences in occupational choice appear to reflect differences in comparative advantage.

A more specific concern is that is that fathers may transmit occupation-specific skills to their sons. If these are not captured in the interacted set of the general skills we measure, the tendency of sons to sort into the same occupation as their fathers could to some extent reflect such comparative advantage. This would exaggerate the true skill mismatch of followers. We address this concern in Appendix A.4, where we proxy for workers' unobserved occupation-specific skills by including their father's occupation in the estimation. We predict earnings in each occupation using the full set of skills and this proxy, estimate the model, and perform the same counterfactual experiments as we describe in Section 7. In short, we find our results to be robust to this alternative specification, implying that the

[21] In addition to this evidence on the importance of skills across occupations, Appendix **??** documents that the average level of skills remains stable over time within occupations.

majority of followers do not follow their fathers because of comparative advantage in that occupation, or other factors that raise their earnings in that occupation.

Our approach to measuring how skills are differently productive across occupations uses the skills of (high-performing) incumbents in occupations. This approach relies on the skills of incumbents—i.e. the supply side—reflecting the skills that are required for performing tasks within that occupation, i.e. the demand side. To evaluate this approach, we compare our measure of skill requirements based on incumbents in an occupation to a measure of skills required to solve the tasks performed in occupations, measured in the O^*Net task-data. As the skill measures in the draft data and the O^*Net task-data do not have a clear mapping, we evaluate this by measuring the skill distances across occupations as measured by the two, essentially normalizing the skill level to the average occupation. In measuring skill distances across occupation in the O^*Net data, we follow the approach in Macaluso (2017). As documented in Appendix A.5, we find that the two measures of occupational skill requirements yield similar results.

5.2 Model Structure

Every individual is endowed with a Q-dimensional vector of skills $x = \{x_1, x_2, \ldots, x_Q\}$, where x_q measures the ability in dimension q. Individuals apply those skills to production in their chosen occupation according to an occupation-specific production function that takes their skills as inputs: $Z(x, n) = V_n(x)$.[22] As in the basic model, individuals supply labor inelastically to the market within perfectly competitive firms. Labor is the only factor of production in a linear production function, as described by (2), and workers are paid their marginal products. Income of worker i with skills x in occupation n is therefore $Y(x(i), n) = P_n A_n Z(x(i), n)$.

Individuals choose the occupation which maximizes their utility. We modify the utility function (6) from our simple model in two ways. First, instead of assuming that utility is linear in earnings, we posit that individuals derive felicity according to the function $g(c_1, \ldots, c_N)$, where c_n represents consumption of goods produced by occupation n. They are subject to a budget constraint,

$$\mathbb{I}_1 Y(x(i), 1) + \ldots + \mathbb{I}_N Y(x(i), N) = Y(x(i), n) = \sum_{n=1}^{N} P_n c_n(i) \tag{7}$$

where P_n is the price of goods produced in occupation n. The left-hand side of the equa-

[22] In our estimation, we use the outcome of the machine learning exercise described in the previous section as an approximation for the function V_n.

tion represents the worker's income, depending on his choice of occupation n, noted with the indicator $\mathbb{I}_n$. This formulation allows us, in general equilibrium, to derive demand functions for different goods given a price vector.

The second modification assumes that utility is influenced by preferences over occupations. We model this with preference shocks $\varepsilon_n(i)$ which are i.i.d. across workers and occupations. These preference shocks serve two purposes: (i) they lead individuals with the same skill set x and father's occupation f to choose different occupations, which helps us match the empirical occupation distribution, similar to an approach common in spatial sorting (Diamond and Gaubert, 2021), and (ii) they convert the decision problem from one of discrete choice to one with nondegenerate choice probabilities (McFadden, 1974).[23]

As before, choosing an occupation n is associated with a utility cost, b_n^f, which consists of a general utility cost and a possible discount on entering the occupation n, which depends on father's occupation, as we describe in more detail below. In the next section, we estimate these costs and discounts such that they match prominent features of the father-son occupational transition matrix in the data.

As before, the model is static with a single period. At the start of the period, each individual i with a father in occupation f takes prices $\{P_n\}_{n=1}^N$ and entry costs across occupations $\{b_n^f\}_{n=1}^{n=N}$ as given and solves the problem by backwards induction. First, he maximizes his consumption utility $g(\cdot)$ subject to the budget constraint and given his skill set x, in every possible occupation n he can choose. This yields the indirect consumption utility function $h(n,x) = (c_1^\star(n,x), \dots, c_N^\star(n,x))$. Finally, individuals maximize their utility by choosing from this menu of indirect utilities across occupations, taking into account the additive cost vector $\{b_n^f\}_{n=1}^{n=N}$ they face and their individual preference shocks. Thus, individual utility can be written as $u(f,n,x)$; due to the preference shocks, each individuals assigns mass $p(f,n,x)$ to each occupation. We can now define the equilibrium in the economy.

Definition 1. *An equilibrium in this economy is a set of prices $\{P_n\}_{n=1}^N$, such that, given costs $\{b_n^f\}_{n=1,f=1}^{n=N,f=N}$ and skills $x(i)$*

[23]To facilitate this, we assume that there is a measure $M_{x,n} \in \mathbb{R}_+$ of individuals in each cell of the skill-occupation distribution. In the data, naturally, we observe a discrete number $\delta_{x,n}$ of individuals in a skill-occupation cell, each of whom can only choose to work in a single occupation. With the assumption of a measure $M_{x,n} = \delta_{x,n}$ in each cell, we are able to smooth the problem, splitting each discrete worker into an infinity of workers. Shares of the measure can then be assigned to different occupations.

- *Supply equals demand in all occupations n:*

$$C_n = A_n Z_n \quad \forall n$$
$$\textit{where } C_n = \int_{i \in \Gamma} c_n(i)\ di, \textit{ and } Z_n = \int_{i \in \Gamma^n} Z(x(i), n)\ di$$

where Γ^n is the set of workers who choose to enter occupation n and Γ is the set of all workers.

- *Given his father's occupation f and his skills x, each worker assigns a choice probability $p(f, n, x)$ to each occupation n, maximizing his utility*

- *Given his occupational choice and skills, each worker chooses a consumption vector $c^*(n, x) \forall n$.*

5.3 Estimation

When estimating the model, we assume the function $g(\cdot)$ to be a Cobb-Douglas aggregator across all the goods produced by different occupations:

$$g(c_1, ..., c_N) = \frac{\prod_n c_n^{\alpha_n}}{\prod_n \alpha_n^{\alpha_n}} \quad \text{with} \sum_{n=1}^{N} \alpha_n = 1 \tag{8}$$

which gives the associated price index $P = \prod_n (P_n)^{\alpha_n}$. This formulation is convenient as, combined with the budget constraint (7), it implies that the optimal expenditure shares on each product is governed by its α coefficient:

$$\alpha_n = \frac{E_n}{E}, \ \forall n \in N \tag{9}$$

where $E_n = P_n C_n$ and $E = \sum_{n=1}^{N} E_n$. Further, the indirect consumption utility function, given an occupational choice n and prices, is a linear function of real income $Y(x, n)$. We postulate that utility from consumption, costs associated with occupational choice, and taste shocks are additively separable. Hence the total utility obtained by an individual with skills x and a father in occupation f who chooses occupation n is

$$u(f, n, x, i) = h(n, x) - b_n^f + \varepsilon_n(i) \tag{10}$$

The taste shocks $\varepsilon_n(i)$ are i.i.d. across workers and occupations. They are distributed according to a Type I Extreme Value distribution with parameter κ.[24]

As outlined in section 3, a striking feature in the data is the fact that a disproportionately large fraction of individuals choose either the same occupation as their fathers, or one that is similar. To account for this in the model, we let the costs $\{b_n^f\}_{n=1,f=1}^{n=N,f=N}$ vary with the occupation of the father in the following way. First, all individuals who enter occupation n pay an entry cost of m_n. These costs are the same for all sons, no matter which occupation their fathers hold. Additionally we assume that, depending on his father's occupation, a son enjoys reductions in occupational entry costs. These reductions are additively separable and come in three stages: sons can (i) choose the same occupational type (blue collar/white collar), (ii) choose the same broad occupational category (one-digit occupational group), or (iii) choose to follow their father into the same occupation. A son who chooses to be a doctor and has a father working as a motor vehicle driver, therefore, enjoys no reductions, facing only the entry cost m_n. If his father was a doctor, however, he would receive all three reductions. Intuitively, the discounts capture multiple forces which may make entry into their father's occupation, or a similar occupation, easier or more pleasant than for young men of different background.

Let $G_n \in \{1, 2\}$ denote whether the occupation, n, is white collar or blue collar. Furthermore, let $g_n \in \{0, ..., 9\}$, be the broad, one digit occupational category of occupation n. The cost that an individual with a father in occupation f has to pay to enter occupation n is given by

$$b_n^f = m_n - \mathbb{I}_{G_f=G_n} d_{1,G_n} - \mathbb{I}_{g_f=g_n} d_{2,g_n} - \mathbb{I}_{f=n} d_{3,n} \tag{12}$$

where d_{G_k} is the discount for individuals choosing the same type of occupation as their father, d_{g_k} is the discount for individuals choosing same broad occupational category as their father and d_k is the discount for individuals choosing the same occupation as their father. Note that in our case there are two d_{G_k}, one for white-collar and one for blue-collar, ten distinct d_{g_k}, and 91 distinct d_k.

Without loss of generality, we normalize $P_n = 1 \ \forall n$, which implies that labor income within an occupation is equal to the number of units or services produced: a legal pro-

[24] The PDF of the Type I EV distribution is $c(\varepsilon) = \kappa e^{-\kappa\varepsilon} e^{-e^{\kappa}\epsilon}$, and its CDF is $C(\varepsilon) = e^{-e^{-\kappa\varepsilon}}$. It can be shown that the mass of workers ψ_n who choose occupation n is

$$\psi_n = Pr(\text{argmax}_n \quad u(f, k, x) = n) \tag{11a}$$

$$= \frac{e^{\kappa u(f,n,x)}}{\sum_n e^{\kappa u(f,n,x)}} \tag{11b}$$

fessional who earns 500,000 SEK per year is assumed to produce 500,000 units of legal services. The normalization has no effect on relative predicted earnings across individuals within occupations, which importantly is what matters for our results. Then, using the earnings predictions based on skills presented in Section 5.1, we obtain a productivity for every individual across all occupations.

Given the aforementioned earnings predictions, we jointly estimate the costs $m = \{m_n\}_{n=1}^{N}$ and discounts $d_1 = \{d_{1,G_n}\}_{G_n=1}^{2}$, $d_2 = \{d_{2,g_n}\}_{g_n=1}^{10}$, and $d_3 = \{d_{3,n}\}_{n=1}^{N}$ to match a set of data moments. We estimate the model separately for six data periods to account for time-varying factors. In the results below we pool the data from all periods, weighted by population. First, we target the shares of individuals in each of the N occupations. We measure this share as the number of sons observed in occupation n divided by the total number of all sons. These moments pin down the entry costs, m. To estimate the discounts d_1, we target (i) the share of individuals who have a father in a white or blue collar occupation and choose the same occupational group. Similarly, for the discounts in d_2, we target the shares of sons who choose an occupation that is within the same broad group of occupations as the father's occupation. Lastly, for the discounts for following into the same occupation as the father, d_3, we, for each occupation, target the share of sons who choose the same occupation as their father. We normalize the entry costs into the Armed Forces occupation, the following discount for white-collar occupations, and the follower discount for children with a father in the military occupation to zero.[25] To calibrate the parameter κ, which governs the variance of preference shocks, we target the level of yearly aggregate earnings in SEK.

5.4 Model Fit

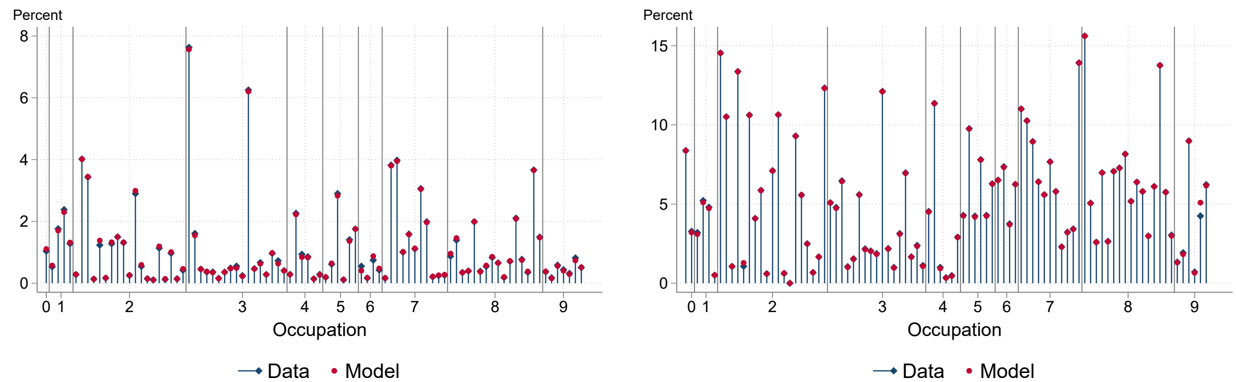
The model closely replicates the targeted moments: the share of sons who have fathers in white (blue) collar occupations and choose a white (blue) collar occupation themselves is 68.70 (59.86) percent in the data and 68.71 (59.85) percent in the model. We report the shares of sons who have an occupation in the same broad one-digit group as their father in Figure A.17 in Appendix E. Again, the model fits very closely to the data.

Figure 8 shows the comparison between other data moments and model estimates. The left panel displays the occupation shares in the model and the data, which pin down the occupation entry costs in the model. The largest difference between the two appears in the second digit 6 occupation, Animal producers and related workers, where the model over-predicts entry by 0.06 percentage points. On average, however, the difference between model results and targets, in absolute values, is close to zero. The right panel of Figure

[25] In Appendix C we describe how we find initial guesses for the respective entry costs and discounts.

Figure 8: Model Fit

(a) Density – Baseline Model and Data (b) Following – Baseline Model and Data



Note: The *Left Panel* shows the fraction of sons who choose each occupation. The blue diamonds represent this fraction for the pooled dataset, the red circles report results for the baseline model. The *Right Panel* shows, by occupation, the fraction of fathers whose child follows them into the same occupation. The blue diamonds represent this fraction for the pooled dataset, the red circles report results for the baseline model. On the x-axis, occupations are ordered according to their 3-digit code in the SSYK-96 classification system, the horizontal lines mark the borders of 1-digit occupational groups. The sample period is 1985-2013.

8 shows the share of sons who follow their fathers, across all occupations. Here, too, the model comes very close to matching the targeted moments.

The model also does well along several other dimensions, as we document in Appendix D. Importantly, the model closely replicates the expenditure shares observed in the data (as shown in Appendix Figure A.9), although they were not explicitly targeted. In addition, the model can reproduce entry probabilities into occupations across the fathers' income distributions. As Appendix Figure A.11 shows, sons of high-income fathers are more likely to become, e.g., health or legal professionals, but less likely to choose blue collar occupations. We show that the model produces the same patterns.

6 Estimation Results

6.1 Entry Costs and Discounts

Figure 9, panel (a), displays the costs of entering different occupations, as estimated by the model. We convert the entry costs and discounts into monetary values.[26] Recall that we normalize the entry cost for Armed Forces to zero. The graph shows strong heterogeneity in entry costs. Among managers and professionals (1-digit occupational code 2), the entry

[26]Because under our Cobb-Douglas assumption for $g(\cdot)$, utility is linear in income, and we can map the cost of choosing an occupation from utils into income by multiplying it with the price index P.

costs are high. For example, becoming a director or chief executive, according to our model, carries the highest utility cost: the equivalent of almost 400,000 SEK *more* than entering a military profession. However, among blue-collar occupations (1-digit occupational codes above 5), relative entry costs fall below zero.

We estimate large discounts for sons to enter their father's occupation.[27] Panel (b) of Figure 9 shows the discount on the entry cost for sons of fathers in a given occupation compared to the average across sons of fathers in other occupations. Evaluated at the occupation with the median value (archivists and librarians), the discount is 81,000 SEK (7,500 USD). To put this into perspective, it is 27 percent of annual prime-age earnings in that occupation.[28]

Among the occupations with the highest discounts for followers are pilots, lawyers, and farmers. Prima facie these discounts capture very different types of exposure: farming businesses may be handed down from father to son, success as a lawyer likely depends on contacts and connections, and there may be significant informational frictions to becoming a pilot, which a father in the same occupation can reduce. In contrast, the occupations with the lowest discount advantage are engineers, office clerks, and other business professionals.

