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

Mattias Almgren
Konjunkturinstitutet

John Kramer
University of Copenhagen

Jósef Sigurdsson
Stockholm University

February 18, 2024

Abstract

Children have a strong tendency to choose the same occupations as their parents, across all professions, earnings, and skill levels. We study the implications for intergenerational mobility and economic efficiency. Using individual-level data on the skills and personality traits of Swedish men, we estimate a general equilibrium Roy model incorporating unequal access to occupations depending on parental background. In a counterfactual economy with equal access, occupational following drops by half and earnings mobility increases by a third. Sons from low-income families gain the most, highlighting the misallocation of talent. Aggregate earnings gains are small in general equilibrium. Using an identification strategy that exploits long-run employment changes in fathers' occupations, we estimate that occupational decline reduces sons' tendency to follow, improves skill-match, and increases earnings, consistent with our structural-model estimates. Our results suggest that creating equal opportunities by removing occupational entry and exit barriers would increase intergenerational mobility without reducing output.

JEL Codes: E24, J24, J62.

Keywords: Occupational Mobility, Misallocation, Roy model, Comparative Advantage.

*We thank Konrad Burchardi, Gustavo de Souza, Mitch Downey, Kory Kroft, Per Krusell, Kieran Larkin, Kurt Mitman, Jay Lee, Emi Nakamura, Arash Nekoei, Peter Nilsson, Miika Päällysaho, David Seim, Fabian Sinn, Jón Steinsson, Xueping Sun, Horng Chern Wong, as well as conference and seminar participants at various institutions helpful feedback and suggestions. We acknowledge financial support from Jan Wallander and Tom Hedelius Foundation. Mattias Almgren: Konjunkturinstitutet. John Kramer: University of Copenhagen. Address: University of Copenhagen, Department of Economics, Øster Farimagsgade 5, 1353 København, Denmark. Email: john.kramer@econ.ku.dk. Jósef Sigurdsson: Stockholm University, CEPR, CESifo, and IZA. Address: Stockholm University, Department of Economics, 106 91 Stockholm, Sweden. Email: josef.sigurdsson@su.se.

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, Chetty, Jaravel, Petkova, and Van Reenen, 2019; Hsieh, Hurst, Jones, and Klenow, 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

[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, Dal Bó, and Snyder, 2009). The same holds true for a range of occupations (Laband and Lentz, 1985).

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 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.

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

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 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.

[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).

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 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-

[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.

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 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 occupation k, $share_{f,k}$, relative to the fraction of children in occupation k, $share_k$. This ratio gives the odds that the child is in occupation k and the parent in occupation f relative to the benchmark situation where occupations of children are independent from those of their parents. 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. 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

[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".

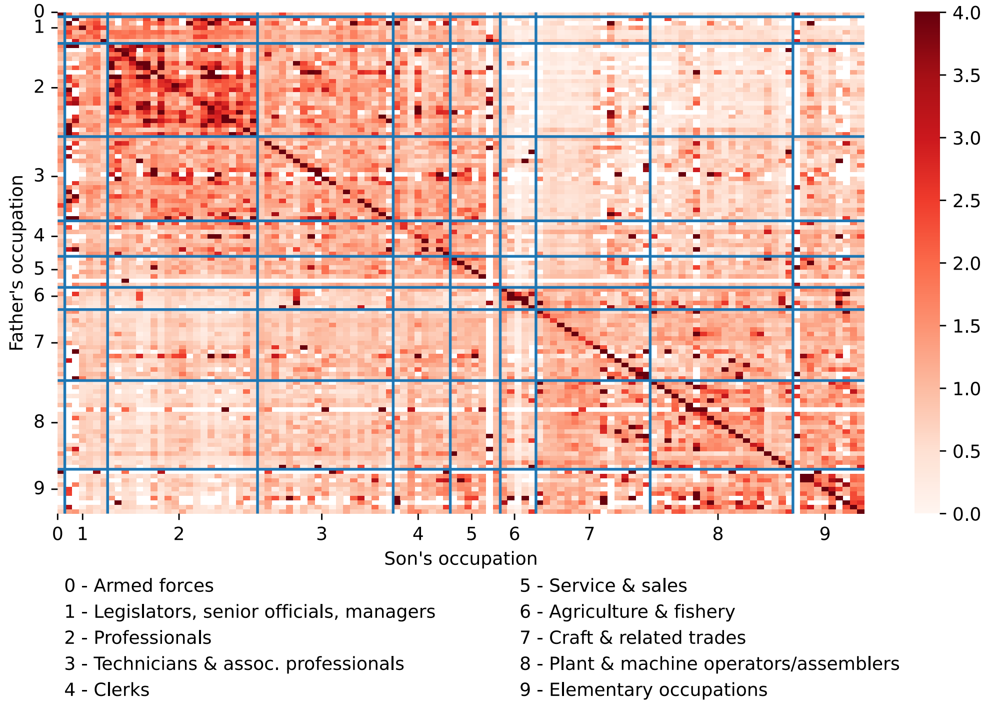
[7]Our measure, OMB, compares the probability of observing a child in occupation k conditional on the father being in occupation f to the unconditional probability of observing a child in occupation k. Dal Bó et al. (2009) compute the probability of observing a father in occupation f conditional on a 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, the two are mathematically equivalent.

[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.

