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

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Abstract

Children disproportionately enter their parents' occupations. We examine the implications of this tendency for intergenerational income mobility and talent allocation in the economy. Using Swedish data on cognitive and non-cognitive skills, we estimate a general-equilibrium Roy model in which access to occupations depends on parental occupation. Equalizing access reduces occupational following by roughly one-half and increases income mobility by about one-third without reducing output. Gains are concentrated among sons of low-earning fathers with skills suited to higher-paying occupations. Quasi-experimental evidence exploiting long-run employment declines in fathers' occupations supports the model estimates: reduced following improves skill matching and raises earnings.

JEL Codes: E24, J24, J62.

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1 Introduction

Decades of research have documented substantial intergenerational persistence in income (Black and Devereux, 2011; Solon, 1999). While this persistence may arise from multiple sources, one important contributing factor is that children often follow their parents into the same occupations. In the U.S., for example, sons of doctors and lawyers are about 20 times more likely to enter those professions than would be expected if occupational choice were independent of that of their fathers (Dal Bó et al., 2009). Although this pronounced tendency has long been recognized (Blau and Duncan, 1967; Laband and Lentz, 1985; Long and Ferrie, 2013; Rogoff, 1953), there is little consensus on the mechanisms driving it or on its economic implications.

On one hand, occupational persistence may reflect sorting on productive skills: parents and children may share abilities that give them a comparative advantage in similar occupations (Roy, 1951). On the other hand, it may reflect unequal opportunities: parental background can facilitate access to, or create barriers against, entry into certain professions, independent of a child's ability (e.g. Bell et al., 2019).

In this paper, we provide new evidence on the consequences of occupational following for intergenerational income mobility. We combine military enlistment data on cognitive and non-cognitive skills with labor market outcomes of both children and parents to estimate a structural general equilibrium model of occupational choice. Our key result is that, in a counterfactual scenario where occupational choice depends solely on skills, general entry requirements, and training costs—but not directly on parental occupation—the extent of occupational following falls by half, and intergenerational income mobility increases by one-third.

We begin our analysis by documenting key patterns in the occupational choices of Swedish children. We show that children are disproportionately likely to choose the same narrow occupation as their parents, relative to children from different backgrounds.[1] There is a strong tendency toward occupational following among both sons and daughters, though 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 12 and 18 times more likely, respectively, to become doctors and lawyers themselves than would be expected if occupational choices were independent across generations. These occupations are not outliers: on average, sons are 18 times more likely to enter the same occupation as their fathers than children from other families. Beyond documenting occupational following itself, we show that occupation-specific earnings are the primary driver of intergen-

[1] Our main analysis is based on a classification of 91 occupations that is consistent from 1960 to the present.

erational earnings persistence—the earnings rank a worker holds within their occupation plays a minor role. We confirm that these findings extend beyond the Swedish context using data for the US.

We use a structural general equilibrium Roy (1951) model to study the impact of parental background on occupational choice, income mobility, and aggregate output. In the model, individuals choose the occupation that provides them with the highest utility. Each occupation offers different prospective earnings, reflecting occupation-specific returns to skills. Entry is subject to utility costs that capture factors such as educational and training requirements, capital or credit needs, licensing and regulatory barriers, as well as search and information costs associated with entering a given occupation. Parental occupation can affect these costs directly—for example, through access to occupation-specific information, networks, or resources. We model this as a "discount" on the entry cost of choosing the parent's occupation. These discounts imply that two individuals with identical skills will differ in their propensity to enter an occupation if one has a parent employed in it.

We estimate entry costs and discounts by matching individuals' observed occupational choices to the predicted choice probabilities given their skills and the occupation-specific returns to those skills. The estimated discounts suggest that parental influence on occupational choices is large: sons who follow their fathers' occupations receive an average reduction in entry costs equivalent to SEK 81,000 (USD 7,500) for the median occupation, relative to sons without a father in that occupation. This corresponds to about 27 percent of annual prime-age earnings. With the estimated costs and discounts, the model closely reproduces the observed occupational distributions and the empirical propensity of children to follow their parents across occupations.