6.2 Interpreting the Entry Costs

To better understand what the estimated entry costs capture, we relate them to time costs of entering an occupation. For this exercise, we utilize data from the BLS Occupational Outlook Handbook of 2020.[29] The BLS reports the typical education and typical work experience in related occupations (in years) needed for entry into an occupation.[30] Both of these measures are proxies for the time cost, and, hence, the utility cost, required to enter an occupation. For this reason, a positive correlation between these statistics and the

[27] In a few cases, the estimated discounts are of the "wrong" sign, indicating the followers pay an extra utility cost for entering, as opposed to receiving a discount. This is because the shares of followers in these occupations are very low, and the model requires an occupation to be *very* unattractive to generate very low choice probabilities for that occupation. In our visual representations we exclude these occupations and top-code discounts at zero.

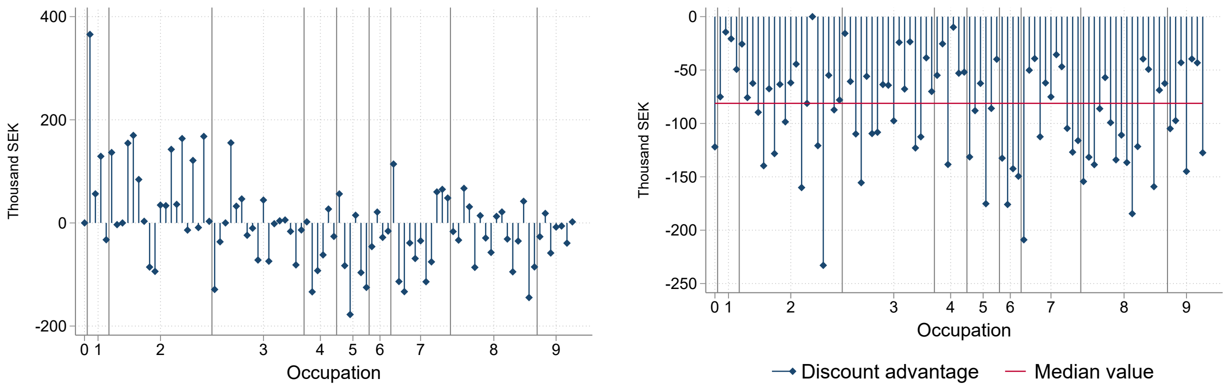
[28] For the military occupations (0-code), which is the reference occupation for entry costs, a person with a father in the military receives a discount of about 120,000 SEK (11,000 USD), compared to the average person without a father in the military.

[29] Source: https://www.bls.gov/emp/tables/occupational-projections-and-characteristics.htm

[30] The educational requirement is split into eight categories: no formal educational credential, high school diploma or equivalent, some college (no degree), post-secondary non-degree award, associate's degree, Bachelor's degree, Master's degree, and doctoral or professional degree. We create a categorical variable that takes values 0 through 7 in the aforementioned order. Work experience is reported in three categories: none, less than five years and more than five years. Again, we assign categorical values from zero to two to each category. We map these statistics into the Swedish SSYK96 occupation classification, as outlined in Appendix A.5.1.

Figure 9: Model-Implied Costs

(a) Model Implied Entry Costs (b) Discount Advantage of Followers

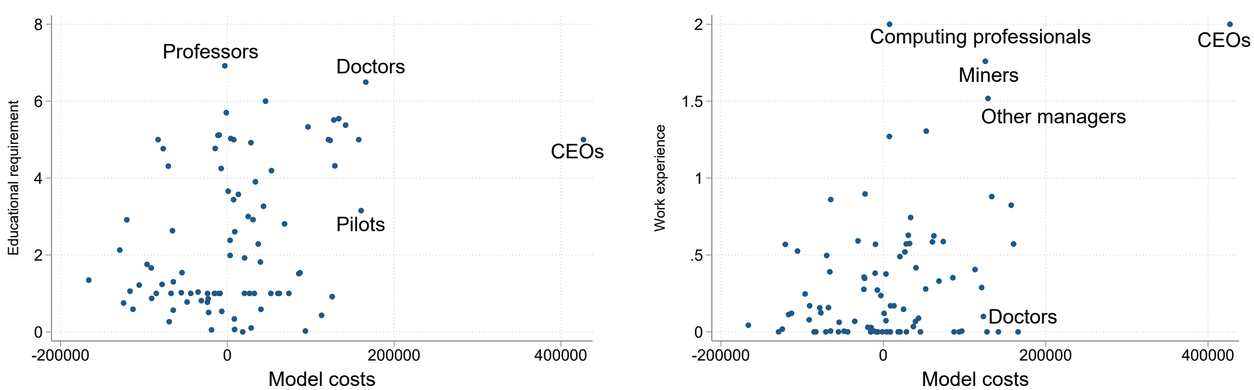


Note: Panel (a) shows the model implied entry costs in SEK (blue diamonds) and the costs for individuals following their father into the same occupation (red circles), i.e., the entry costs including all discounts. Estimated entry costs and discounts are period and occupation-specific. In the current graph we present averages, where entry cost, and entry cost including all discounts, respectively, is weighted in proportion to the number of fathers in each occupation in each year. Panel (b) displays the entry cost discounts available to followers, relative to an average non-follower. Discounts are top-coded at zero. The figure displays averages across periods. The red line represents the discount advantage of the median follower. See text for more details. On the x-axis, occupations are ordered according to their 3-digit code in the SSYK-96 classification system, the horizontal lines mark the borders of 1-digit occupational groups.

model implied costs will serve as an indication that the model, together with our earnings predictions, captures key aspects of occupational choice and its drivers.

Figure 10: Model Cost and Occupation Entry Requirements

(a) Model Costs and Educational Requirements (b) Model Costs and Usual Work Experience

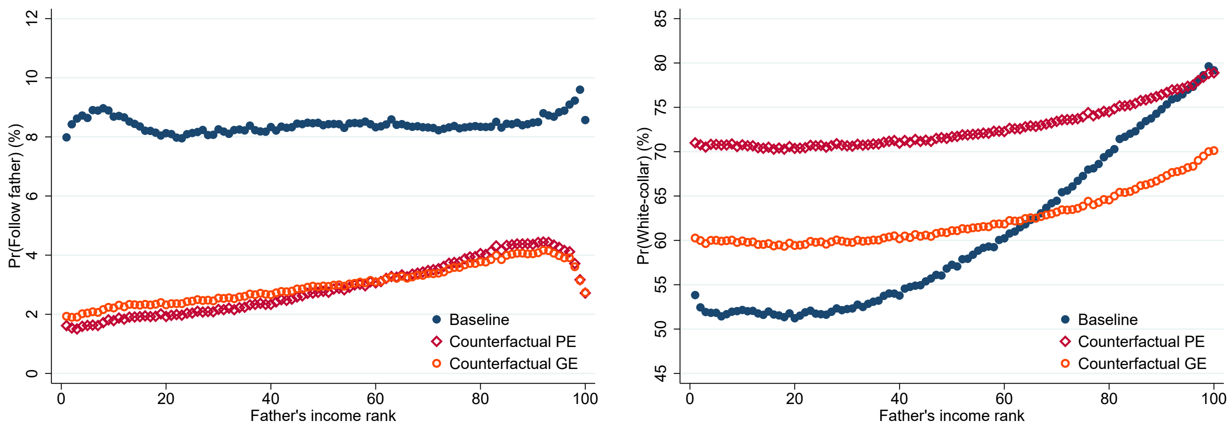


Note: Panel (a) plots the relationship between the entry costs estimated in the model (x-axis) and the educational requirements (y-axis), for different occupations. The educational requirement is coded as a categorical variable between 0 and 7 (see main text). Panel (b) plots the relationship between the entry costs estimated in the model (x-axis) and the work experience in other occupations required for entry into an occupation (y-axis). The work experience is coded as a categorical variable between 0 and 2. Both educational and work experience requirements are obtained from the BLS' Occupational Outlook Handbook for 2020.

Figure 11: Occupational Choice – Baseline and Counterfactual Economies

(a) Occupational Following

(b) Holding a White-Collar Occupation



Note: The figure shows the propensity for occupational following (panel a) and the propensity to hold a white-collar occupation (panel b) in the baseline and counterfactual economies, separately for the partial and general-equilibrium. Both figures plot the average propensities by father's income rank. White-collar occupations include occupations classified with codes below 600. This includes Legislators, senior officials, managers; Professionals; Technicians and associated professionals; Clerks; Service and sales personnel.

Figure 10, panel (a), plots the relationship between the model-estimated entry costs and the educational requirements, and panel (b) plots the relationship to work experience for different occupations. In both cases the costs estimated in our model calibration are strongly positively correlated with these measures of occupation entry requirements. Our model estimates imply that CEOs, pilots, managers, and medical professionals face the highest entry costs. These professions require either higher education (e.g. health professionals), or a lot of work experience (e.g. CEOs, managers, and pilots).

7 Counterfactual Analysis

Our main counterfactual exercise aims to mimic an experiment where all workers have equal access and opportunities for entering occupations. We assign all individuals the same entry-cost discounts, leaving unchanged the general entry costs. This levels the playing field for all sons. In practice, we assign the military son's discounts to all sons. This occupation is the reference occupation for normalizing entry costs in our baseline model. We then solve the model again: first, at baseline prices and second, letting the prices P_n adjust to clear the market. Below, we refer to the former as our partial equilibrium experiment, and the latter as our general equilibrium experiment. As for the baseline economy, we estimate the counterfactual economy for each of our six periods and report the pooled results.

7.1 Effects on Occupational Choice and Occupational Following

Figure 11 shows the effect of the removal of the discount on occupational choices.[31] Panel (a) shows, for the baseline model, the strong tendency for sons to pursue the occupation of their fathers. As summarized in Table 1, this averages at 8.4 percent. Still, there is a greater propensity to follow among sons of the lowest- and highest-income fathers. The orange circles plot the counterfactual follower share when discounts are removed. The results are striking: occupational following drops by more than half, down to 3.0 percent on average. This drop is considerably more pronounced among sons of lower-income fathers, whereas sons of fathers in the top quintile of their earnings distribution are roughly twice as likely to follow their fathers when selecting into occupations only based on skills than sons of fathers in the bottom quintile. At the very top, however, the pattern reverses.

Panel (b) in Figure 11 plots the share of workers in white-collar occupations, both in the baseline and counterfactual economies. In the counterfactual, the share of sons of fathers with below-median earnings who enter white-collar occupations increases while the share of sons of fathers with above-median earnings falls. This reflects an increase in the share of workers who do not enter their fathers' occupations. The share of sons of blue-collar fathers who enter white-collar jobs increases by 14 percentage points, from 45.4 to 59.1 percent. In general equilibrium, the wages (i.e. occupation-specific prices) of blue-collar workers rise by 4.35% relative to wages of white-collar workers. This change makes the former occupations more attractive to all sons, leading to the downward shift in the probability of sons holding a white-collar occupation in Figure 11.

A natural concern is that this large drop in occupational following in the counterfactual economy results from unobserved occupation-specific skills inherited from fathers. That is, that fathers possess certain skills that give them a comparative advantage in their occupation, which they pass on to their sons. Omitting these skills from the model exaggerates the skill mismatch of their sons and the counterfactual drop in following. We address this concern in Appendix A.4 by incorporating a proxy for the effect of occupation-specific skills in fathers occupation on earnings in that occupation. While this improves the prediction accuracy, the effects on occupational following and intergenerational mobility are almost indistinguishable from those presented in Table 1.

In Appendix Figure A.18 we show how occupational following changes across occupations in the counterfactual economy. As already hinted at by the results above, following drops across all occupations. The occupation for which the decrease in following is most pronounced is farming, where the share of followers drops from 15.3 percent to 1.8 percent. Wood and metal-plant operators and religious professionals see similar decreases.

[31] The results are insensitive to substituting our Cobb-Douglas specification with a CES utility function.

Table 1: Counterfactual Model Results

	Occupational following	Pr($Q1 \rightarrow Q5$)	Δ P90/P10	Δ Aggregate earnings	Δ Wage of blue collar
Baseline	8.4%	9.7%	-	-	-
Counterfactual PE	2.9%	12.6%	-3.9%	2.0%	-
Counterfactual GE	3.0%	12.5%	-4.5%	0.1%	4.35%

Note: The table shows important model aggregates in (i) the baseline economy, (ii) the partial equilibrium economy without parental occupational entry discounts but at baseline prices and (ii) the economy without discounts and general equilibrium prices. The first column shows the percentage of sons who choose the same occupation as their fathers. The second column shows the probability of a son with a father in the first quantile of the father's income distribution moving to the top quantile of the son's income distribution. The third column shows the change in inequality measured by the Gini index. The fourth column shows the change in aggregate real earnings from the baseline economy. The fifth column shows the change in the wage index of blue collar workers, relative to white collar workers.

7.2 Effects on Earnings and Intergenerational Mobility

To understand how removing discounts affects earnings and intergenerational earnings mobility, we first consider a simple measure of upward mobility: the probability that a son born to a father in the bottom quintile of the earnings distribution reaches the top quintile of the earnings distribution. As reported in Table 1, we measure these odds to be 9.7 percent in the baseline, increasing to 12.5 percent in the counterfactual economy, or by 29 percent. This result highlights the misallocation among sons from lowest-earning fathers.

Next, we measure the association between the income ranks of fathers and sons in the baseline economy and in the counterfactual. The result is presented in panel (a) of Figure 12 and shows that equal opportunity for occupational entry increases intergenerational mobility. The correlation between the earnings ranks of sons and fathers decreases from 0.387 to 0.278, or by 28%. The largest relative earnings gains accrue to sons of fathers in the lowest income quintile. On average, sons of fathers in the bottom quintile of their earnings distribution move up the income distribution by 4.1 ranks while sons of fathers in the top quintile move down by 4.6 ranks.

These changes in relative mobility reflect absolute earnings changes of the same sign. Panel (b) of Figure 12 documents the change in sons' real earnings between the baseline and counterfactual economies, as opposed to relative earnings documented in panel (a). We present this in two steps. First, we show the change in earnings in partial equilibrium, i.e. under the allocation of workers that results from a removal of discounts, without an adjustment of prices to clear the labor market. Second, we show the change in earnings in general equilibrium, i.e. after prices have adjusted. To compute the change in real earnings, we calculate each individual's nominal earnings in the baseline and counterfactual economies, and divide them by their respective price indices.

Among sons of fathers in the bottom quintile, annual earnings increase by 2.8 percent on average, while among sons of fathers in the top quintile earnings fall by 3 percent. In partial equilibrium the average change in earnings is larger than after prices have adjusted, both due to larger earnings increases among sons from poorer backgrounds and smaller earnings declines among those of richer fathers. As reported in Figure 11, the decline in occupational following is larger among sons of poorer backgrounds, many of whom move from blue collar occupations to white collar occupations. This increase in the supply of talented workers to higher-paying (white-collar) occupations leads wages to rise in blue-collar occupations but decline in white-collar occupations. As a result, the price level in the economy rises, lowering real earnings in general equilibrium. We return to the aggregate implications of this below.

The counterfactual experiment allows us to decompose the observed intergenerational correlation in earnings into the contribution from individuals' abilities and the contribution of their background, as captured by their father's occupation. The benchmark for this decomposition is one of perfect mobility, i.e., one in which, irrespective of father's income rank, the average earnings rank of sons is 50. We measure the deviation from this benchmark both in the baseline and the counterfactual economies and base the decomposition on the change in this deviation. We measure parental background as accounting for 25.7 percent of the observed earnings persistence, with the remainder accounted for by skills.[32] These results are consistent with prior work documenting strong intergenerational correlation in both cognitive and non-cognitive skills (e.g. Grönqvist, Öckert, and Vlachos, 2017; Björklund and Jäntti, 2012). In particular, Grönqvist et al. (2017), using the same data we use, document that the correlation between sons' and fathers' cognitive and non-cognitive skills is 0.48 and 0.42, respectively.