[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 1: Mobility Bias Across Occupations



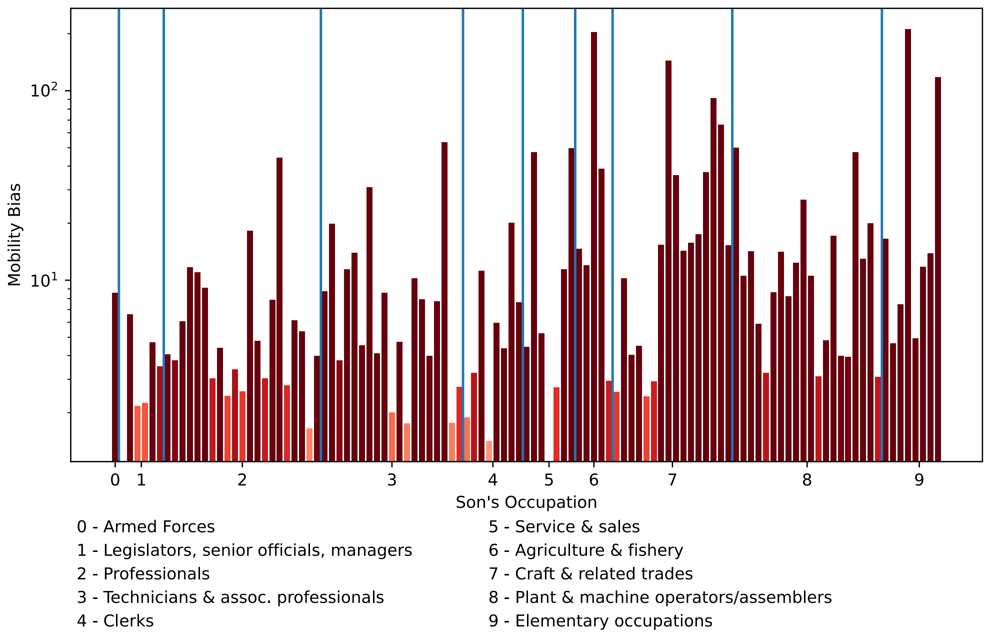
Note: This figure shows the mobility bias estimates across different occupations. The y-axis displays the father's occupation, the x-axis displays the son's occupation. On the x-axis, occupations are ordered according to their 3-digit code in the SSYK-96 classification system. The vertical and horizontal 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.

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 occupations 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

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.

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 importance of intergenerational occupational persistence for intergenerational earnings persistence, we assign every son in our sample the average earnings of his occupation.

[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 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).

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.

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 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 pro-

[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.

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

duce 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 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

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

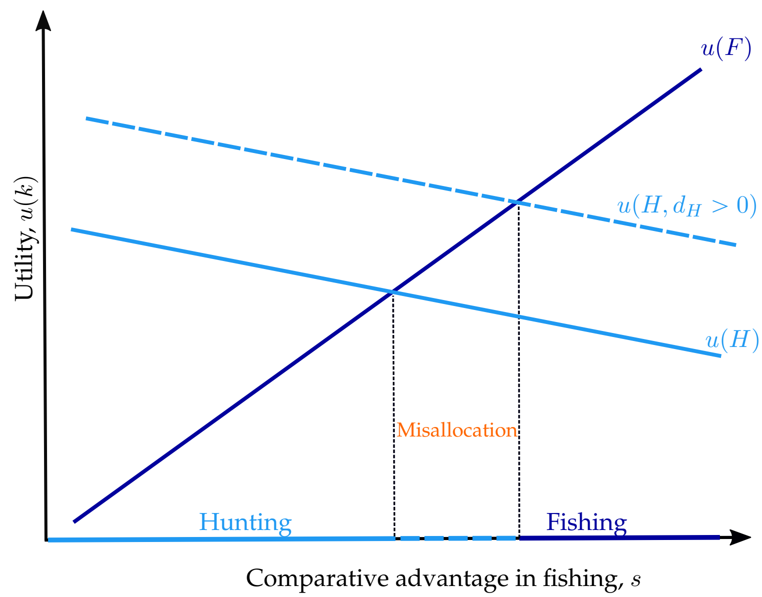
$$y_H^g(i) = w_H + \beta_H z_H^g(i), \tag{5b}$$

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

[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).

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.

(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 $u(F)$ 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.

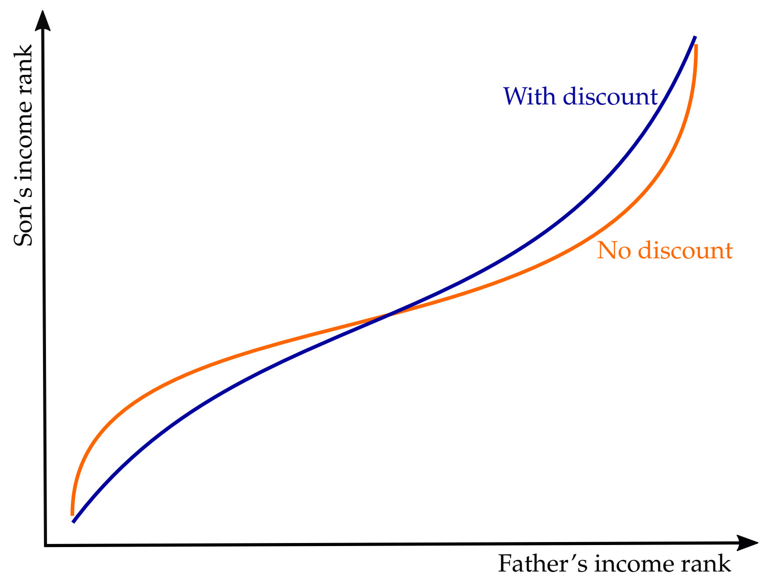
Occupational choice in this model is directly influenced by parents' occupational choices. Figure 4 displays this influence on the occupational choices of children of hunters.[16] Having hunter parents shifts the line reflecting utility in hunting upwards, inducing more children to follow their parents 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

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

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).

values of z_H will choose 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 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.