A crucial ingredient in the model is a measure of how well individuals match to different occupations based on their skills, and of the income they would earn given the returns to skills across occupations. To construct these measures, we use data on a range of cognitive skills (inductive, verbal, spatial, and technical ability) and personality traits (social maturity, intensity, psychological energy, and emotional stability) for men assessed in connection with the Swedish military enlistment. While these measures should not be interpreted as innate abilities, they capture a broad set of skills and are recorded at age 18, before labor market entry. Previous work has shown that these skills have precisely estimated returns, even conditional on educational attainment and demographics (Edin et al., 2022; Fredriksson et al., 2018).

Our empirical approach builds conceptually on the "task framework," in which occupations differ in the types of tasks they involve and in how productive different skills are in performing these tasks (Acemoglu and Autor, 2011). This framework implies that occupations employ skills with different weights (Lazear, 2009), leading workers to sort into occupations according to their heterogeneous skill profiles—a pattern documented in prior work (e.g. Autor and Handel, 2013; Fredriksson, Hensvik, and Skans, 2018) and one that we also observe in our data. We therefore use the skills of incumbent workers to infer the skill requirements and returns associated with each occupation. Specifically, we train a model on the skills of incumbents in each occupation—excluding occupational followers—and use it to predict for every potential entrant both his potential earnings ("Roy productivity") and the probability of entry ("skill fit") given his skill set.

We use the model to construct a counterfactual experiment that equalizes entry costs across children, such that occupational choices are driven solely by heterogeneous skill sets rather than family-specific advantages. In this counterfactual, the rate of occupational following falls sharply—by 65 percent, from 8.4 to 3.0 percent. In the baseline, the propensity for occupational following is roughly uniform across the fathers' income distribution. When entry costs are equalized, however, the decline in following is substantially larger among sons of lower-income fathers.

Increased occupational mobility increases income mobility by almost 30 percent, measured either by the probability of sons of fathers in the bottom income quintile moving to the top quintile, or the change in the correlation in the income rank of sons and fathers. This reflects both relative and absolute income changes. Among sons of the lowest earning fathers, real income rise by 2.8 percent while their percentile rank increases by 4.1 ranks. In contrast, the real income of sons of the highest earning fathers decline by 3 percent and their relative earnings by 4.6 ranks. These results allow us to decompose the observed intergenerational persistence in income into its underlying components. Relative to a benchmark of perfect mobility—where sons' incomes are independent of their fathers'—we estimate that 26 percent of the observed intergenerational persistence is attributable to the influence of fathers' 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, reflecting better allocation of skills to tasks. 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 income mobility while leaving aggregate real incomes almost unchanged.

Our model estimates and counterfactual experiments rely on identifying heterogeneous entry costs that rationalize the differences between observed occupational choices and those predicted by individuals' heterogeneous skills. These estimated costs may therefore capture not only barriers to entry and exit, but also other factors, including preferences. To support the interpretation of our model results, we complement them with quasi-experimental evidence. Specifically, we exploit long-run structural declines in employment within fathers' occupations as a source of variation in sons' opportunities to follow their fathers. We hypothesize that a decline in employment in the father's occupation affects some of the factors captured by the entry-cost discounts in our model—such as the value of the father's network—while being unrelated to time-invariant preferences for occupational following.

Consistent with this hypothesis, we estimate a strong first stage: when employment in the father's occupation declines, sons are significantly less likely to enter that occupation. In turn, sons who do not follow their fathers due to such employment declines earn higher incomes in adulthood. These effects are concentrated among sons of low-income fathers and among sons whose skills are poorly matched to their fathers' occupations. Finally, we replicate the same reduced-form regressions using model-generated data in response to changes in entry-cost discounts and find qualitatively similar patterns.