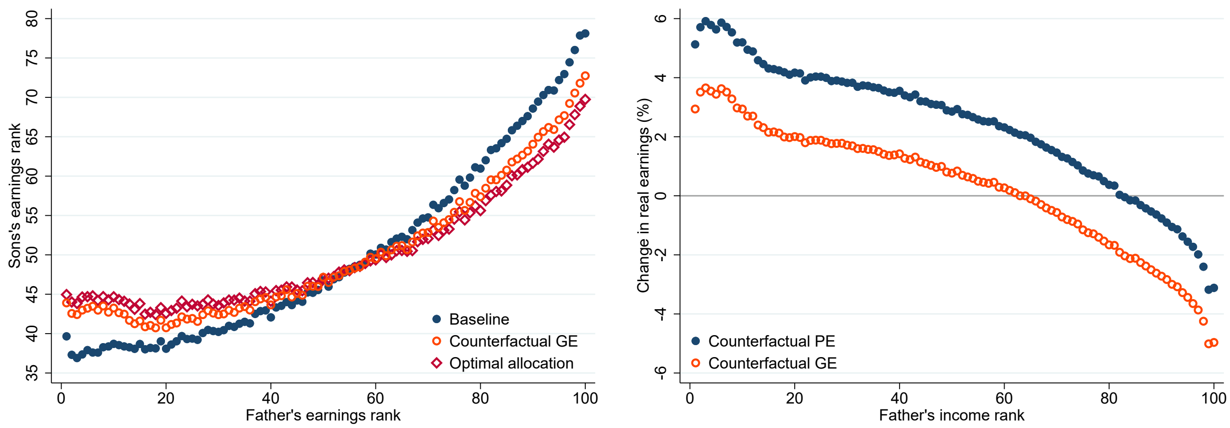
7.3 Effects on Aggregate Earnings

Our results show that equal access to occupations increases mobility, both occupational mobility, as measured by the odds that a son of blue-collar worker becomes a white-collar worker, and intergenerational earnings mobility. In addition, we find a decrease in inequality in the counterfactual economy. We measure inequality by the ratio of earnings of the top earnings decile to the bottom decile (P90/P10). As reported in Table 1, this ratio falls by 4.5 percent in the counterfactual economy relative to baseline.

[32]Studies of earnings correlation among children and their biological vs. adoptive parents find a somewhat larger role for nurture than would be implied by our estimates. Björklund et al. (2006) find that the correlation between earnings of adopted children and their adoptive parents is about 50 percent larger than the correlation between adopted children and their biological parents.

Figure 12: Earnings of Sons in the Baseline and Counterfactual Economies

(a) Earnings Rank Association (b) Change in Real Earnings



Note: The figure shows sons' earnings in the baseline and counterfactual economies. Panel (a) plots the association between sons' and fathers' income ranks. Fathers are placed into 100 percentile bins. For each income bin for fathers, we calculate the average income rank of the sons, which is plotted on the y-axis. Blue dots are based on results from the baseline model and the orange circles are based on the results from the counterfactual model in general equilibrium. For comparison, the figure also plots in red diamonds the same association resulting from an optimal allocation of workers to occupations. See main text for details. Panel (b) shows the average change in sons' real earnings, between the baseline model and the counterfactual, conditional on the income ranks of fathers. Blue dots are earnings in partial equilibrium, i.e. do not include price effects. Orange circles are real earnings in general equilibrium in the counterfactual economy, i.e. including price effects. Fathers are placed into 100 percentile bins. For each income bin for fathers, we calculate the average earnings change for sons, which is plotted on the y-axis.

What is the effect on productive efficiency? We answer this question in two steps. First, we equate all following discounts without adjusting prices. In this partial equilibrium exercise, output grows by 2%. This reflects efficiency gains from better allocation of workers to occupations, partly through a reallocation of workers who now move from blue-collar to white-collar occupations. These occupations have higher entry costs, but provide higher incomes. Thus, aggregate earnings, which equal output in the model, increase.

However, real aggregate earnings in general equilibrium are almost unchanged from the baseline economy, increasing by 0.1 percent. The large inflow of formerly blue-collar workers into white-collar occupations in partial equilibrium is not compatible with constant expenditure shares. Thus, wages need to adjust such that expenditure shares remain the same as in the baseline economy. Prices for goods in blue-collar occupations, which equal wages per efficiency unit, increase by more than 4% relative to prices for white-collar goods (see Appendix Figure A.16). The effect of price changes in the model is opposite of that of a change in entry costs: a higher price for a given occupation implies higher earnings for all individuals who choose the occupation. Thus, the endogenous price changes in general equilibrium revert some of the reallocation.[33] This highlights that accounting for general-equilibrium effects is important when evaluating policies aimed at increasing intergenerational earnings mobility.

The pooled results reported here mask considerably heterogeneous effects over time. As presented in Appendix Figure A.19, while the overall partial equilibrium effect is always positive, the general equilibrium effect is actually negative after the mid 1990s. This is due to price changes becoming large enough to decrease real earnings.

7.4 Optimal Allocation of Workers to Occupations

Our benchmark for the counterfactual results is the allocation of workers to occupations that maximizes aggregate income. We assume that in each period the economy requires a certain number of workers in each occupation, and that this number is unaffected by our re-sorting.[34] Under this assumption, we reassign individuals to occupations such that aggregate earnings are maximized, subject only to the occupation size constraints.[35]

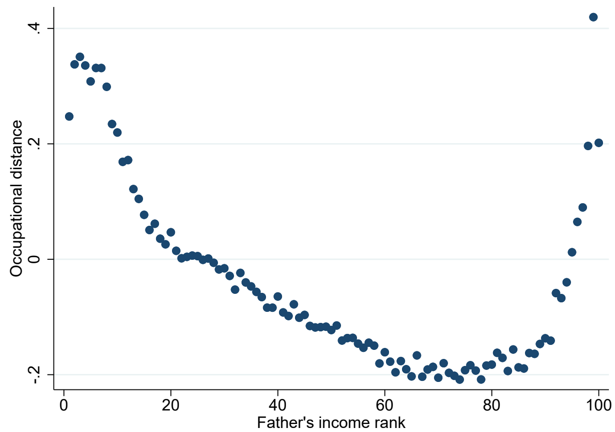
Output under the optimal—or earnings-maximizing—allocation is 7 percent higher than it is in the baseline model. Next, we plot, in Figure 12 panel (a), the association between the earnings ranks of fathers and sons under their optimal allocation to occupations. As the figure shows, the effects are qualitatively similar to our counterfactual experiment, but more pronounced quantitatively. Relative to the model counterfactual, the sons of fathers in the lowest earnings quantile move up by 1.6 more ranks, while sons of fathers in the top quantile move further down by 2.3 ranks. The probability that a son born to a father in the bottom quintile of the earnings distribution reaches the top quintile of the earnings distribution, a measure of upward mobility, increases by 40 percent under optimal allocation. Overall, the results suggest that equalizing entry-cost discounts in our structural model comes close to having the same impact on intergenerational mobility as the earnings-maximizing allocation, while the effect on aggregate income is substantially smaller. As this does not account for general equilibrium effects,however, this outcome would not be achieved without changing the structure of the economy.

[33]The changes in prices across occupations further reduce inequality in the economy compared to the partial equilibrium model, as they increase more in lower-paying occupations.

[34]An alternative and more demanding setup would assume that the economy requires a certain *output* from each occupation, implying that, e.g., a smaller number of builders is required if the new builders can produce more output. Such an exercise is beyond the scope of this paper.

[35]While solving such assignment problems is computationally demanding, we employ a methodology proposed by Jonker and Volgenant (1987) which provides an efficient solution algorithm. In practice, we rely on the `do_lap` function in the `iGraphMatch` R-package. To reduce computational load, we split each period into three groups (five for 1990), with individuals randomly assigned to each. We then reassign individuals within each group such that the within group output is maximized. In practice, we find this not to be a restrictive assumption, as we obtain very similar results with fewer groups or different randomisation.

Figure 13: Occupational Skill Distance Moved



Note: The figure plots the skill distance between occupations held in the baseline and the counterfactual economies across the father's income distribution. Distances are standardized within the population by the mean and standard deviation of the skill distance measure.

7.5 Occupational Skill Distance

Another measure of the misallocation of talent in the baseline economy is the distance in skill space between the son's initial occupation and his occupation in the counterfactual economy without entry cost discounts. We quantify the skill distance between each occupational pair in our sample as the Manhattan distance between the skill requirements of all occupations, where skill requirements are based on the O*Net database.[36]

Figure 13 plots the average skill distance moved across the father's income distribution. Skill distances are standardized within the population by their mean and standard deviation. There is systematically more misallocation among sons of lower-income fathers and among sons of the very high earners. Once parental discounts are removed, the sons of the lowest income fathers move between 0.1 and 0.2 standard deviations further than the average individual. Recall from Figure 12 that when discounts are removed, sons of lowest-income fathers earn higher incomes while sons of the highest-income fathers experience an earnings decline. Together with Figure 13, these results mean that sons of the lowest-income fathers are the most misallocated and gain the most from diverging from their father's occupation towards an occupation where they earn higher returns on their skills. Sons of the highest-income fathers are also misallocated, but their background allows them to stay in high-income occupations and earn more than they would if competing on a level ground. These results are in line with those illustrated using the simple model

[36] Macaluso (2017) uses the same measure to quantify skill distances between occupations. We have carried out a similar analysis quantifying occupational distance using the outcome of our machine learning algorithm. Appendices A.5 and A.6 provide details on the data used and the measure.

in Section 4.

8 Quasi-Experimental Evidence

The welfare and policy implications of our findings depend on the drivers of occupational following. The model estimates are based on quantifying heterogeneous entry costs that capture all forces that lead sons to follow their fathers. These may consist of frictions or barriers to entry and exit that bind sons to their fathers' occupations. In reality, however, these may also capture inherited preferences for same occupation as the father.

To facilitate interpretation of the heterogeneous entry costs in our model, we complement our structural model with a reduced-form analysis. We exploit quasi-experimental variation in individuals' abilities to pursue their fathers' occupations that are unrelated to potential inherited preferences. To validate the model we present similar estimates using the data generated by the structural model.

8.1 Employment Decline in Father's Occupation

We study the effect of a structural employment change in the fathers' occupations on the sons' occupational choices and labor market outcomes. We hypothesize that a son whose father's occupation is in decline is less likely to pursue that occupation due to (information about) reduced labor demand, weakening of the father's network, or other related factors. Thus, how the share of sons pursuing an occupation is affected by the occupation declining is the first stage in our analysis. In terms of our structural model, this is similar to changes in occupational following in response to changes in the entry cost discounts. Using these results, we can estimate the effect of following a father on the child's earnings and other labor market outcomes.

For every son at prime age, we construct the employment change in his father's occupation as the change in the share of workers employed in the occupation between the father's and the son's prime ages.[37] Our identification strategy exploits the variation in employment change within fathers' occupations across cohorts of sons. We estimate this with:

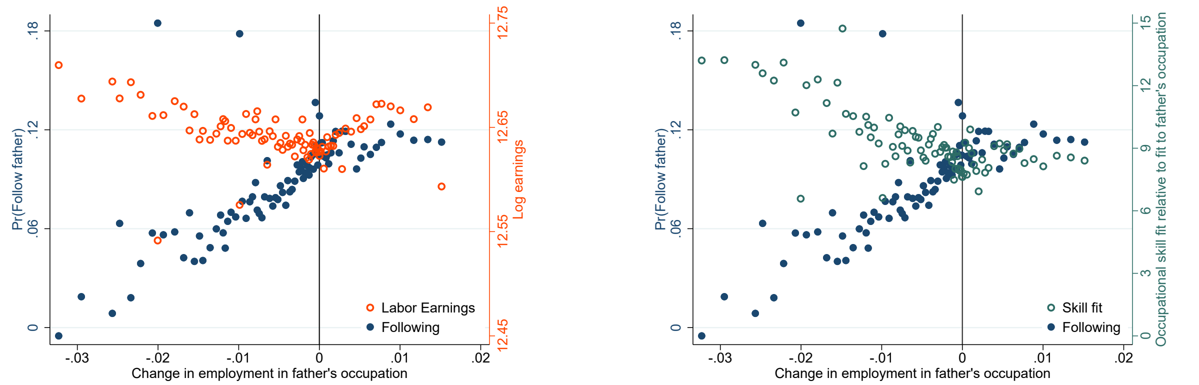
$$y_{int} = \alpha_n + \beta \Delta emp_{int} + \delta_t + \boldsymbol{X}_i'\gamma + \varepsilon_{int} \tag{13}$$

where y_{int} is the outcome of interest, e.g., the propensity of individual i to follow his father into occupation n, α_n are father's occupation fixed effects, Δemp_{nt} is the change in

[37] As we document in Appendix Figure A.20, employment declines in fathers' occupations are strongly correlated with advances in labor-saving technologies in the occupations, measured either by the probability of occupations disappearing due to computerization (Frey and Osborne, 2017) or share of tasks done by robots (Webb, 2019).

Figure 14: Effect of Change in Employment in Father's Occupation

(a) Occupational Following and Labor Income (b) Occupational Following and Skill Fit



Note: Panel (a) plots the relationship between (i) the change in the employment share in a father's occupation between the father's and son's prime ages on the x-axis and (ii) both the propensity of sons following into same occupation as their father (left) and labor earnings at prime age (right) on the y-axes. The figure is a graphical representation regression (13). It plots a binned scatter plot controlling for occupation and cohort fixed effects, as well as demographic controls including sibling indicator and birth order dummies. Panel (b) plots the relationship between (i) the change in the employment share in a father's occupation between the father's and son's prime ages on the x-axis and (ii) both the propensity of sons to pursue same occupation as their father (left) and sons' skill fit to their occupation relative to their skill fit to their father's occupation (right) on the y-axes. A son's relative skill fit is measured by the difference in his rank of predicted probability of entering his own occupation and the rank of predicted probability of entering his father's occupation.

employment in the father's occupation, δ_t are year-at-prime-age (i.e. birth cohort) fixed effects, and $\boldsymbol{X}_i$ is a vector of controls, consisting of number of siblings and sibling order, included to increase precision of the estimates. The occupation and cohort fixed effects absorb cross-occupation and cross-cohort differences in occupational following and economic outcomes. The coefficient of interest is β, which measures the effect of employment change on the outcome of interest. Finally, ε_{int} is an error term that captures other determinants of occupational following and labor market outcomes.

Figure 14, panel (a), provides a graphical representation of regression (13). First, in blue, it plots a binned scatter of the propensity to follow and the change in the employment share in the father's occupation, Δemp_{nt}. Here, we control for father's occupation and cohort fixed effects, as well as demographic controls. In line with our hypothesis, a decline in the father's employment coincides with a reduction in occupational following. We present the corresponding regression estimates in Table 2. In the first stage regression, the estimate of β is 2.5, implying that a 1 percentage point decline in employment in father's occupation as share of total employment leads to a reduction in occupational following by 2.5 percentage points. Second, in orange, Figure 14 also plots a binned scatter of log earnings and employment change in father's occupation. In the reduced-form regression,

Table 2: Effect of Occupational Following on Labor Market Outcomes

	Follow	Log Earnings	Log Earnings	Log Pred. Earnings	Skill-fit Log Earnings	Father's income Log Earnings
	(1)	(2)	(3)	(4)	(5)	(6)
	First stage	**Reduced-form estimates**				
Δemp	2.529***	-1.401**	-1.450***	-1.311***		
	(0.559)	(0.566)	(0.535)	(0.476)		
Low$\times\Delta emp$					-1.868***	-1.777***
					(0.531)	(0.578)
High$\times\Delta emp$					-0.687	-0.437
					(0.630)	(0.602)
		IV-estimates				
Follow		-0.554**	-0.576**	-0.518***		
		(0.267)	(0.242)	(0.194)		
Low$\times$Follow					-0.844***	-0.642***
					(0.288)	(0.183)
High$\times$Follow					-0.262	-0.192
					(0.271)	(0.312)
F-statistic	–	20.5	22.0	20.5	5.4	8.1
Controls	X	X	X, Father's income	X	X	X
Observations	635,126	635,126	635,126	635,126	635,126	635,126

Notes: This table reports difference-in-differences regression estimates. The first stage and reduced-form estimates are based on estimates of equation (13). The IV estimates are based on the same difference-in-difference regression, but where the propensity to follow is instrumented with the change in employment. "High" and "Low" are indicators that split the sample in half at the median, in column (5) by skill-fit to father's occupation, measured by son's rank of predicted entry probabilities into their father's occupation, and in column (6) by father's prime-age income. All regressions control for indicators of whether individual has a sibling and of birth order. Robust standard errors, clustered at father's occupation level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

the estimate of β is -1.4, implying that a 1 percentage point decline in employment in a father's occupation leads to about 1.4 percent increase in the son's earnings. To obtain an estimate of the effect of following into—or, in this case, departing from—father's occupation on earnings, the reduced-form estimate can be scaled by the first stage. We do this estimating the following regression

$$y_{int} = \alpha_n + \theta follow_{int} + \delta_t + \boldsymbol{X}_i'\gamma + \varepsilon_{int} \tag{14}$$

where an indicator for following, $follow_{int}$, is instrumented by the employment change in father's occupation, Δemp_{int}. Presented in Table 2, the IV estimate is -0.55, suggesting that sons who do not pursue their father's occupation as a result of an employment decline in that occupation earn roughly 50 percent more than they otherwise would. This indicates that sons who are induced to enter occupations other than their father's, enter occupations to which they are better matched and therefore receive higher returns on their skills. Figure 14, panel (b), presents further evidence consistent with this interpretation. It plots a binned scatter plot of the average skill fit of sons to their occupation, relative to their skill fit to their father's occupation. The figure shows that sons enter occupations in which their skills are better matched to those of the incumbents, compared to incumbents in their father's occupation.[38] Table 2 presents estimated effects of following on earnings predicted by skills, showing that sons enter occupations where their skills earn a substantially higher return.