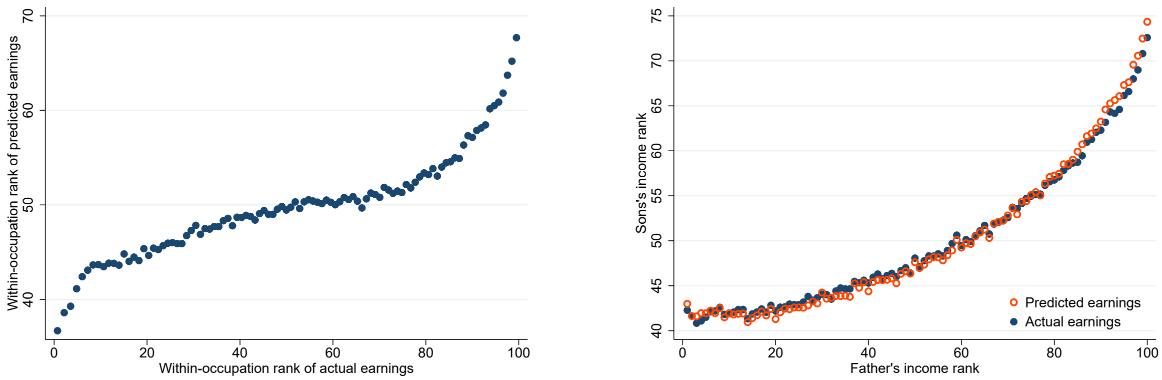
Our empirical approach to measuring skill-based potential earnings is to first train a machine-learning algorithm using the combination of skills and earnings of incumbents in each occupation and then predict potential earnings for all individual-occupation pairs. This procedure approximates an individual's '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 oc-

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

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.

cupation 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 predicted residuals into values in Swedish Kronor (SEK),

[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.

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.

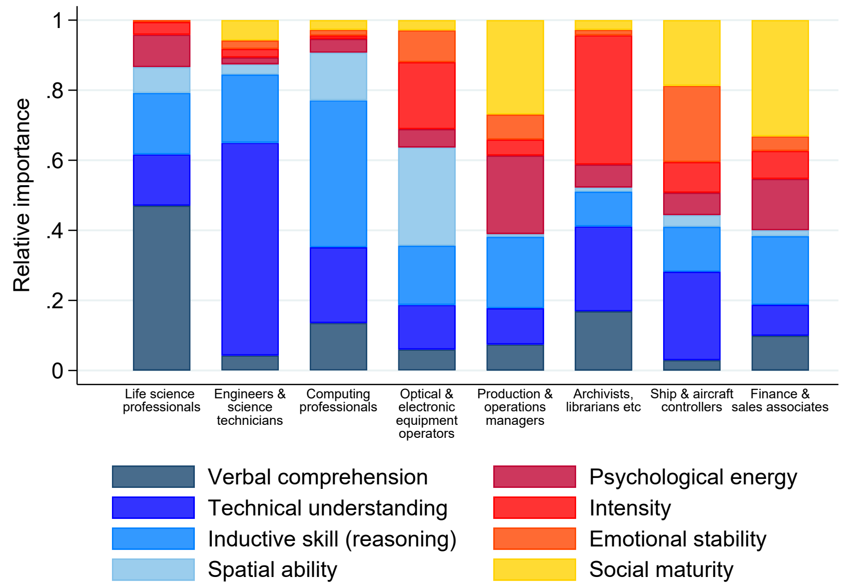
We find that cognitive and non-cognitive skills have substantial predictive power for entry probability and earnings within occupations.[19] Figure 6 shows the relationship between the earnings predictions obtained from our random-forest algorithm and actual earnings of incumbents. Figure 6a is a plot 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 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

[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.

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

[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.

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 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: $Z(x, n) = V_n(x)$. 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 equation 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).[22]

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,

[22]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.

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 $\{x_n^f\}_{n=1}^{n=N}$ as given and solves the problem by backwards induction. First, he maximizes his consumption utility $g(\cdot)$ subject to the budget constraint, given his skill set x and every possible occupation n he can choose. This yields the indirect consumption utility function $h(n,s) = (c_1^\star(n,x),\ldots,c_N^\star(n,x))$. To choose their optimal occupation, individuals maximize their utility $u(f,k,x)$, subject to the cost vector they face and their individual preference shocks. 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 $\{b_n^f\}_{n=1,f=1}^{n=N,f=N}$,*

- *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.

- *Workers choose occupations optimally and maximize their utility.*

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:

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

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.[23]

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

[23]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

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

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

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 professional 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.[24] To calibrate the parameter κ, which governs the variance of preference shocks, we target the level of yearly aggregate earnings in SEK.