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., Blau and Duncan, 1967; Laband and Lentz, 1985; Long and Ferrie, 2013; Rogoff, 1953) and incomes (Black and Devereux, 2011; Solon, 1999). 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 (Dal Bó et al., 2009; Kramarz and Skans, 2014; Staiger, 2023), provision of information (Laband and Lentz, 1983, 1992; Lentz and Laband, 1989, 1990), or transfers of wealth or rent (nepotism) (Aina and Nicoletti, 2018; Mocetti, 2016; Mocetti et al., 2022). 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. Aghion, Akcigit, Hyytinen, and Toivanen, 2017; Bryan and Morten, 2019; Chetty, Hendren, and Katz, 2016; Munshi and Rosenzweig, 2016; Murphy, Shleifer, and Vishny, 1991; Nakamura, Sigurdsson, and Steinsson, 2021). 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 (Celik, 2023; Lo Bello and Morchio, 2021). 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.[2]

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

In the next section we describe our data. In Section 3 we document patterns of occupational choice and intergenerational persistence in occupations. In Section 4, we develop our structural general equilibrium model in which parental background affects occupational entry costs and discounts and describe how we measure individual skill fit to occupations. We present the results from model estimation in Section 5. Section 6 contains the results from our counterfactual experiment. In Section 7 we present supporting quasi-experimental evidence. Section 8 is the conclusion. Additional background material is relegated to an online appendix.

[2]These results contribute to a literature documenting the intergenerational correlation in abilities (e.g. Björklund and Jäntti, 2012; Collado, Ortuño-Ortín, and Stuhler, 2023; Grönqvist, Öckert, and Vlachos, 2017) 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).

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.[3]

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.[4] Appendix A.1 provides details on the occupation classification and our cross-walks.

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

[3]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).

[4]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.

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:[5]

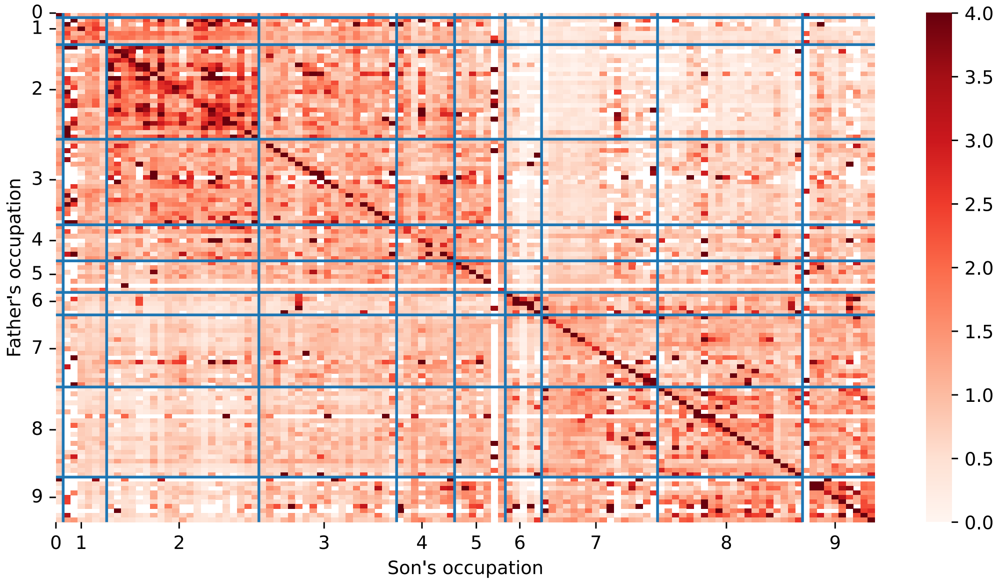
$$OMB_{f,k} = \frac{share_{f,k}}{share_k}$$

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, $share_k$. 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.[6]

[5] 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".

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

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.