Naturally, these IV estimates only capture the causal effect of following on earnings under the exclusion restriction that an employment decline in a father's occupation affects future earnings of sons only through occupational choice. While this is a strong assumption, one would expect that other direct effects of a decline in father's occupation, such as reduced employment or earnings of fathers, would lead to a *decrease* rather than increase in son's earnings in adulthood. In line with this, Hilger (2016) finds that parental layoffs during a child's teen years or early adulthood affect their early career earnings negatively, but only slightly. To evaluate the concern, we add parental income at prime age as a control in the regression. Presented in Table 2, the resulting estimate is slightly larger in absolute value, suggesting that, if anything, our main estimate might be an underestimate.

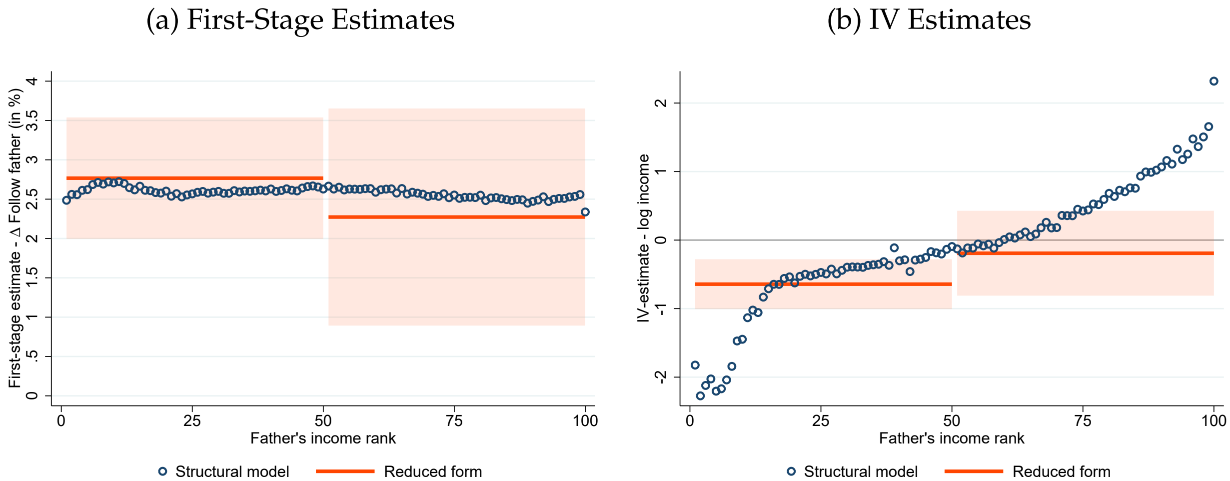
To study the heterogeneity of these estimates, we divide sons into groups according to their skills and family background. Table 2 presents the results. First, we divide sons into two groups according to whether their skill match to their father's occupation—measured by their predicted entry probability—is above or below the median. The earnings gain for sons who choose an occupation other than their father's is entirely driven by sons whose skills are a relatively worse fit to that occupation. Second, we split sons in two groups according to their father's income. We estimate that the effect on earnings is concentrated among sons of low income fathers. These results imply that occupational following among sons from poorer households represents, at least to some extent, misallocation of talent.

8.2 Estimates Using Data Generated by the Structural Model

To validate our structural model and our interpretation of the effect of a change in discounts, we can obtain (partial-equilibrium) estimates from our structural model that are directly comparable to our quasi-experimental estimates. That is, we can directly estimate changes in the propensities of individuals to follow their fathers in response to changes in the following discounts—i.e., a first-stage estimate—and the effect of following as a result of a change in discounts on labor income—i.e. an IV estimate.

[38] Appendix Figure 14 presents a binned scatter plot of occupational skill distance between sons' and fathers' occupations, measured using O*NET data. The two figures show the same pattern.

Figure 15: Effects of Discounts: Structural Model vs. Reduced-Form Estimates



Note: The figure plots the estimated effects of a change in following discounts based on our structural model and corresponding quasi-experimental estimates. Panel (a) plots in circles the change in following probabilities in response to a small change to following discounts. Results are averaged within 100 percentile bins of fathers' earnings and scaled such that following discounts increase by the utility equivalent of 30,000 SEK. For comparison, we show in bars the quasi-experimental estimate of the first stage, i.e. the effect of employment change in father's occupation on the propensity to follow. The estimates are based on a sample split in half at the median by fathers' earnings. For details see Table 2 and main text. Panel (b) plots in circles the IV estimates based on the structural model which are the ratio of the change in individual's earnings and following probability, both in response to small changes in following discounts. Results are averaged within 100 percentile bins of fathers' earnings. We plot in bars the corresponding quasi-experimental estimates.

We obtain, for every individual with a father in occupation n, the numerical derivatives of the probability of pursuing occupation n with respect to the discount of entering occupation n. This provides us with a first-stage estimate for every individual. We then obtain the numerical derivatives of earnings with respect to changes in occupational following in occupation n. This gives us a reduced-form estimate for every individual. To obtain an IV estimate, we take the ratio of the reduced-form and first-stage estimates.

Figure 15, panel (a), plots the first-stage estimates based on the model, showing how the following probability changes in response to an increase in discounts equivalent to 30,000 SEK, for sons across their father's earnings distribution. An increase in the discounts raises following probability almost uniformly but with somewhat larger responses among sons of lower income fathers. For comparison, the figure adds the quasi-experimental first-stage estimates exploiting the change in employment in father's occupation, splitting the sample in half by father's earnings. As the figure documents, these first-stage estimates show a similar pattern. Panel (b) plots the IV estimates based on the structural model and the corresponding quasi-experimental estimates. The IV estimates are -0.097 on average, implying that following leads to 10 percent lower earnings. However, the estimates are highly heterogeneous. Among sons of fathers earning below the median, following leads to a 75 percent reduction in earnings. Among sons of fathers earning above the median, following leads to a 55 percent increase in earnings. The figure also includes the comparable quasi-experimental estimates. The two sets of estimates are qualitatively and quantitatively in line, especially the estimates for sons of low-income fathers, for which the reduced-form estimates imply that following leads to 64 percent decrease in earnings.[39]

To summarize, the structural estimates are in line with reduced-form estimates which leverage changes in the ability to follow but hold constant potential preferences for following. This lends support to our interpretation that the counterfactual results reflect the effect of removing entry and exit barriers to occupations rather than removing utility gains and amenities that children get from following their parents.

9 Conclusion

We show that the strong tendency of children to choose the same occupations as their parents leads to misallocation of talent. We use individual-level administrative data to estimate a structural general equilibrium Roy model that incorporates both heterogeneity in individuals' skill sets and, therefore, occupation-specific productivity, as well as heterogeneous entry costs into occupations based on parental background. Our central finding is that in a counterfactual scenario in which all sons are faced with the same entry costs, independent of their family background, occupational following decreases by more than half, compared to the baseline. As a result of this reallocation, intergenerational earnings mobility increases by almost a third. Moreover, we estimate that a quarter of the observed intergenerational earnings persistence among sons can be explained by the influence of their fathers' occupational background.

Importantly, our estimates are likely a lower bound on the aggregate consequences of distortions in the allocation of talent. First, due to data limitation, our analysis is limited to men, excluding women and migrants who likely face different labor market opportunities. Alleviating gender and race-related barriers has been found to have a substantial effect on aggregate output (Hsieh et al., 2019). Second, reallocation may have spillovers on the productivity of other workers, as well as a dynamic rather than a static effect on output. For example, previous work has documented how background affects who becomes an inventor (Bell et al., 2019). Reallocating talented individuals toward innovation may affect both their own incomes and economic growth. This is beyond the scope of our analysis.

[39] The quasi-experimental estimates rely on variation in employment in father's occupation, i.e. essentially employment decline. This loads more heavily on lower-paying than higher-paying occupations. This may influence the comparison of the estimate for sons of higher-earning fathers.

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Online Appendix of:

It Runs in the Family: Occupational Choice and the Allocation of Talent

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A Additional Analysis and Background Material

A.1 Mapping Swedish Occupational Codes Over Time

The occupational codes in our dataset change over time. Before 1985, occupations are coded according to a three digit code named YK80; between 1985 and 1990, occupations are coded according to YK85, a five digit coding; and after that, occupations are coded according to SSYK96, a three digit coding. In order to facilitate our analysis, we elect to convert all codings into the most current one, SSYK96, at the three digit level.

We obtain a crosswalk between YK85 and SSYK96 from the Swedish statistical office (SCB). Conveniently, the former maps into the latter "m:1", i.e., multiple YK85 occupations map into the same SSYK96 occuption, but not vice versa.

The oldest occupational coding, YK80 also maps into SSYK96, but that mapping is "1:m", implying each of the older occupations maps into multiple recent ones. We tackle this problem by assigning each of the YK80 occupations exactly one SSYK96 counterpart, based on the highest overlap between the two. The tables describing crosswalks between the different occupational codings, produced by the Swedish statistical office, also indicate how many individuals assigned to occupation o in YK80 are assigned to each occupation P in SSYK96. In order to isolate a single SSYK96 occupation to which to assign each YK80 occupation, we pick the one to which most individuals are assigned, separately for men and women. We believe that this creates a credible crosswalk between the two codings. In almost 80 percent of all cases (for men), more than 70 percent of all individuals in a YK80 occupation are coded to one specific SSYK96 occupation and in 60 percent of all cases (for men), more than 90 percent of all individuals in a YK80 occupation are coded to one specific SSYK96 occupation.

A.2 Sensitivity to the Age at Skill Measurement

The data on skills used in this paper are based on measures at age 18. While these measures are intended to capture general skills, they may not reflect innate abilities. Instead, the skills and their measures may be influenced by the environment in various ways. Depending on how quantitatively important such endogeneity is, it could have important implications for our results. Importantly, if fathers invest in the skills of their sons that are most productive in their own occupation, and, in particular, if higher-income fathers engage more in such training than lower-income fathers, we may underestimate the true effect of parental occupation on intergenerational mobility. If skills are endogeneous in this way, we would expect that the relationship between the son's own skills and his father's skills and income would grow stronger over time.

To evaluate this concern, we leverage another source of data where individuals' skills are measured at younger ages. We use data on scores from tests administered as part of the *Evaluation Through Follow-up*, a large survey of Swedish families. These tests are taken when individuals are in 6th grade, at ages 12-13. The data cover around 10 percent of the birth cohorts 1948, 1953, 1967, 1972, and 1977.[40] Härnqvist (2000) and Svensson (2011) provide details on the tests. Importantly, both data sources include tests for logical reasoning and vocabulary knowledge, which were unchanged across the cohorts.[41]

We restrict our sample to individuals for whom we have skills measured in both data sets. Restricting further to individuals for whom we also measure skills of their fathers reduces the sample substantially. We therefore report results both in terms of skills of fathers as well as father's income. We observe the number of questions that each person answered correctly on each test, both in the military enlistment and in the Evaluation Through Follow-up survey, out of a total of 40. We rank individuals by the test score distribution in their cohort. For fathers, we instead aggregate these to decile ranks of skills, due to fewer observations, while using percentile ranks of their income.

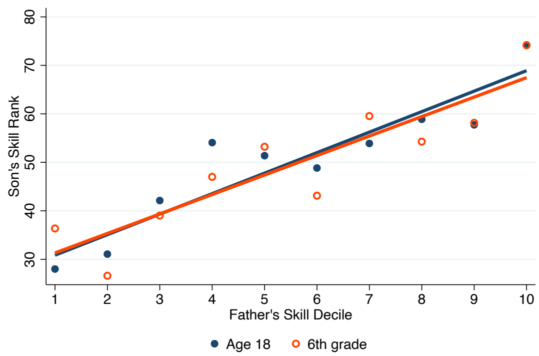
Figure A.1 presents the intergenerational relationships between father's and son's skills, and between father's income and son's skills. Panel (a) plots the relationship between son's and father's logic-inductive ability, at ages 18 and 12/13. Not surprisingly and in line with extensive earlier literature, there is a strong intergenerational correlation of skills. However, this pattern is remarkably similar at both younger and older ages, indicating limited

[40] The sample size of the survey, pooling across all cohorts, is roughly 20,000 individuals.

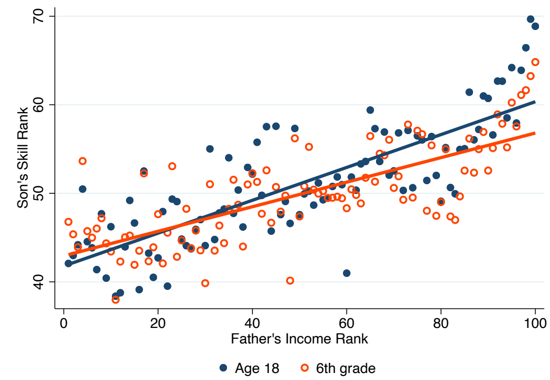
[41] In the *Evaluation Through Follow-up* survey, the test on logical reasoning is to guess a number in a sequence of numbers, and the vocabulary knowledge test is to recognize antonyms (Svensson, 2011). In the military enlistment data, the logical reasoning test consisted of drawing correct conclusions based on statements that are made complex by distracting negations or conditional clauses and numerical operations, and the vocabulary knowledge test consisted of correctly identifying synonyms to a set of words (Carlsted and Mårdberg, 1993).

Figure A.1: Comparison of Skills Measured at Age 18 and Age 12/13

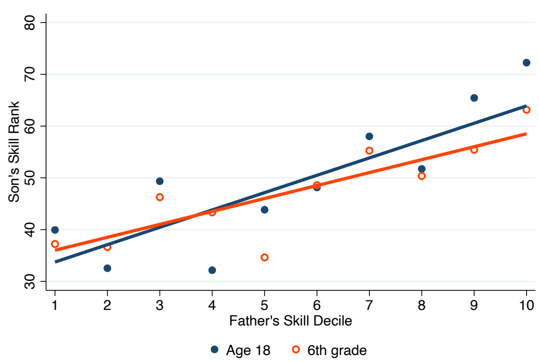
(a) Logic-Inductive Ability by Fathers Skills



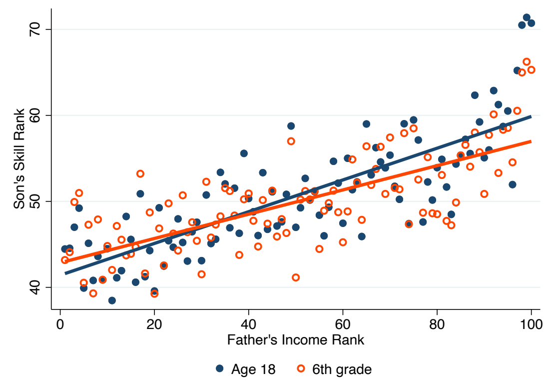
(b) Logic-Inductive Ability by Fathers Income



(c) Verbal Comprehension by Fathers Skill



(d) Verbal Comprehension by Fathers Income



Note: This figure presents the intergenerational relationships between sons' and fathers' skills, and sons' skills and fathers' income rank. Skills are two cognitive skill measures: logic-inductive ability and verbal comprehension. Skills are measured in 6th grade (ages 12/13). The former is based on the *Evaluation Through Follow-up* while the latter is measured in tests administered as part of the military draft. The latter is our main measure used in this paper. Son's skills are measured as the percentile rank in their cohort. Father's skills are measured as a decile in the distribution of fathers within son's cohort, and father's income is measured as percentile rank in the distribution of fathers within son's cohort.

effect of parental skills on their children's skills, above and beyond their initial inheritance. As explained above, the sample size is small where we have the triplet of skills measured at two ages for the sons and skills measured for their fathers. We therefore also present results where we relate skills of sons to income rank of fathers, which we can measure for almost all sons in the sample. As expected, there is a positive relationship between sons' skills and fathers income rank. As with father skills, this relation is almost the same when measured at ages 18 and 12/13. Panels (c) and (d) repeat the same exercise for the case of verbal comprehension, showing similar results.