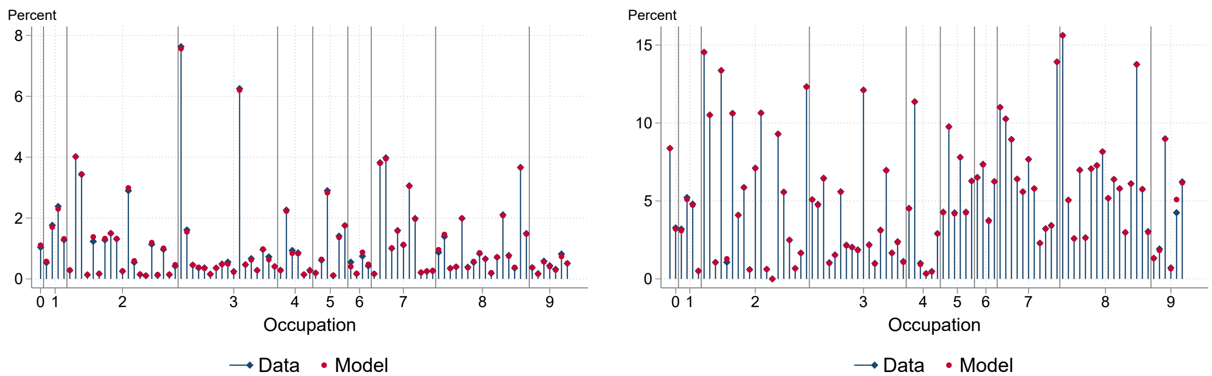
5.4 Model Fit

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

[24] 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.

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 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.[25] 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 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.[26] 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.[27]

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

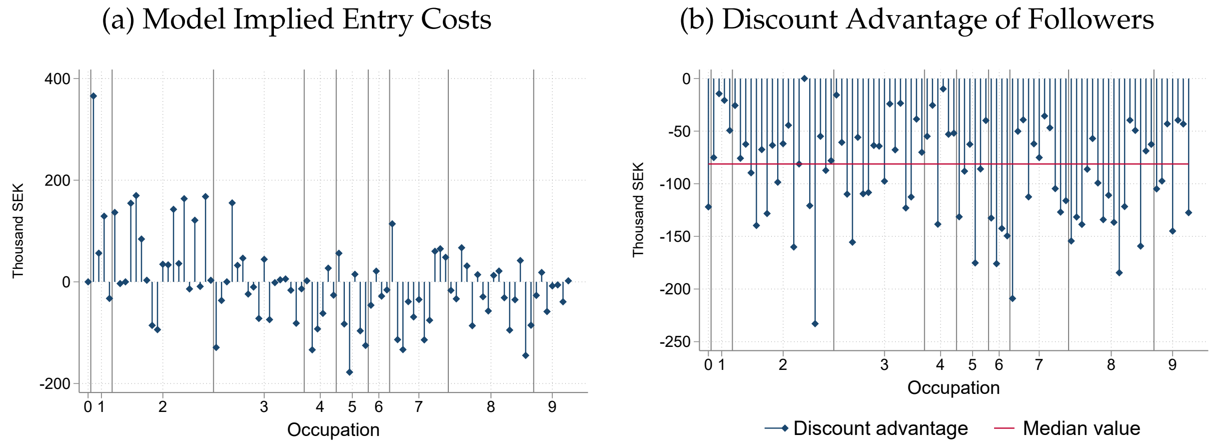
To better understand what the estimated entry costs capture, we relate them to time costs of entering an occupation. For this exercise, we utilize data from the BLS Occupational

[25] 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.

[26] 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.

[27] 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.

Figure 9: Model-Implied Costs



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.

Outlook Handbook of 2020.[28] The BLS reports the typical education and typical work experience in related occupations (in years) needed for entry into an occupation.[29] 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 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.

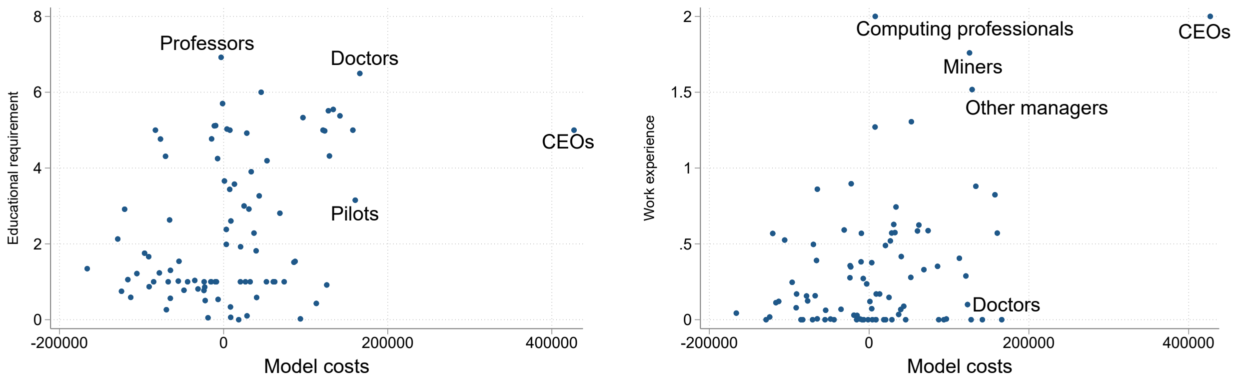
Figure 10, panel (a), plots the relationship between the model-estimated entry costs and the educational requirements, and panel (b) plots the relationship to work experience for different occupations. In both cases the costs estimated in our model calibration are strongly positively correlated with 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

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

[29]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 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.

professionals), or a lot of work experience (e.g. CEOs, managers, and pilots).