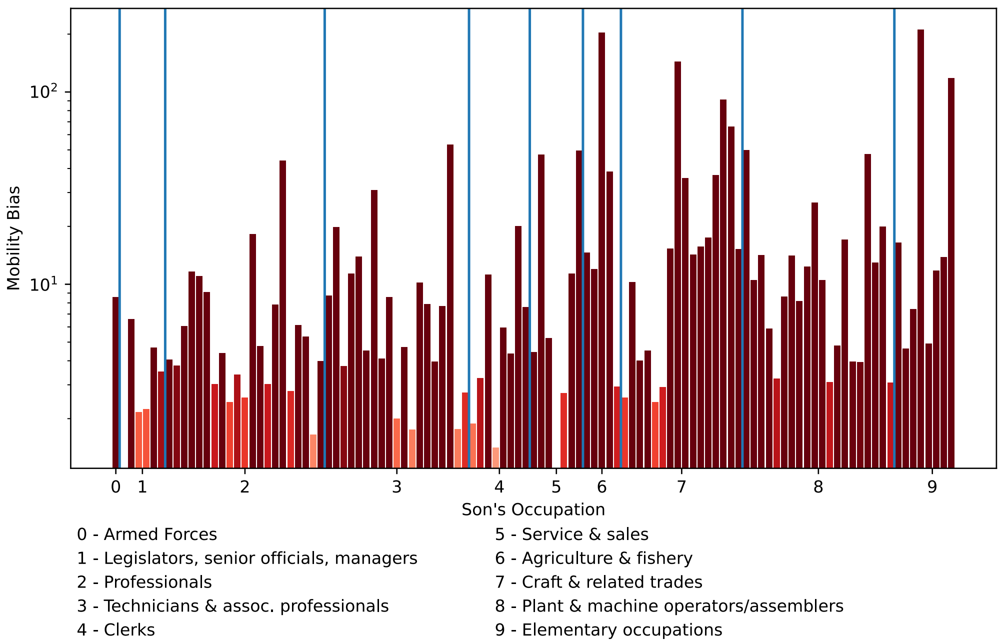
Figure 1 documents the occupational mobility bias across all combinations of fathers' and sons' occupations.[7] The y-axis represents the father's occupation, while the x-axis represents the son's occupation. Each row or column in the matrix is a specific three-digit occupational code in the Swedish SSYK-96 system, the vertical and horizontal lines partition the space into one-digit occupational categories.[8] 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 ran-

measure.

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

[8]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.15, A.16, and A.17.

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.

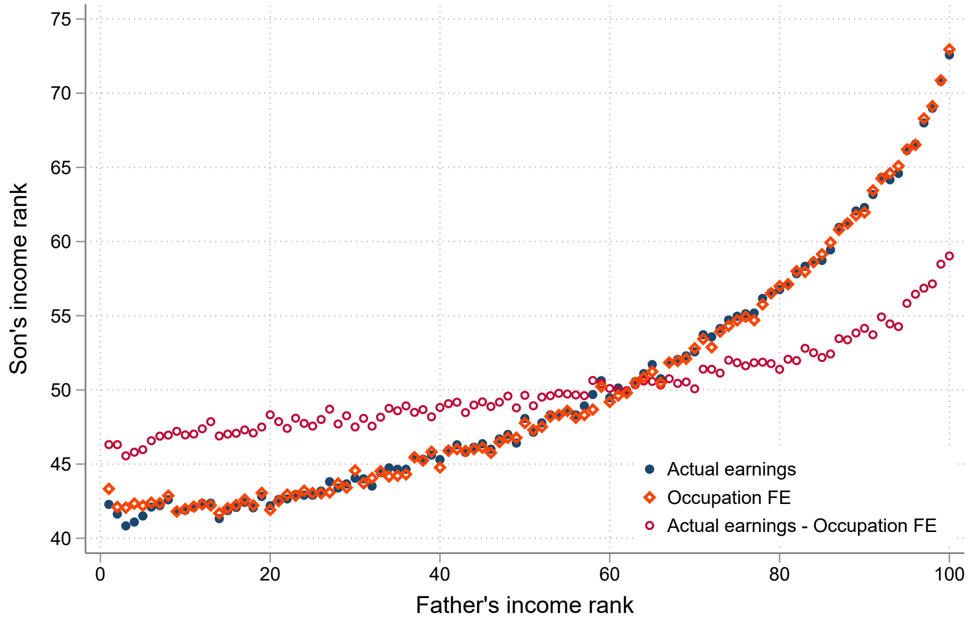
dom.[9] To highlight the magnitudes along the diagonal, as well as the heterogeneity, Figure 2 presents the mobility bias only along the diagonal of the matrix (note that the y-axis displays the bias in log-scale). While the bias is highly heterogeneous across occupations, it is almost always greater than one, across all occupations irrespective of skill requirements or earnings levels. We register the highest mobility bias among sons who choose agricultural professions, with values exceeding 100. The only profession for which the mobility bias is smaller than one can be found among clerks. These findings are in line with previous studies that have documented substantial occupational mobility bias, e.g., in the US labor market (Blau and Duncan, 1967; Dal Bó et al., 2009; Rogoff, 1953).