We conclude from this exercise that we find limited evidence suggesting that skills of sons of high-skilled and high-income fathers change differently than that of lower-skilled and lower-income fathers over their early lives.

A.3 Family Environment and Brother Comparison

A general concern regarding our methodology is that the relationship between skills and occupational choice may reflect upbringing and the family environment. For example, as highlighted by Becker and Tomes (1986), parents may invest in their child's human capital, e.g., by training them to succeed in their own occupation. Moreover, occupational choice may reflect unobserved skills, perhaps passed on from parents to children.

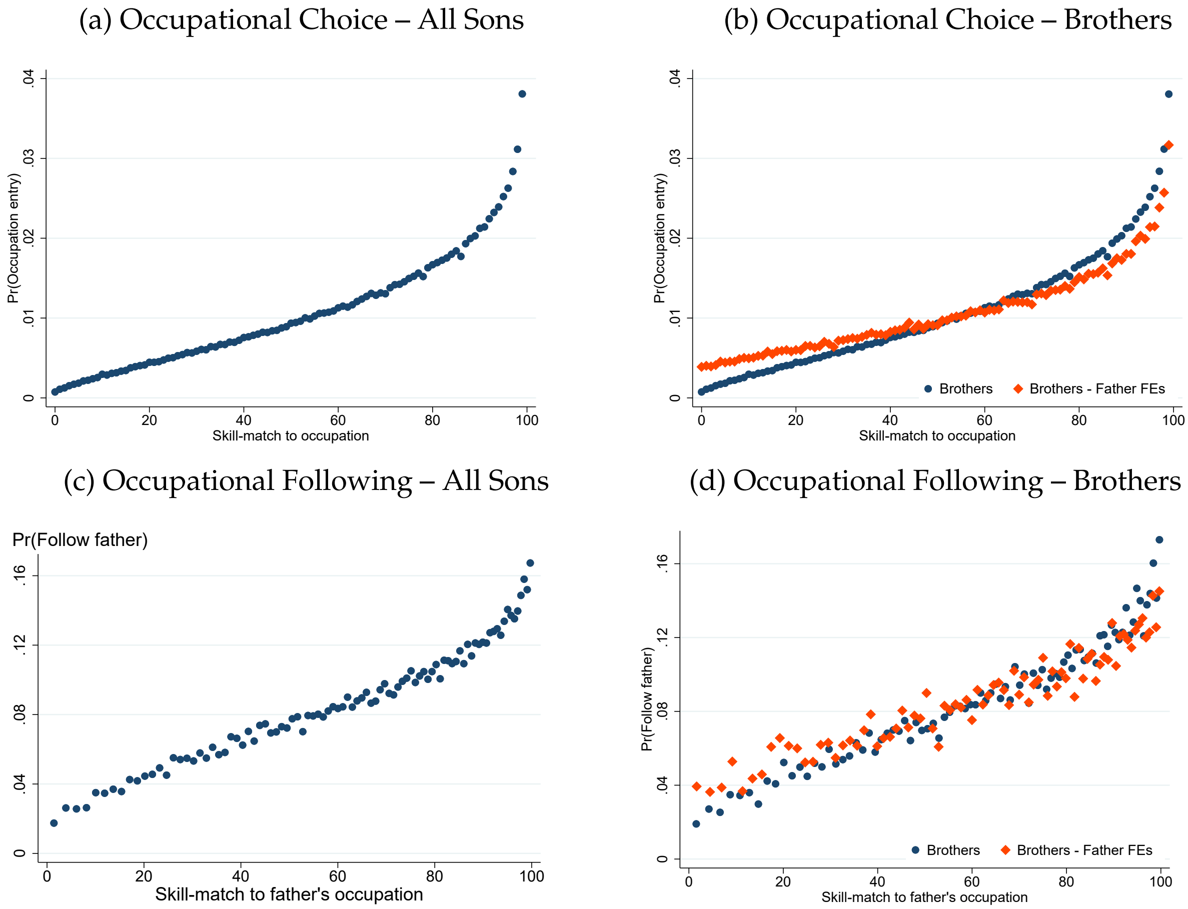
To evaluate this concern, we study sons in our data have a brother for whom we also have a measure of skills and occupation. If skills are endogenous to parental background, or occupational choice reflects unobserved skills that are common among brothers, this can be differenced out. That is, we can study how the differences in observed skills among brother relates to differences in their propensity to enter occupations.

Figure A.2 nonparametrically investigates the relationship between skill-fit, i.e., the entrance probability predicted by our machine learning algorithm, and a son's propensity to choose a given occupation. In all four panels of Figure A.2, skill-fit is plotted on the x-axis. In order for the measure to be comparable across many occupations we generate percentile ranks of probabilities within occupations, such that those with the lowest entry probability have a rank of 1 but those with the highest have a rank of 100. Panel (a) validates our approach by documenting that sons are more likely to enter a given occupation the better their skills match to that occupation. Panel (c) similarly shows that the same is true about occupational following: sons are more likely to enter their fathers' occupation the better their skills match to that occupation. As emphasized above these patterns may both reflect endogeneity of skills to the family environment or skills that are unobserved but important for occupational choice.

To investigate this, panels (b) and (d) first restrict the sample to brothers (blue dots) and then partials out a father fixed effect (orange diamonds). This leaves the relationship between the differences in brothers' skills and their differences in the propensity for occupation entry. If the driver behind the patterns in panels (a) and (c) is family environment, training, or unobserved skills common among brothers, we would expect the line of orange diamonds to be flatter than blue dots. That is, brothers should exhibit a similar propensities for occupation entry. This is not the case. The introduction of fixed effects leaves the slope almost unchanged.

We extend this analysis in Figure A.3 by studying brothers separately by birth order (panel a) and biological and adopted sons separately (panel b). While there is a strong relationship between skill match and following for all sons, first born sons are most likely

Figure A.2: Occupational Choice – Skill Match and Family Background



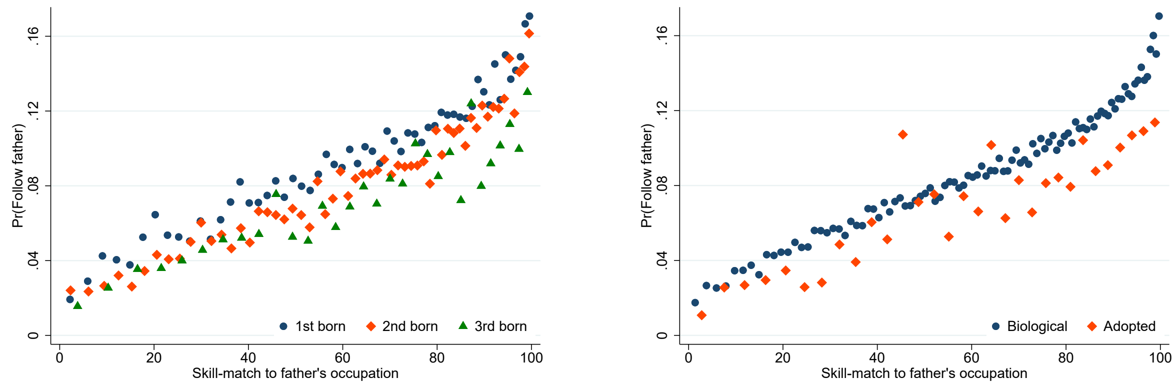
Note: This figure plots binned scatter plots of relationship between (i) the propensity to choose an occupation and (ii) the skill-match to that occupation, measured as the probability of entry predicted based on skills and presented in percentile ranks. All figures are based on regressions that partial out fixed effects for father's occupation. Panel (a) plots the relationship between skill-match and propensity to occupation entry, reflecting the average probability across occupations. Panel (b) plots the relationship between the occupation entry probability and skill match for the sample of sons that have a brother in our sample, where blue dots show the raw relationship and orange diamonds show the relationship in differences across brothers, estimated using a regression including father fixed effect. Panels (c) and (d) plot these relationships restricting to occupations of fathers, i.e. showing the relationship between skill-match and propensity to follow into father's occupation.

to follow irrespective of skills, roughly 1 percentage points more likely than the second born and 2 percentage points more than the third born. This result speaks to prior studies documenting that earlier born children tend to attain more education (Black et al., 2005), have greater leadership skills, and are more willing to assume responsibility (Black et al., 2018), consistent with parents investing more in earlier than later born children. Lastly, in panel (d) we document that biological sons are 1.4 percent more likely to follow than adopted sons, but we still find a strong skill-gradient of following for both groups.

Figure A.3: Occupational Following – Birth Order and Biology

(a) Brothers by Birth Order

(b) Biological and Adopted Sons



Note: This figure plots binned scatter plots of relationship between (i) the propensity to choose an occupation and (ii) the skill-match to that occupation, measured as the probability of entry predicted based on skills and presented in percentile ranks. The figures are based on regressions that partial out fixed effects for father's occupation. Panel (a) plots the relationship between the propensity to follow and skill match by birth order for the sample of sons that have a brother in our sample. The group of "3rd born" sons includes third and later born sons. Panel (b) plots the relationship between the propensity to follow and skill match for biological and adopted sons.

A.4 Robustness to Approximating Occupation-Specific Skills

A specific concern in our setting is that having a father in a given occupation may mean that his children have skills that are specific to that occupation or result in them developing such skills. If these occupation-specific skills are not captured in the interacted set of the general skills, we might falsely attribute occupational following to heterogeneous entry costs which in fact results from selection on comparative advantage based on unobserved skills.

To address this concern, we proxy for workers' unobserved occupation-specific skills by their father's occupation. That is, for the full population of sons, including followers, we predict their earnings in a given occupation by their general skills as well as father-occupation-specific skills approximated by an indicator of whether his father holds a given occupation. We view this as an important test of the robustness of our results. Adding this proxy significantly improves the accuracy of the prediction. The average R^2 increases from 9.3% in the benchmark model with general skills to 15.7% when adding this proxy for occupation-specific skills.

To evaluate the robustness of our results to this alternative measure of occupation-specific earnings, we estimate our model using these newly predicted earnings and perform the same counterfactual experiment as described in Section 7. Table A.1 summarizes the key model aggregates using this alternative earnings predictions and, for comparison,

Table A.1: Robustness Evaluation of Counterfactual Model Results

	Occupational following	Pr($Q1 \rightarrow Q5$)	Rank-Rank slope	Δ Aggregate earnings
A. Cognitive & non-cognitive skills + proxy for occupation-specific skills				
Baseline	8.4%	9.7%	0.386	-
Counterfactual PE	2.9%	12.5%	0.275	1.8%
Counterfactual GE	3.0%	12.5%	0.277	0%
B. Cognitive & non-cognitive skills				
Baseline	8.4%	9.7%	0.387	-
Counterfactual PE	2.9%	12.6%	0.275	2.0%
Counterfactual GE	3.0%	12.5%	0.278	0.1%

Note: The table presents an evaluation of the robustness of important model aggregates to an alternative prediction of occupation specific earnings. Panel A reports the model estimates and the counterfactual based on a prediction of earnings using cognitive and non-cognitive skills as well as an indicator for having a father in a given occupation as proxy for occupation-specific skills. Panel B reports the same for the benchmark model using cognitive and non-cognitive skills to predict earnings, repeating what is reported in Table 1 in the main text. The table shows aggregates in (i) the baseline economy, (ii) the partial equilibrium economy without parental occupational entry discounts but at baseline prices and (ii) the economy without discounts and general equilibrium prices. The first column shows the percentage of sons who choose the same occupation as their fathers. The second column shows the probability of a son with a father in the first quantile of the father's income distribution moving to the top quantile of the son's income distribution. The third column shows the slope of the relation between the income rank of sons and fathers. The fourth column shows the change in aggregate real earnings from the baseline economy.

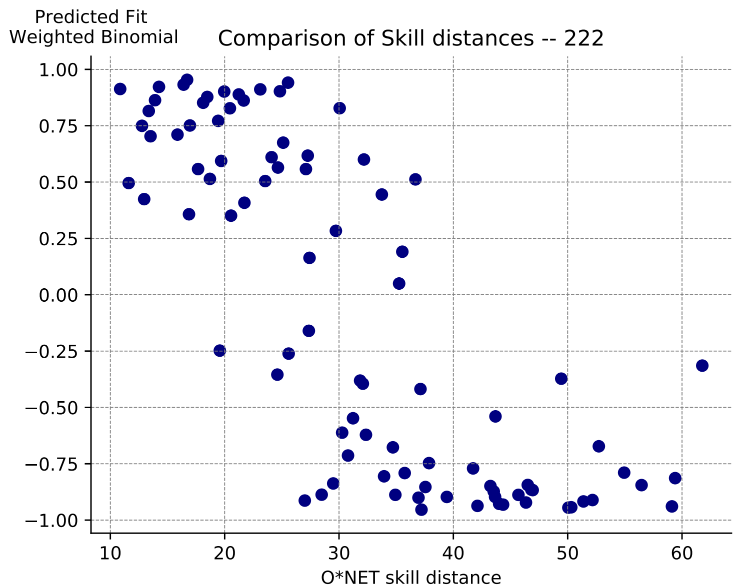
the same aggregates based on our benchmark model. Importantly, we find the results to be robust. The effect of neutralizing entry-cost discounts on occupational following and intergenerational mobility is virtually the same as estimated using our benchmark model. The effect on aggregate earnings is slightly lower, indicating that our benchmark model may attribute some productive skills to unproductive cost discounts. However, these differences are small.

These results suggest that observed occupational following is largely unrelated to occupation-specific skills in father's occupation or other factors that raise earnings of sons in their fathers occupation.

A.5 O^*Net Skill Distance Robustness

As a validation exercise for our ideal occupation predictions, we construct measures of skill distance using them, which can be compared to measures of skill distance calculated using different data.

Figure A.4: Skill Distance and Occupation Similarity for Medical Doctors



Note: This figure shows the skill distance between two occupations, constructed according to Macaluso (2017), using O*NET data, on the x-axis and our measure of occupational similarity on the y-axis. The latter is the outcome of ranking all individuals according to their predicted entry probabilities (i.e., fit probabilities) in two different occupations and then calculating the Spearman correlation coefficient between the two rankings.

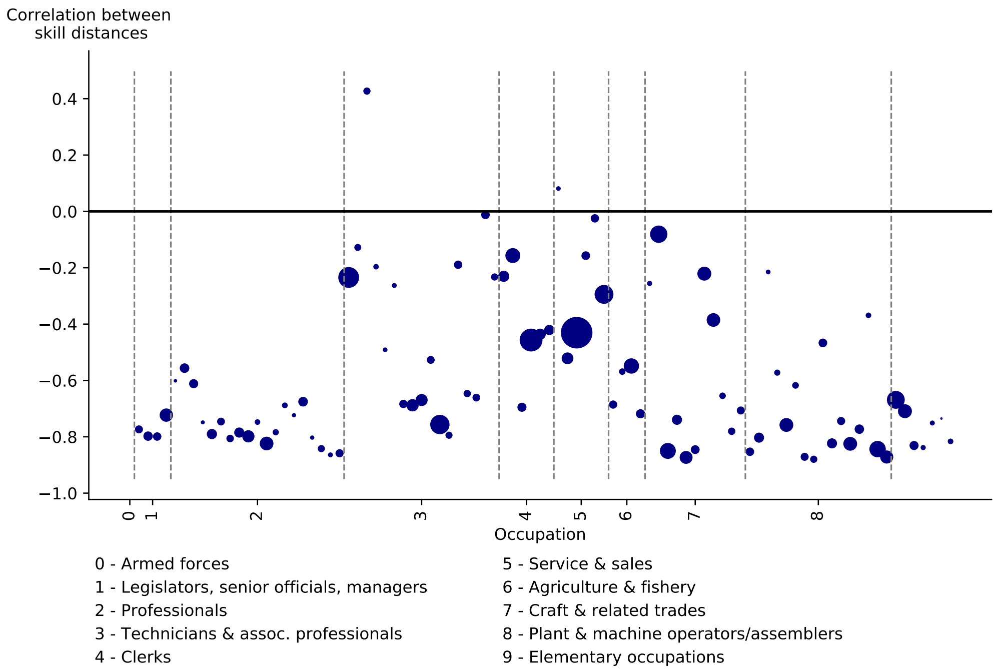
Macaluso (2017) estimates skill distance between two occupations using the O*Net database. Based on surveys, this dataset contains information on the average skillset of incumbents in each occupation, summarized as a 52-dimensional vector. She constructs the distance between occupations as the Manhattan-distance between the two skill vectors in each occupation pair.