7 Counterfactual Analysis

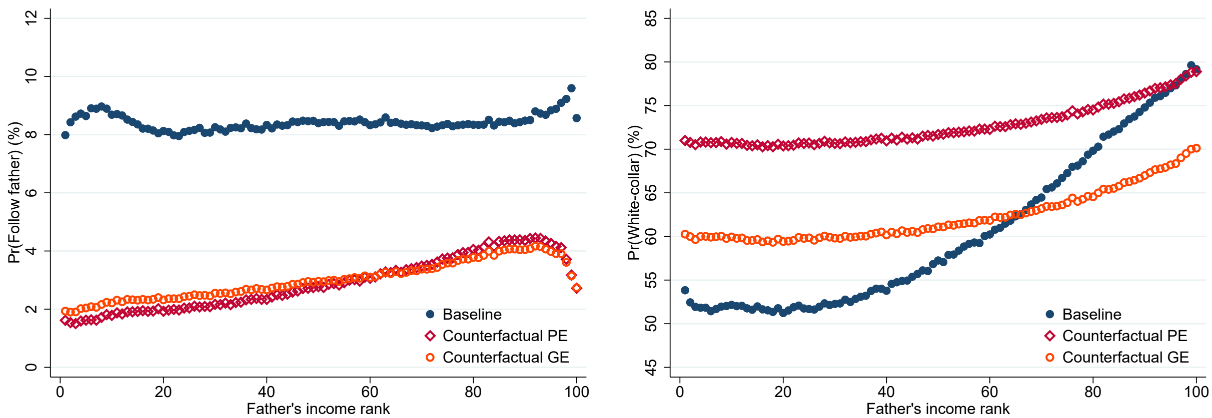
Our main counterfactual exercise aims to mimic an experiment where all workers have equal access and opportunities for entering occupations. We assign all individuals the same entry-cost discounts, leaving unchanged the general entry costs. This levels the playing field for all sons. In practice, we 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. 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

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.

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.

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.

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.

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.

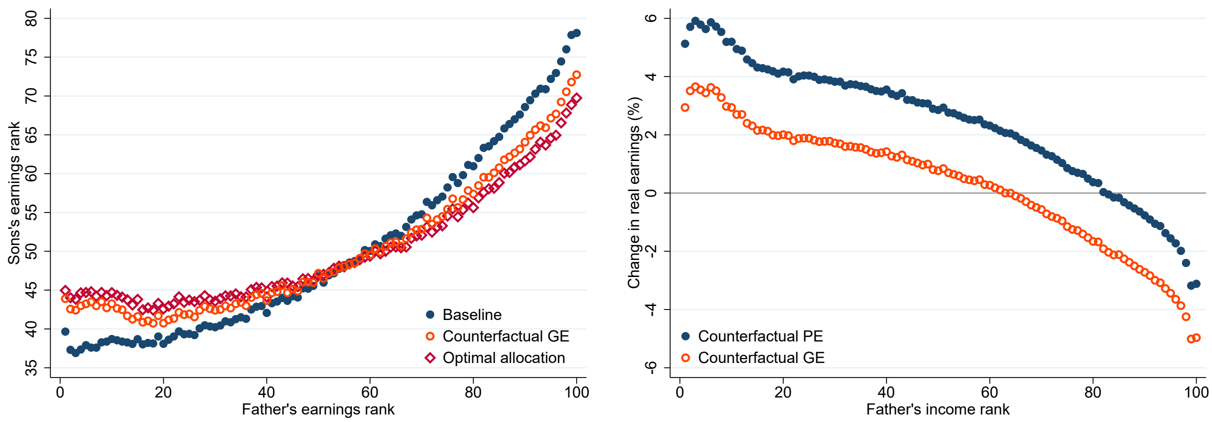
Among sons of fathers in the bottom quintile, annual earnings increase by 2.8 percent on average, while among sons of fathers in the top quintile earnings fall by 3 percent. In partial equilibrium the average change in earnings is larger than after prices have adjusted, both due to larger earnings increases 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

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.

by skills.[30] 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

[30]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.

falls by 4.5 percent in the counterfactual economy relative to baseline.

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.[31] 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.[32] Under this assumption, we reassign individuals to occupations such that

[31]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.

[32]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.

aggregate earnings are maximized, subject only to the occupation size constraints.[33]

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.

7.5 Occupational Skill Distance

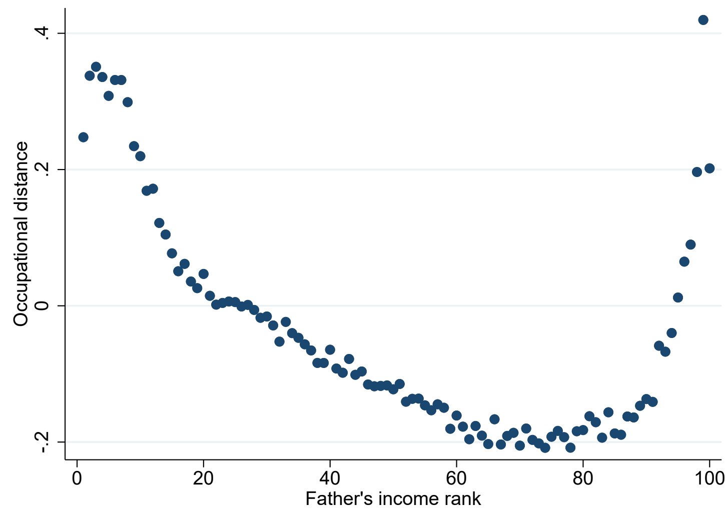
Another measure of the misallocation of talent in the baseline economy is the distance in skill space between the son's initial occupation and his occupation in the counterfactual economy without entry cost discounts. We quantify the skill distance between each occupational pair in our sample as the Manhattan distance between the skill requirements of all occupations, where skill requirements are based on the O*Net database.[34]

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 ex-

[33]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.

[34]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.