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

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

Figure 3: Association between Sons' and Fathers' Incomes



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

quadrants along white-collar vs. blue-collar axes. The north-west and the south-east quadrants show noticeably higher levels of occupational mobility bias; the north-east and south-west corners show noticeably less. Occupations with one digit codes from one to five can mostly be characterized 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.

We argue that understanding the drivers of intergenerational persistence in occupations is not only conceptually important for understanding social mobility, but also quantitatively important for explaining intergenerational persistence in incomes. To illustrate this point, Figure 3 plots the relationship between fathers' and sons' prime-age income ranks, constructed within cohort-year cells.[10] To assess the role of occupational choice in

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

shaping this persistence, we plot two additional rank–rank associations. First, in orange diamonds, we show the association when sons' income is replaced by the average income of their occupation. Strikingly, the relationship is almost identical to that using actual income. Second, we plot in red circles the rank–rank association after removing occupation fixed effects from incomes, which yields a markedly flatter relationship. In Appendix A.2 we conduct the same decomposition utilizing the US National Longitudinal Survey of Youth (1979). The results are similar. Together, these exercises suggest that a substantial share of intergenerational income persistence operates through occupational sorting.

4 General Equilibrium Model of Occupational Choice

In this section we develop a structural model of occupational choice that we can estimate using administrative data and use to perform counterfactual experiments. We build on and extend Roy models presented in Ohnsorge and Trefler (2007), Adão (2015), Nakamura, Sigurdsson, and Steinsson (2021). Our model is a Roy-style model (Roy, 1951) in which sons make occupational choices based on their utility in each of 91 occupations. Utility can be affected by occupation-specific entry costs and by the parents' occupations—we allow for three different levels of discounts on entry costs, depending on how close the chosen occupation is to the parents'. Workers derive utility from consuming all goods and services produced in the economy, which allows us to solve for a general equilibrium in which quantities and prices are endogenously determined by the earnings and price distribution across occupations. 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 in more detail, we describe this procedure. We present a more stylized, partial-equilibrium version of the model with two occupations in Appendix C, which illustrates the key mechanisms in a more transparent setting.

4.1 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" (Ace-

measures income as total taxable earnings, including zeros (Chetty et al., 2014). For comparison, Appendix Figure A.8 plots the rank–rank association for our sample when income is measured as total taxable earnings. This produces a nearly linear relationship with a slope of 0.19. The resulting slope is substantially flatter than that documented for the United States (0.341) (Chetty et al., 2014), but close to, though somewhat steeper than, those reported for Denmark (0.180) (Boserup et al., 2013) and Canada (0.174) (Corak and Heisz, 1999).

moglu and Autor, 2011; Autor et al., 2003; Gibbons and Waldman, 2004).[11] 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, assigning zero to everyone else. For earnings we instead use the whole distribution of earnings within an occupation to measure the productivity of different skills and skill compositions, exploiting that earnings are increasing in skills but differently across occupations. In both cases, the training sample for the prediction is based on a sample of incumbents that excludes individuals who follow their fathers into the same occupation. This is to avoid the influences of characteristics other than skills that may influence earnings and entry probability.[12]