First, following her approach, we construct the same measure for our dataset, after mapping the O*NET occupations into Swedish SSYK occuapations, as described in Section A.5.1. Second, to construct the skill distance between two occupations i and j using **our** predictions, we do the following: Using our Random Forest algorithm, we ascertain, occupation-by-occupation, where an individual ranks, in terms of skill fit, *within an occupation*. Using this information, we calculate the Spearman correlation coefficient between the rankings of individuals for every occupation pair i and j in our dataset. If two occupations are more similar, we expect the fit-ranking of individuals to be more similar.

Figure A.4, for medical doctors, shows a clear negative relationship between the skill distance estimated according to the O*NET data (Macaluso, 2017) on the x-axis and our measure of similarity on the y-axis. This gives us some confidence that our random forest algorithm is able to map skill sets into occupations faithfully.

Figure A.5 plots the correlations between the different measures of skill distance across

Figure A.5: Occupational Distance



Note: This figure shows the correlation between two skill distance measures. The first is constructed according to Macaluso (2017), using O*NET data, the second is the outcome of ranking all individuals according to their predicted entry probabilities in two different occupations and then calculating the Spearman correlation coefficient between the two rankings. The y-axis in the figure shows the correlation between the two measures. On the x-axis, ccupations are ordered according to their 3-digit code in the SSYK-96 classification system, the vertical and horizontal lines mark the borders of 1-digit occupational groups.

all occupations.[42] It is negative in almost all cases. The two approaches seem most consistent for the occupations including legislators and professionals, groups 1 and 2. Towards the blue collar occupations, while still negative, the two measures correlate less clearly.

A.5.1 Mapping International Occupational Codes into Swedish Codes

The O*NET database classifies occupations according to an SOC code. In order to map these into the Swedish SSYK96 system, we first map the SOC2010 code into an ISCO-08 code, which can then be mapped into SSYK2012, and finally into SSYK96.

The mapping between SOC2010 and the four-digit ISCO-08 classification is many-to-many. To calculate an ISCO-08 occupation's intensity in each of the different 52 different skills contained in the ONet database, we take the average of each of the skill measures across all SOC2010 occupations that map into it. For hypothetical ISCO occupation $I-1$, we first find all SOC occupations that are linked to it, e.g., hypothetical occupations $S-1$ and $S-2$. To calculate the "oral comprehension" intensity of the $I-1$ occupation, we take

[42]Note that the O*NET database contains no information on military occupations.

an average of the intensity in that skill across $S-1$ and $S-2$, weighted by the employment shares in $S-1$ and $S-2$.[43]. We proceed the same way for all other skills, e.g., "written comprehension" etc; and all other ISCO-08 occupations. Having done this, we obtain a dataframe containing the skill intensity for each of the ISCO-08 occupations, and all skills measured in the ONet database.

ISCO-08, in turn, maps into SSYK12 many-to-many. We use the same approach as before. First, to each SSYK12 occupation, we match all the ISCO-08 occupations that are linked to it. Then, we take the average over all the ISCO-08 occupations within each SSYK12 occupation, by skill. Thus, we obtain a dataframe containing the skill intensity for each of the SSYK12 occupations, and all skills measured in the ONET database.

From SSYK12 we proceed as in step one: merging SSYK12 to SSYK96 occupations and then obtaining average skill intensities for each skill-occupation pair by taking weighted averages, by SSYK12 occupation size.

A.6 Skill Distance

Recall that each individual in our model has mass 1 which is potentially distributed across all occupations (due to the preference shocks). Thus, when moving from the baseline to the counterfactual economy, occupational changes do not occur discretely, i.e., from one occupation to another, but rather as a change in an individual's mass distribution across occupations. To quantify the distance between these distributions, we proceed in two steps. First, we take their difference, to determine how much mass is shifted. We assume that all *reductions* in mass allocated to occupations (when moving from baseline to counterfactual) are distributed randomly to those occupations which *gain* mass in the counterfactual economy. Then, in the second step, we determine how far, on average, the mass lost in each occupation travels to the new occupations. We take the average of these distances, within each sender occupation, across all receiver occupations, weighted by the share mass received in each occupation. This procedure quantifies, for each sender occupation, the average distance to receiver occupations. The final step is to average these distances across sender occupations, weighted by the share of total mass sent. This gives us, at the individual level, the average distance the shifted mass traverses when moving from baseline to counterfactual economy.

[43]We obtain employment shares for all SOC occupations in 2014 from the BLS https://www.bls.gov/oes/tables.htm

A.7 Earnings Measure and The Extensive Margin

In our main analysis, we measure earnings as the wage earnings in worker's primary job and measure occupation as the occupation of that job. For this we use administrative data from the salary structure statistics (Lönestrukturstatistiken), which contains data sampled from firms. Every year, this data includes half of firms in the private sector, sampled at random, and all of the public sector. As income and occupation is measured at prime age, defined as age 30-40, most individuals in our cohort are observed at least several years in this data.

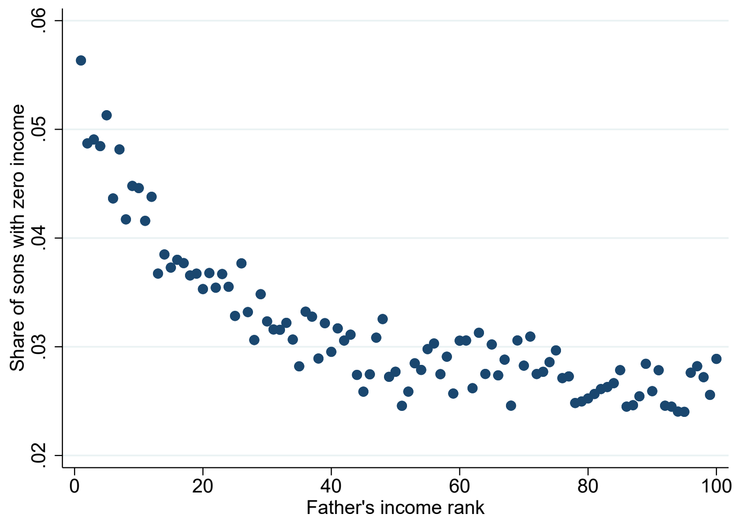
Importantly, with this measure of wage earnings, we restrict our earnings measure to include those that are employed. In addition, we measure earnings in full-time equivalent terms, meaning that apply the monthly salary also to months when workers are not working, e.g. due parental leave, sickness absence, unemployment etc. We argue that this measure is preferable to average annual earnings for two reasons. First, we consistently measure earnings associated with work in a given occupation. Second, this measure of labor income is closer to a measure of wage than earnings, which is preferable when measuring the returns to skills, as we do when measuring potential earnings across occupations. In addition, since our analysis attaches a single prime age occupation to each individual and focuses on occupational choice, it is not trivial to incorporate decisions about the extensive margin into our analysis.

To evaluate this decision, we have also carried out analysis using a measure of total annual labor earnings according to tax records. Although this has some effects on the measured earnings, our main results, such as the difference in the association between son's and father's earnings ranks between the baseline and the counterfactual are broadly similar to when using our preferred earnings measure.

The key difference between the two earnings measures is the extensive margin. We recognize that this has implications for our measures of intergenerational income mobility to the extent that it captures differences in employment. Figure A.6 shows the resulting relationship between the sons' average non-employment incidence and their fathers' income ranks. As before we measure earnings during ages 30-40. For each individual, we compute the fraction of times that we do not observe an income. Since the cohorts that we consider in this exercise are born between years 1950 and 1979, they will be active in the labor market at different points in time, and therefore, simply because of timing, be more of less exposed to periods with high or low aggregate unemployment rates.[44] For this reason, we partial out cohort fixed effects from the aforementioned fractions.

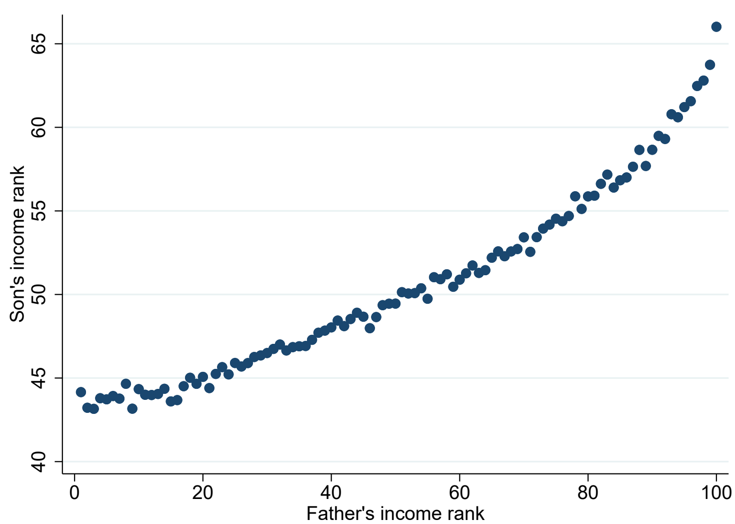
[44] The cohort that was born in year 1960 will be in the prime age bracket between years 1990-2000. During many of those years, the unemployment rate in Sweden was unusually high.

Figure A.6: Share of Individuals with Zero Earnings



Note: This figure shows the share of individuals between the ages 30 and 40 who do not have an income observation. The fraction is adjusted for cohort fixed-effects. The sample period is 1985-2013.

Figure A.7: Association between Son's and Father's Incomes



Note: The figure shows the relationship between son's and their fathers' income ranks. Income is measured as total taxable income according to tax records. Income of sons is measure as the average income at ages 30-32 and income of fathers is measured as the average income at ages 45-47. The sample period is 1985-2013. Zero income is given a rank of zero. Fathers are placed into 100 percentile bins. For each such bin, we calculate the average income rank of sons, which is then plotted on the y-axis. Fathers and sons are ranked within cohort-year cells. The rank-rank slope, estimated wit OLS regression, is 0.190 (SE 0.005)

Figure A.6 documents that the non-employment share is declining with fathers income. This has implications for the shape of the rank-rank association. Prior work has documented that measuring intergenerational mobility in terms of income ranks is useful as the relationship is linear in ranks (Chetty et al., 2014). Our figure 3 shows a pattern that is slightly convex. This reflects the differences in the non-employment incidence by father income rank. Figure A.7 plots the rank-rank association using a measure based on total labor earnings, including the extensive margin, where those with zero earnings are given the lowest rank. As the figure displays, the association is more linear when accounting for non-employment.

B Prediction of Potential Earnings and Occupation Entry

An important input in our structural model and our empirical analysis more generally are measures of potential earnings that an individual would have across all occupations depending on his skills, and similarly the likelihood of entry into occupations (i.e. skill match). To this end, we take a machine-learning approach, where we use a random forest algorithm to flexibly use individuals' skill sets to predict earnings and entry probability.

B.1 Data Preparation for Predicting Earnings

As the prediction is carried out sequentially by occupation we prepare for each occupation two data sets: training data and test data. The former includes all the incumbents in the occupation, excluding those that have fathers with the same occupation (*followers*). We tune the parameters of the algorithm (e.g. depth of trees, learning rate, etc) by drawing a random 10% sample from the training data and predicting for the remaining 90%. Once the algorithm is tuned, train the model on the training data and predict for everyone (test data). This gives us predicted earnings for every individual in all possible occupations.

The prediction is based on residualized income in logs. That is, we estimate the following regression:

$$\ln(earn_i) = \rho_o + \delta_c + \gamma_y + \varepsilon_i$$

where ρ_o, δ_c, and γ_y are, respectively occupation, birth cohort, and calendar year fixed effects. Then we use our machine learning approach to predict the earnings residuals across individuals and occupations. When translating the earnings predictions into SEK, we add fixed effects from the aforementioned regression. For comparability across the sample of individuals, we normalize earnings within each occupation by age and time, such that the reference age is 40 in a period. We split our sample into six periods, two per decade. Children are assigned to the period in which we observe their prime income, i.e., the income in their modal occupation between ages 30 and 40. The six periods are: 1985, 1990, 1996-1999, 2000-2004, 2005-2009, 2010-2013.

B.2 Data Preparation for Predicting Probabilities

The procedure for predicting entry probabilities is analogous to the procedure for predicting earnings, except for the fact that the prediction is binary as opposed to linear. The test sample is as for the earnings prediction. The training sample adds another restriction as we restrict incumbents to the top 20% earners in each occupation. Our results are not very sensitive to changing the size of this group.

B.3 Prediction

For each individual and each possible occupation, we predict the potential earnings and the probability that the individual takes up that occupation based only on his skills. Training the algorithm on the skills of incumbents in each occupation, this results in a measure of returns to skills in a given occupation (potential earnings) and a measure of how well individuals fit into a given occupation (entry probability). To account for the fact that occupations vary a lot in size, which will influence how accurately we can predict probabilities for small occupation, we use occupational-size weights in the model estimation.

The prediction process is a Random Forest estimation with cross validation (i.e. out-of-sample testing). The Random Forest algorithm is standard, where the number of splits are penalized if they do not yield a sufficient increase in prediction power.[45] The cross-validation procedure works as follows:

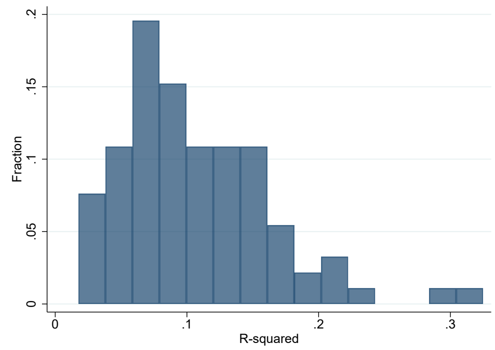
1. The dataset X is split into n subsamples, $X_1, X_2 ... X_n$.

2. The XGBoost algorithm fits a boosted tree to a training dataset comprising $X_1, X_2, ..., X_{n-1}$, while the last subsample, X_n is held back as a validation (out-of-sample) dataset. The chosen evaluation metrics (RMSE) are calculated for both the training and validation dataset and retained.

3. One subsample in the training dataset is now swapped with the validation subsample, so the training dataset now comprises $X_1, X_2 ... X_{n-2}, X_n$, and the validation (out-of-sample) dataset is now X_{n-1}. Once again, the algorithm fits a boosted tree to the training data, calculates the evaluation metrics and so on.

[45]We use the XGBoost package in **R**.

Figure A.8: R^2 across Occupation-Level Predictions



Note: This figure plots the distribution of R^2 from random-forest predictions in each occupation. Prediction is based on the eight cognitive and non-cognitive skills of incumbents in each occupation. The sample period is 1985-2013.

4. This process repeats n times until every subsample has served both as a part of the training set and as a validation set.

5. Now, another boosted tree is added and the process outlined in steps 2-4 is repeated. This continues until the total number of boosted trees being fitted to the training data is equal to the number of rounds (i.e. the forest size).

6. There are now n calculated evaluation scores for each round for both the training sets and the validation sets. The prediction is then based on the round that best satisfies the evaluation metric (minimizes RMSE).

Based on the resulting model for a given occupation, we then construct predicted earnings (or entry probabilities) for all individuals. The same procedure is then carried out for all occupations. Figure plots the histogram of R^2 across all occupation-level predictions of earnings. The average R^2 is 0.093.

C Computation Appendix

C.1 Calibration of Baseline Economy

As described in Section 5.3, the baseline economy is calibrated to match data moments related to occupational choices. Costs and discounts are estimated jointly, as each of them affects all model moments. When we estimate the model, we do so in utility terms:

$$u(i,k) = \frac{Y(x(i),k)}{P} - b_k^f \tag{15}$$

where $Y(x(i), k)$ is the nominal income (and nominal expenditure) of individual i who works in occupation k, and P is the aggregate price index in the economy. b_k^f is the utility cost for entering occupation k, when individual i's father is in occupation f. See Equation (12) for more details.