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.

perience 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 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.[35] Our identification strategy exploits the variation in employment change within fathers' occupations across cohorts of sons. We estimate this with:

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

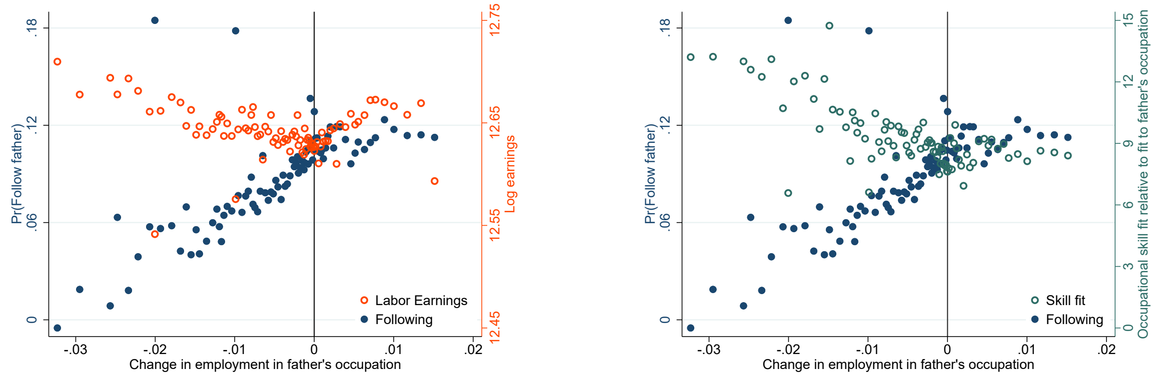
where y_{int} is the outcome of interest, e.g., the propensity of individual i to follow his father into occupation n, α_n are father's occupation fixed effects, Δemp_{nt} is the change in employment in the father's occupation, δ_t are year-at-prime-age (i.e. birth cohort) fixed effects, and $\boldsymbol{X}_i$ 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

[35] 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.

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, 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

Table 2: Effect of Occupational Following on Labor Market Outcomes

					Skill-fit	Father's income
	Follow	Log Earnings	Log Earnings	Log Pred. Earnings	Log Earnings	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

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.[36] 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

[36]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.

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.

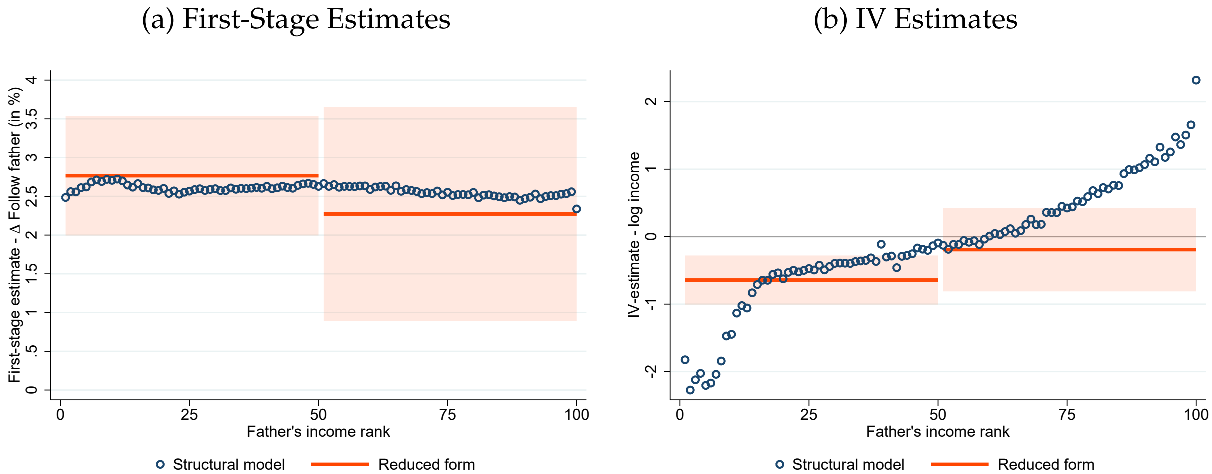
8.2 Estimates Using Data Generated by the Structural Model

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.

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

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.

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, in particular the estimates for sons of low-income fathers, for which the quasi-experimental estimates imply that following leads to 64 percent decrease in earnings.[37]

To summarize, the structural estimates are in line with reduced-form estimates which

[37]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.

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.

However, our results highlight the importance of accounting for general equilibrium effects. At the margin, reallocating workers to occupations that better match their skills increases individual and aggregate earnings. Our results clearly demonstrate, however, that in the aggregate, reallocation is likely to affect wages. We estimate that the general equilibrium effect on wages is almost large enough to undo the productivity gain from the partial equilibrium reallocation, leaving aggregate real earnings almost unchanged. Still, there are substantial changes in relative and absolute individual earnings.

It is worth emphasizing that our results are probably a lower bound on the aggregate consequences of the distortions in the allocation of talent. First, our analysis is limited to men who undergo Swedish military enlistment testing. Our sample, therefore, excludes women and migrants who likely face very different labor market opportunities compared to men. 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 having a dynamic rather than a static effect on output. For example, prior work has documented how background affects who becomes an inventor (Bell et al., 2019; Aghion et al., 2017). Reallocating talented individuals towards innovation may affect both their own incomes and economic growth. Incorporating these effects is beyond the scope of our analysis.

References

ACEMOGLU, D. AND D. AUTOR (2011): "Skills, tasks and technologies: Implications for employment and earnings," in *Handbook of labor economics*, Elsevier, vol. 4, 1043–1171.

ADÃO, R. (2015): "Worker heterogeneity, wage inequality, and international trade: Theory and evidence from brazil," *Working paper, MIT*.