We find initial guesses for our solution method as follows:

1) We consider entry costs only and target the share of sons in different occupations. The entry cost into military occupations is normalized to zero. Once we find an entry cost vector that yields shares that closely align with the corresponding data moments, we stop and store the vector as $m^{0,1}$.

2) Next, we target the shares of sons who choose the same occupational type (blue collar/white collar) as their fathers, taking $m^{0,1}$ as given. We iterate until we find that the model moments are close to their corresponding data moments. Call the resulting vector $d_1^{0,1}$. We normalize the discount for choosing a white-collar occupation to zero. This requires adjustments to the blue collar discounts and the entry cost vector, in order to keep incentives the same. Label the adjusted vectors m^0 and d_1^0, respectively.

3) In the next step, we take take m^0 and d_1^0 as given and search for a vector of one-digit following discounts that brings the model close to the data. Once the model matches the data in this dimension, we store the resulting vector and call it d_2^0.

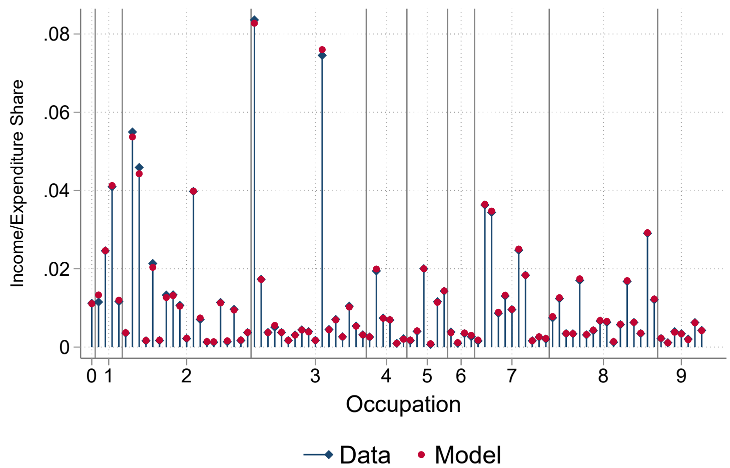
4) Last, we find a first guess for the set of follower discounts, holding all other discounts and costs fixed. We call this vector d_3^0. We normalize the follower discount into armed forces to zero.

Next, we iterate on all costs and discounts simultaneously, starting with the initial guesses obtained according to the above procedure, until the model moments match the data moments that we target. The estimated vectors are $m,\ d_1,\ d_2$, and d_3.

C.2 Counterfactual

In the counterfactual economy, we remove all discounts related to occupational following, and, following the use of the Cobb-Douglas aggregator for preferences, target the expenditure shares at their baseline values. To clear product markets, all prices $\{P_n\}_{n=1}^N$ adjust. For the baseline economy, we assumed that $P_n = 1\ \forall n$. As mentioned in Section 5.3, this normalization has no effect on relative predicted earnings across individuals within occupations, which is what matters for the results in the baseline economy. To find a new price vector $\{P_n^c\}_{n=1}^N$, given the entry costs m, estimated productivities $Z(x, n)$, and expenditure

Figure A.9: Expenditure shares—Data and Baseline model



Note: This figure shows the fraction of income accruing to each three-digit occupational group in the data (blue diamonds) and the model (red circles). On the x-axis, occupations are ordered according to their 3-digit code in the SSYK-96 classification system, the horizontal lines mark the borders of 1-digit occupational groups.

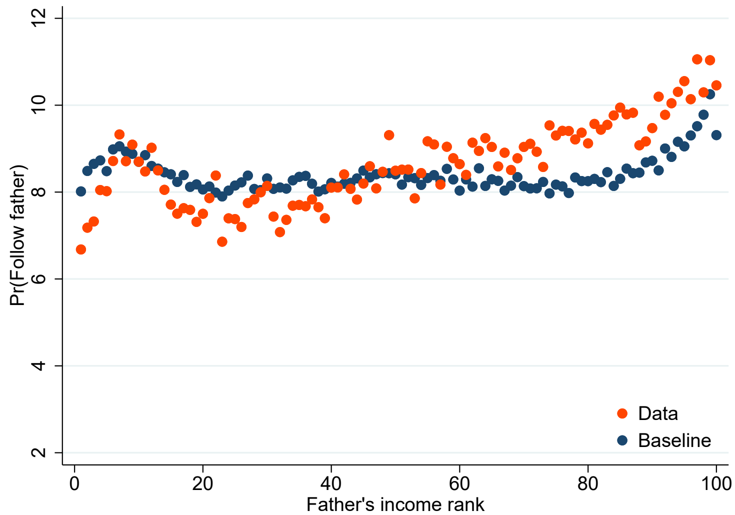
shares $\{\alpha_n\}_{n=1}^N$, we iterate on the price vector until the expenditure shares converge to the data values. As entry costs are measured in utils, we transform income to consumption utility by deflating nominal earnings by the price index $P^c = \prod_n \left(\frac{P_n^c}{\alpha_n}\right)^{\alpha_n}$, like in Equation (15).

D Untargeted Moments

When estimating the occupational-specific entry costs and following discounts, we target the occupational densities, i.e., the share of individuals in each occupation, and parts of the occupational transition matrix between fathers and sons. Encouragingly, the model replicates other, untargeted, features of the data well. First, and most importantly, the model is able to match the expenditure shares across different occupations (which are equivalent to income shares). Figure A.9 shows that although our estimation only targets the share of *individuals*, the model replicates the corresponding shares of *incomes*. This is not a mechanical relationship, and implies that the model reproduces a similar average skill level in each occupation as we see in the data.

Secondly, we document that the model is able to replicate the propensity to follow over the father's earnings distribution. Figure A.10 plots occupational following in the data and in the baseline economy, by father's earnings rank. In general, the model is able to capture both the level of following as well as the differences in following by background.

Figure A.10: Occupational Following in Data vs. Model Baseline



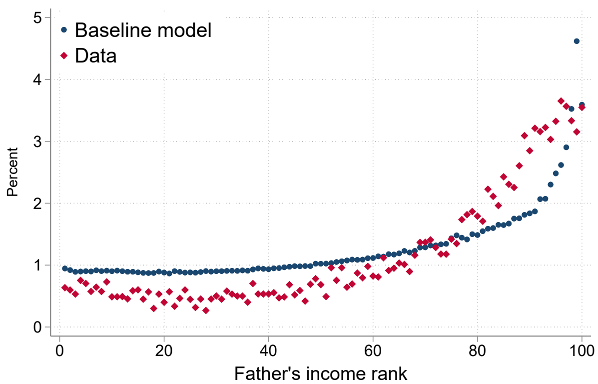
Note: This figure shows share of workers following into the occupation of their father in the data and the propensity for occupational following in the baseline model. The figure plots averages by fathers income percentile rank.

Finally, Figure A.11 shows the shares of children who choose four different occupations, sorted by their fathers' income ranks, comparing the model to the data. Importantly, followers, a fraction which was explicitly targeted in our calibration, are excluded from these graphs. The data shows that individuals born to fathers at the top of the income distribution are close to three times more likely to become health or legal professionals than sons born to fathers at the low end of the income distribution. Conversely, the children of low-earning fathers are much more likely to choose to become cleaners or mechanics than children of high-earning fathers. The model replicates these patterns fairly closely.

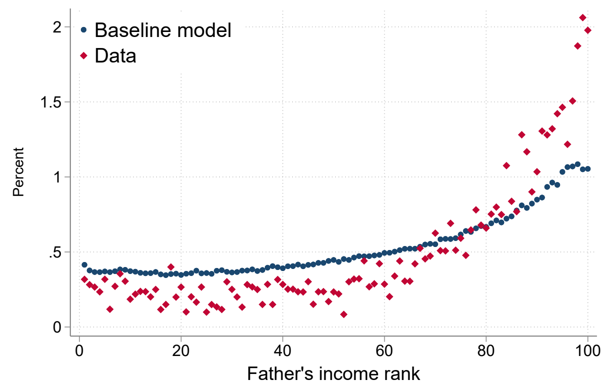
E Supplementary Figures and Tables

Figure A.11: Occupational Choice by Father's Income Rank

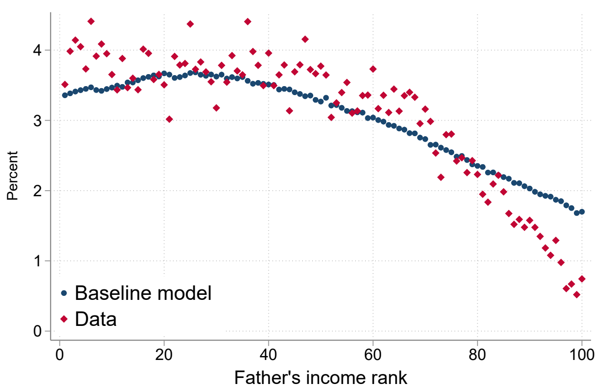
(a) Health Professionals (Except Nurses)



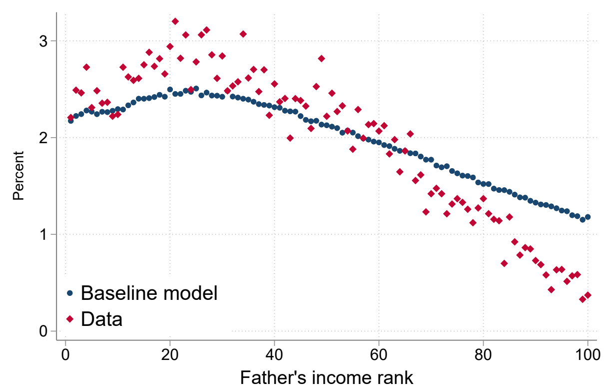
(b) Legal Professionals



(c) Helpers and Cleaners



(d) Machinery Mechanics and Fitters



Note: These figures plot the shares of individuals who choose four different occupations, depending on their fathers' income ranks. All figures exclude sons who choose the same occupation as their father, i.e., occupational followers. The blue dots represent the shares in the data; the red diamonds represent the shares in the calibrated baseline model. Panel (a) plots the share of sons who become health professionals, panel (b) plots the share of sons who choose to become legal professionals, panel (c) plots the share of sons who become helpers and cleaners, and panel (d) plots the share of sons who become mechanics and fitters. The sample period is 1985-2013.

Figure A.12: Mobility Bias across Occupations – Mothers and Daughters

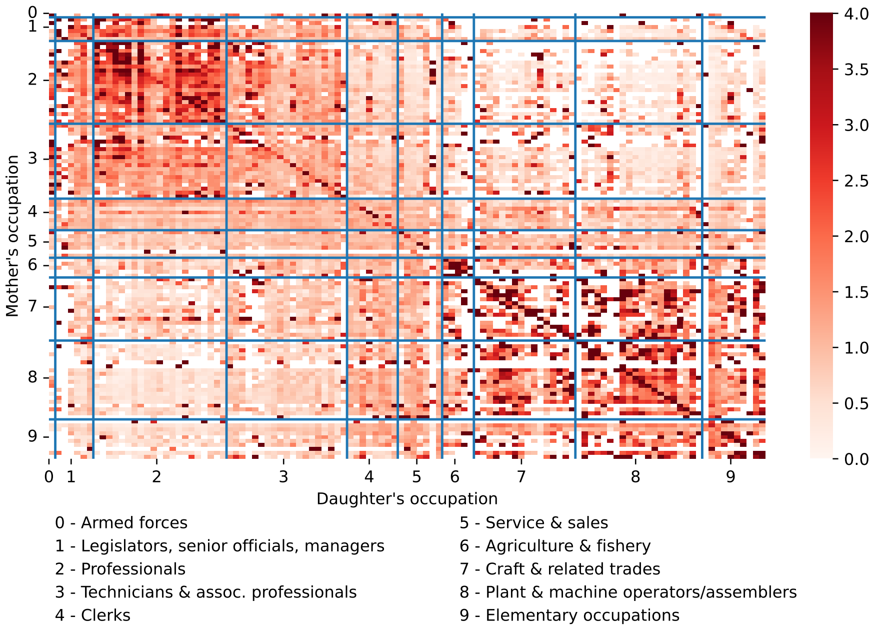


Figure A.13: Mobility Bias across Occupations – Mothers and Sons

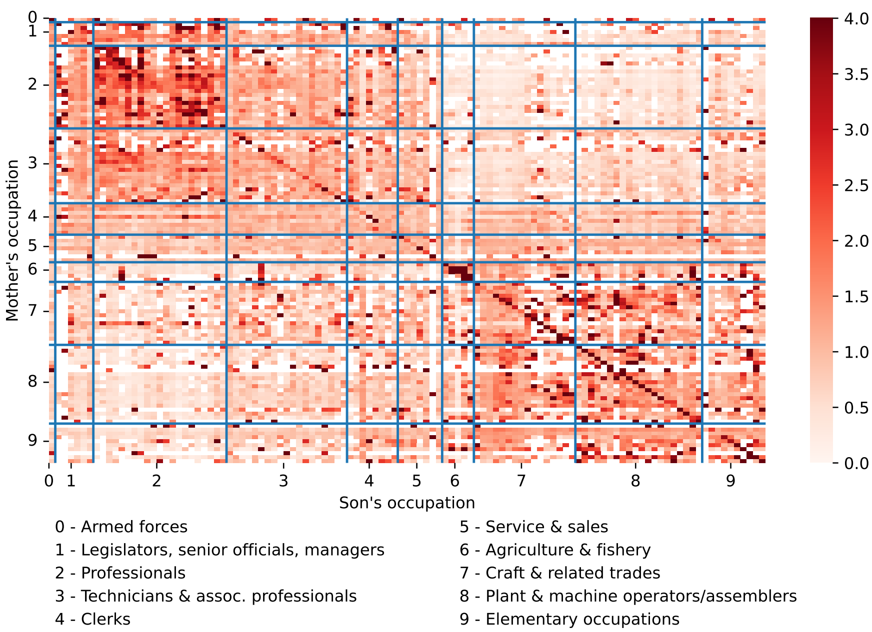


Figure A.14: Mobility Bias across Occupations – Fathers and Daughters

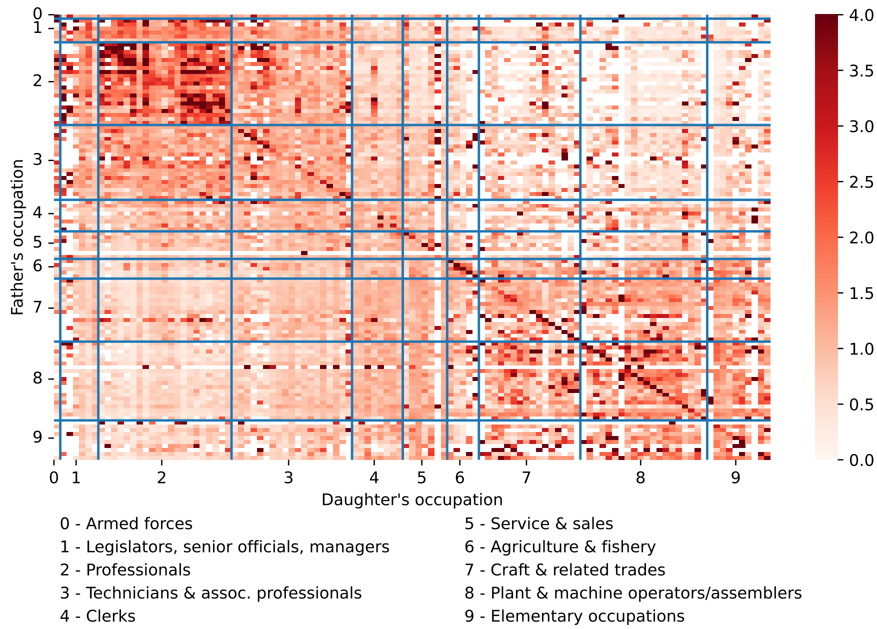
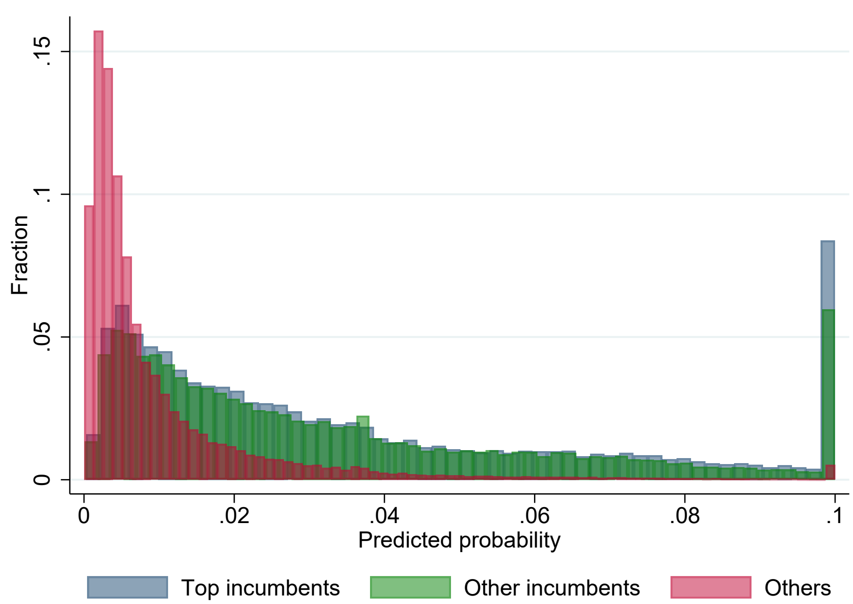
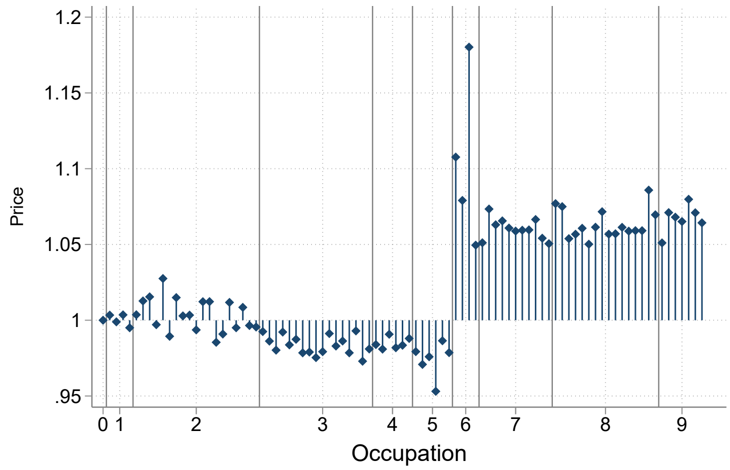