AGHION, P., U. AKCIGIT, A. HYYTINEN, AND O. TOIVANEN (2017): "The social origins of inventors," Tech. rep., National Bureau of Economic Research.

AINA, C. AND C. NICOLETTI (2018): "The intergenerational transmission of liberal professions," *Labour Economics*, 51, 108–120.

ALTMEJD, A. (2023): "Inheritance of fields of study," Tech. rep., IFAU-Institute for Evaluation of Labour Market and Education Policy.

AUTOR, D. H. AND M. J. HANDEL (2013): "Putting tasks to the test: Human capital, job tasks, and wages," *Journal of labor Economics*, 31, S59–S96.

AUTOR, D. H., F. LEVY, AND R. J. MURNANE (2003): "The skill content of recent technological change: An empirical exploration," *The Quarterly journal of economics*, 118, 1279–1333.

BECKER, G. S. AND N. TOMES (1986): "Human capital and the rise and fall of families," *Journal of labor economics*, 4, S1–S39.

BELL, A., R. CHETTY, X. JARAVEL, N. PETKOVA, AND J. VAN REENEN (2019): "Who becomes an inventor in America? The importance of exposure to innovation," *The Quarterly Journal of Economics*, 134, 647–713.

BERTRAND, M. (2011): "New perspectives on gender," in *Handbook of labor economics*, Elsevier, vol. 4, 1543–1590.

BJÖRKLUND, A. AND M. JÄNTTI (2012): "How important is family background for labor-economic outcomes?" *Labour Economics*, 19, 465–474.

BJÖRKLUND, A., M. LINDAHL, AND E. PLUG (2006): "The origins of intergenerational associations: Lessons from Swedish adoption data," *The Quarterly Journal of Economics*, 121, 999–1028.

BLACK, S. E. AND P. J. DEVEREUX (2011): "Recent Developments in Intergenerational Mobility," *Handbook of Labor Economics*, 4, 1487–1541.

BLACK, S. E., P. J. DEVEREUX, AND K. G. SALVANES (2005): "The more the merrier? The effect of family size and birth order on children's education," *The Quarterly Journal of Economics*, 120, 669–700.

BLACK, S. E., E. GRÖNQVIST, AND B. ÖCKERT (2018): "Born to lead? The effect of birth order on noncognitive abilities," *Review of Economics and Statistics*, 100, 274–286.

BLAU, P. M. AND O. D. DUNCAN (1967): "The American occupational structure." .

BOSERUP, S. H., W. KOPCZUK, AND C. T. KREINER (2013): "Intergenerational wealth mobility: Evidence from danish wealth records of three generations," *Univ. of Copenhagen mimeo*.

BREIMAN, L. (2001): "Random forests," *Machine learning*, 45, 5–32.

BRYAN, G. AND M. MORTEN (2019): "The aggregate productivity effects of internal migration: Evidence from Indonesia," *Journal of Political Economy*, 127, 2229–2268.

CARLSTED, B. AND B. MÅRDBERG (1993): "Construct validity of the Swedish enlistment battery," *Scandinavian Journal of Psychology*, 34, 353–362.

CELIK, M. A. (2023): "Does the cream always rise to the top? The misallocation of talent in innovation," *Journal of Monetary Economics*, 133, 105–128.

CHETTY, R., N. HENDREN, AND L. F. KATZ (2016): "The effects of exposure to better neighborhoods on children: New evidence from the Moving to Opportunity experiment," *American Economic Review*, 106, 855–902.

CHETTY, R., N. HENDREN, P. KLINE, AND E. SAEZ (2014): "Where is the land of opportunity? The geography of intergenerational mobility in the United States," *The Quarterly Journal of Economics*, 129, 1553–1623.

COLLADO, M. D., I. ORTUÑO-ORTÍN, AND J. STUHLER (2023): "Estimating intergenerational and assortative processes in extended family data," *The Review of Economic Studies*, 90, 1195–1227.

CORAK, M. AND A. HEISZ (1999): "The intergenerational earnings and income mobility of Canadian men: Evidence from longitudinal income tax data," *Journal of Human Resources*, 504–533.

DAHL, G. B., D.-O. ROOTH, AND A. STENBERG (2020): "Intergenerational and Sibling Peer Effects in High School Majors," Tech. rep., National Bureau of Economic Research.

DAL BÓ, E., P. DAL BÓ, AND J. SNYDER (2009): "Political dynasties," *The Review of Economic Studies*, 76, 115–142.

DEMING, D. J. (2017): "The growing importance of social skills in the labor market," *The Quarterly Journal of Economics*, 132, 1593–1640.

DIAMOND, R. AND C. GAUBERT (2021): "Spatial Sorting and Inequality," .

EDIN, P.-A., P. FREDRIKSSON, M. NYBOM, AND B. ÖCKERT (2022): "The rising return to noncognitive skill," *American Economic Journal: Applied Economics*, 14, 78–100.

FREDRIKSSON, P., L. HENSVIK, AND O. N. SKANS (2018): "Mismatch of talent: Evidence on match quality, entry wages, and job mobility," *American Economic Review*, 108, 3303–38.

FREY, C. B. AND M. A. OSBORNE (2017): "The future of employment: How susceptible are jobs to computerisation?" *Technological forecasting and social change*, 114, 254–280.

GALOR, O. AND D. TSIDDON (1997): "Technological progress, mobility, and economic growth," *The American Economic Review*, 363–382.

GARDBERG, M., F. HEYMAN, P.-J. NORBÄCK, AND L. PERSSON (2020): "Digitization-based automation and occupational dynamics," *Economics Letters*, 189, 109032.