Figure A.15: Predicted Probability of Occupation Entry



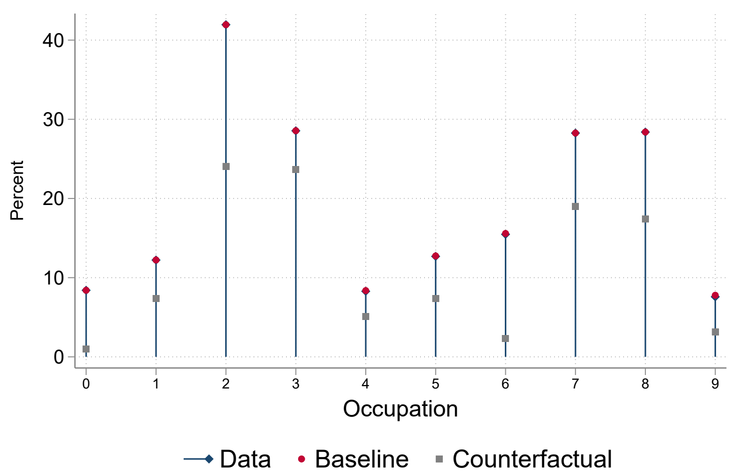
Note: The figure shows predicted probability of entry into occupations. The figure separated three groups: "Top incumbents" which are incumbents in the occupation in the top quintile of the earnings distribution and those used for training the machine-learning algorithm, "Other incumbents" which includes all other incumbents in the occupation, and "Others" which are workers in other occupations. The figure is winterized from above at 10 percent probability of entry.

Figure A.16: Price changes in General Equilibrium



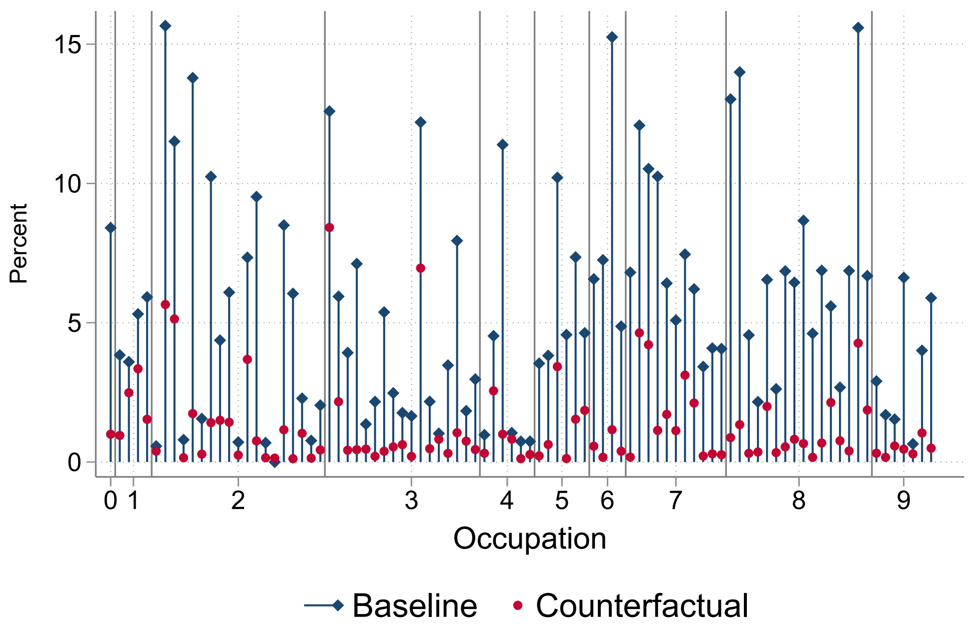
Note: This figure shows the change in the prices for goods produced in each of 91 occupations in the counterfactual economy. Prices in the baseline economy are normalized to one, as is the price for military occupations occupations in general equilibrium (occupational group zero). Occupations are ordered according to their 3-digit code in the SSYK-96 classification system, the vertical and horizontal lines mark the borders of 1-digit occupational groups. For the definition of the mobility bias, see the text. The sample period is 1960-2013.

Figure A.17: Single Digit Occupational Following – Data, model, and counterfactual



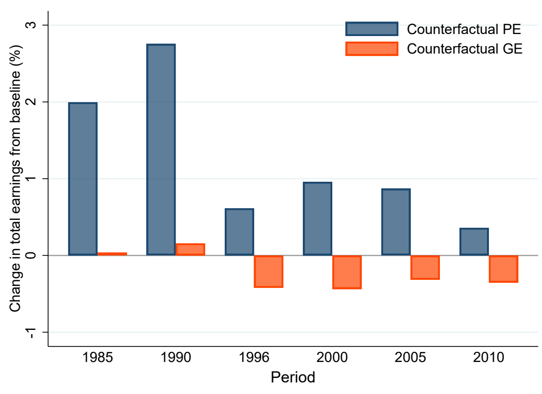
Note: This figure shows the fraction of fathers whose child follows them into the same broad occupational category, i.e., one-digit occupational classification. The blue diamonds represent this fraction for the pooled dataset, the red circles report the results for the baseline model and the gray squares report the results from our counterfactual exercise (see text). On the x-axis, occupations are ordered according to their 3-digit code in the SSYK-96 classification system, the horizontal lines mark the borders of 1-digit occupational groups. The sample period is 1985-2013.

Figure A.18: Following in the Counterfactual Economy

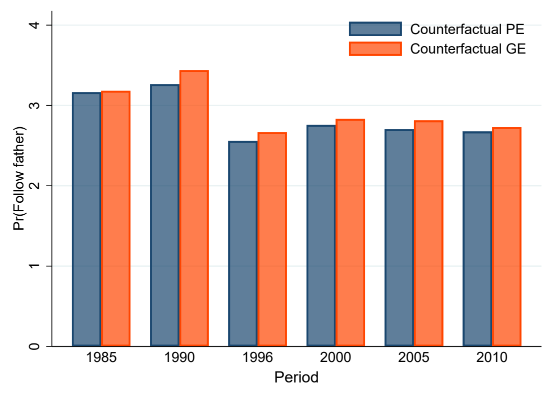


Note: This figure shows the fraction of fathers whose child follows them into the same occupations, for each occupation. The blue diamonds represent this fraction for the baseline model, the red circles report results for the counterfactual economy. On the x-axis, occupations are ordered according to their 3-digit code in the SSYK-96 classification system, the horizontal lines mark the borders of 1-digit occupational groups.

Figure A.19: Aggregate Earnings and Following in Counterfactual Economy by Period



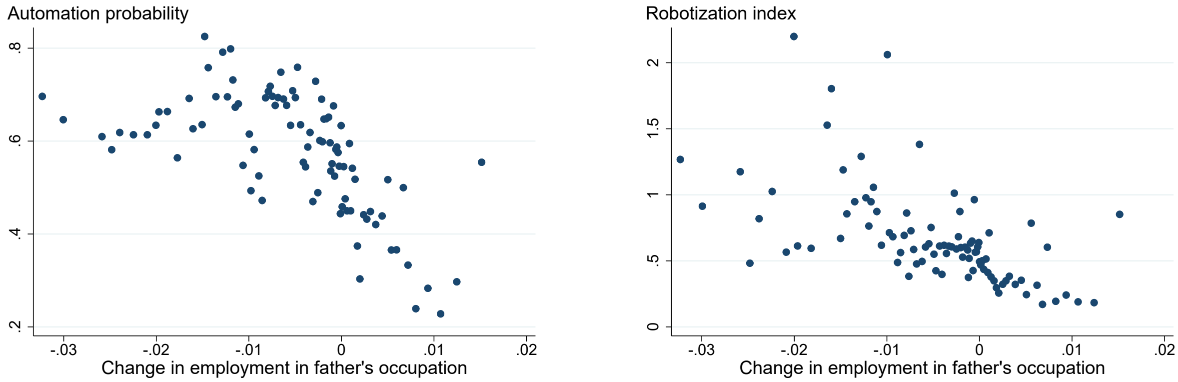
(a) Aggregate Earnings



(b) Occupational Following

Note: The figure plots the partial equilibrium (blue) and general equilibrium (orange) effects of removing all entry cost discounts from the model for each of our six model sub-periods. Panel (a) plots the effects on aggregate earnings, measured as the percentage change in total real earnings relative to the baseline economy. Panel (b) plots occupational following probability. The six periods are: 1985, 1990, 1996-1999, 2000-2004, 2005-2009, 2010-2013.

Figure A.20: Occupational Decline: Automation and Robotization

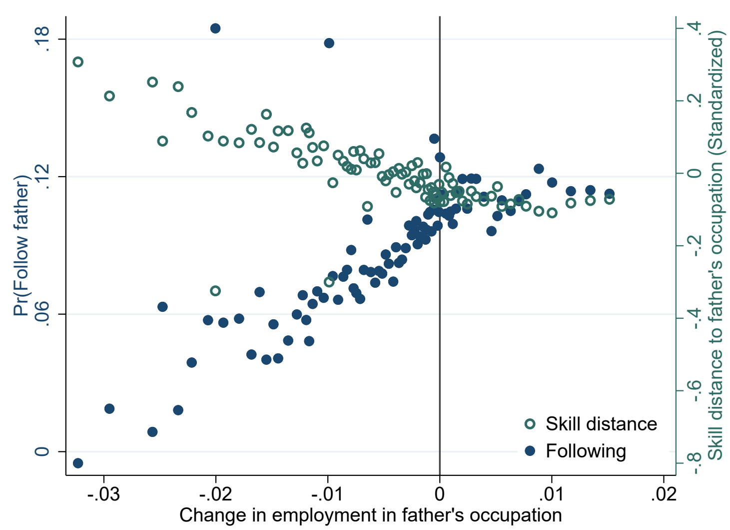


(a) Automation

(b) Robotization

Note: The figure plots a binned scatter of the correlation between (i) a change in employment share in fathers' occupation for all sons in our sample and (ii) two measures of labor-saving technological change. In panel (a) we plot occupation-specific automation probabilities based on Frey and Osborne (2017). This measure is based on analysis of 702 US occupation and measures probability in 2010 that an occupation will disappear within 10-20 years due to computerization. Using this measure, Gardberg et al. (2020) also document a decline in employment share since the 1990s in occupations more exposed to risk of automation. In panel (b) we plot occupation-specific measure of exposure to automation measured by tasks that can be performed by industrial robots, as measured by Webb (2019).

Figure A.21: Effect of Employment Decline in Father's Occupation on Skill Distance



Note: The figure plots the relationship between (i) the change in employment share in fathers' occupation since prime age and (ii) both the propensity of sons following into same occupation as their father (left axis) and the occupational skill distance to father's occupation (right axis). The figure is a graphical representation of difference-in-differences regression (13) as it plots a binned scatter plot controlling for occupation and year-at-prime-age (cohort) fixed effects, as well as demographic controls including sibling indicator, and birth order dummies.

Table A.2: List of Occupations: SSYK-96 Codes and their Descriptions

SSYK96 code	Description
011	Armed forces
121	Directors and chief executives
122	Production and operations managers
123	Other specialist managers
131	Managers of small enterprises
211	Physicists, chemists and related professionals
213	Computing professionals
214	Architects, engineers and related professionals
221	Life science professionals
222	Health professionals (except nursing)
223	Nursing and midwifery professionals
231	College, university and higher education teaching professionals
232	Secondary education teaching professionals
233	Primary education teaching professionals
235	Other teaching professionals
241	Business professionals
242	Legal professionals
243	Archivists, librarians and related information professionals
244	Social science and linguistic professionals (except social work professionals)
245	Writers and creative or performing artists
246	Religious professionals
247	Public service administrative professionals
248	Administrative professionals of special-interest organisations
249	Psychologists, social work and related professionals
311	Physical and engineering science technicians
312	Computer associate professionals
313	Optical and electronic equipment operators
314	Ship and aircraft controllers and technicians
315	Safety and quality inspectors
321	Agronomy and forestry technicians
322	Health associate professionals (except nursing)
323	Nursing associate professionals
331	Pre-primary education teaching associate professionals
332	Other teaching associate professionals
341	Finance and sales associate professionals
342	Business services agents and trade brokers
343	Administrative associate professionals
344	Customs, tax and related government associate professionals
345	Police officers and detectives
346	Social work associate professionals
347	Artistic, entertainment and sports associate professionals
412	Numerical clerks
413	Stores and transport clerks
415	Mail carriers and sorting clerks
419	Other office clerks
421	Cashiers, tellers and related clerks
422	Client information clerks
511	Travel attendants and related workers
512	Housekeeping and restaurant services workers
513	Personal care and related workers
514	Other personal services workers
515	Protective services workers
522	Shop and stall salespersons and demonstrators
611	Market gardeners and crop growers
612	Animal producers and related workers
613	Crop and animal producers
614	Forestry and related workers
711	Miners, shotfirers, stone cutters and carvers
712	Building frame and related trades workers
713	Building finishers and related trades workers
714	Painters, building structure cleaners and related trades workers
721	Metal moulders, welders, sheet-metal workers, structural-metal preparers and related trades workers
722	Blacksmiths, tool-makers and related trades workers
723	Machinery mechanics and fitters
724	Electrical and electronic equipment mechanics and fitters
731	Precision workers in metal and related materials
734	Craft printing and related trades workers
741	Food processing and related trades workers
812	Metal-processing-plant operators
814	Wood-processing- and paper-making-plant operators
815	Chemical-processing-plant operators
816	Power-production and related plant operators
821	Metal- and mineral-products machine operators
822	Chemical-products machine operators
823	Rubber- and plastic-products machine operators
824	Wood-products machine operators
825	Printing- binding- and paper-products machine operators
826	Textile-, fur-, and leather-products machine operators
827	Food and related products machine operators
828	Assemblers
829	Other machine operators and assemblers
831	Locomotive-engine drivers and related workers
832	Motor-vehicle drivers
833	Agricultural and other mobile-plant operators
912	Helpers and cleaners
913	Helpers in restaurants
914	Doorkeepers, newspaper and package deliverers and related workers
915	Garbage collectors and related workers
919	Other sales and services elementary occupations
932	Manufacturing labourers
933	Transport labourers and freight handlers