GIBBONS, R. AND M. WALDMAN (2004): "Task-specific human capital," *American Economic Review*, 94, 203–207.

GOLDIN, C. (2014): "A pollution theory of discrimination: male and female differences in occupations and earnings," in *Human capital in history: The American record*, University of Chicago Press, 313–348.

GRÖNQVIST, E., B. ÖCKERT, AND J. VLACHOS (2017): "The intergenerational transmission of cognitive and noncognitive abilities," *Journal of Human Resources*, 52, 887–918.

HÄRNQVIST, K. (2000): "Evaluation through follow-up. A longitudinal program for studying education and career development," *Seven Swedish longitudinal studies in behavioral science*, 76–114.

HAUSER, J. R. (2014): "Consideration-set heuristics," *Journal of Business Research*, 67, 1688–1699.

HILGER, N. G. (2016): "Parental job loss and children's long-term outcomes: Evidence from 7 million fathers' layoffs," *American Economic Journal: Applied Economics*, 8, 247–283.

HSIEH, C.-T., E. HURST, C. I. JONES, AND P. J. KLENOW (2019): "The allocation of talent and us economic growth," *Econometrica*, 87, 1439–1474.

JONKER, R. AND A. VOLGENANT (1987): "A shortest augmenting path algorithm for dense and sparse linear assignment problems," *Computing*, 38, 325–340.

JOVANOVIC, B. (2014): "Misallocation and growth," *American Economic Review*, 104, 1149–1171.

KRAMARZ, F. AND O. N. SKANS (2014): "When strong ties are strong: Networks and youth labour market entry," *Review of Economic Studies*, 81, 1164–1200.

LABAND, D. N. AND B. F. LENTZ (1983): "Occupational inheritance in agriculture," *American Journal of Agricultural Economics*, 65, 311–314.

——— (1985): *The roots of success: Why children follow in their parents' career footsteps*, Greenwood.

——— (1992): "Self-recruitment in the legal profession," *Journal of Labor Economics*, 10, 182–201.

LAZEAR, E. P. (2009): "Firm-specific human capital: A skill-weights approach," *Journal of political economy*, 117, 914–940.

LENTZ, B. F. AND D. N. LABAND (1989): "Why so many children of doctors become doctors: Nepotism vs. human capital transfers," *Journal of Human Resources*, 396–413.

——— (1990): "Entrepreneurial success and occupational inheritance among proprietors," *Canadian Journal of Economics*, 563–579.

LINDQUIST, M. J., J. SOL, AND M. VAN PRAAG (2015): "Why do entrepreneurial parents have entrepreneurial children?" *Journal of Labor Economics*, 33, 269–296.

LO BELLO, S. AND I. MORCHIO (2021): "Like father, like son: Occupational choice, intergenerational persistence and misallocation," *Quantitative Economics*.

LONG, J. AND J. FERRIE (2013): "Intergenerational occupational mobility in Great Britain and the United States since 1850," *American Economic Review*, 103, 1109–37.

MACALUSO, C. (2017): "Skill remoteness and post-layoff labor market outcomes," .

MAYER, A. (2008): "Education, self-selection, and intergenerational transmission of abilities," *Journal of Human Capital*, 2, 106–128.

MCFADDEN, D. (1974): "The measurement of urban travel demand," *Journal of public economics*, 3, 303–328.

MOCETTI, S. (2016): "Dynasties in professions and the role of rents and regulation: Evidence from Italian pharmacies," *Journal of Public Economics*, 133, 1–10.

MOCETTI, S., G. ROMA, AND E. RUBOLINO (2022): "Knocking on Parents' Doors Regulation and Intergenerational Mobility," *Journal of Human Resources*, 57, 525–554.

MOOD, C., J. O. JONSSON, AND E. BIHAGEN (2012): "Socioeconomic persistence across generations: cognitive and noncognitive processes," .

MUNSHI, K. AND M. ROSENZWEIG (2016): "Networks and misallocation: Insurance, migration, and the rural-urban wage gap," *American Economic Review*, 106, 46–98.

MURPHY, K. M., A. SHLEIFER, AND R. W. VISHNY (1991): "The allocation of talent: Implications for growth," *The quarterly journal of economics*, 106, 503–530.

NAKAMURA, E., J. SIGURDSSON, AND J. STEINSSON (2021): "The Gift of Moving: Intergenerational consequences of a mobility shock," *The Review of Economic Studies*, Forthcoming.

NICOLAOU, N., S. SHANE, L. CHERKAS, J. HUNKIN, AND T. D. SPECTOR (2008): "Is the tendency to engage in entrepreneurship genetic?" *Management Science*, 54, 167–179.

OHNSORGE, F. AND D. TREFLER (2007): "Sorting it out: International trade with heterogeneous workers," *Journal of political Economy*, 115, 868–892.

ROGOFF, N. (1953): "Recent trends in occupational mobility." .

ROY, A. D. (1951): "Some thoughts on the distribution of earnings," *Oxford economic papers*, 3, 135–146.

SATTINGER, M. (1993): "Assignment models of the distribution of earnings," *Journal of economic literature*, 31, 831–880.

SOLON, G. (1999): "Intergenerational mobility in the labor market," in *Handbook of labor economics*, Elsevier, vol. 3, 1761–1800.

STAIGER, M. (2023): Tech. rep., Opportunity Insights, Harvard University.

SVENSSON, A. (2011): "Utvärdering genom uppföljning. Longitudinell individforskning under ett halvsekel," *Acta Universitatis Gotoburgensis*, 305.

WEBB, M. (2019): "The impact of artificial intelligence on the labor market," *Available at SSRN 3482150*.