For our training and prediction, we use the XGBoost algorithm, 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

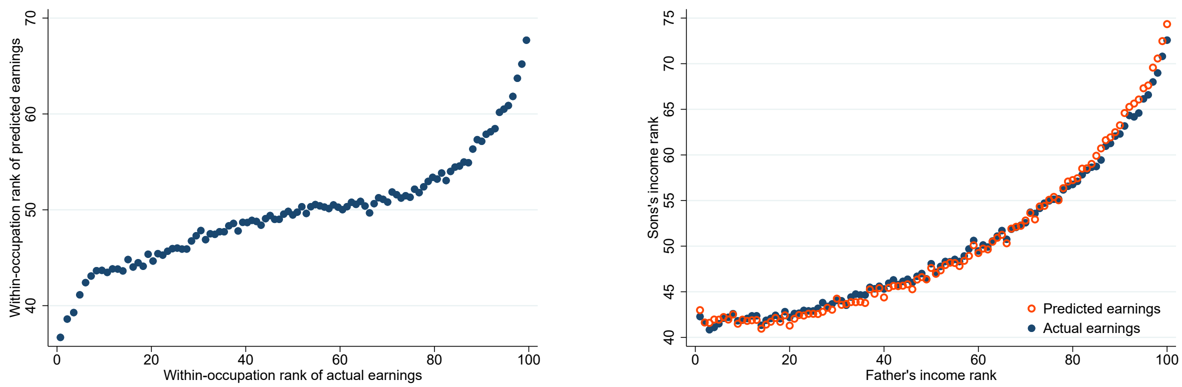
[11]Our approach is also consistent with the model in Lazear (2009), where skills are general but different jobs attach different weights to them.

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

Figure 4: Actual and Predicted Earnings

(a) Within-Occupation Rank of Earnings

(b) Rank of Sons' and Fathers' Earnings



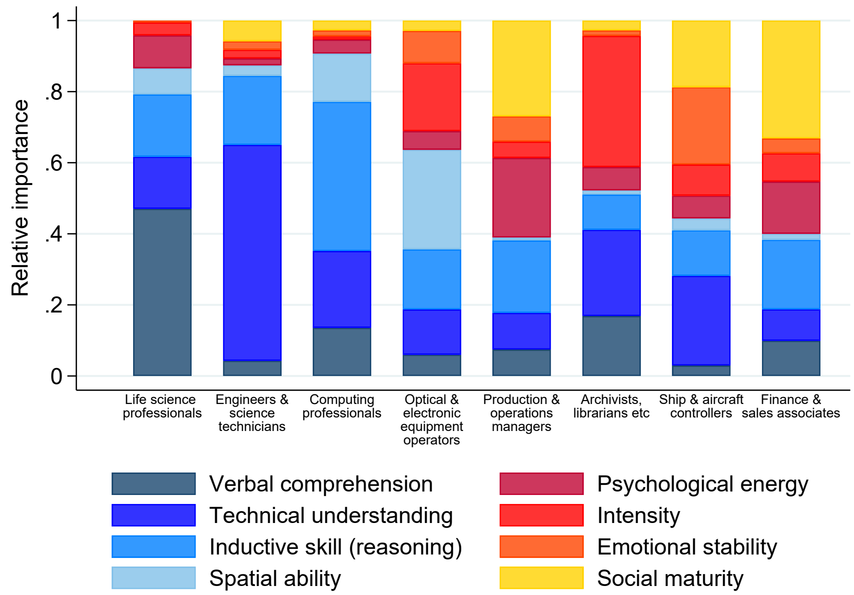
Note: This figure plots the relationship between predicted and actual earnings, presented in ranks for comparability across occupations. Panel (a) plots the average within-occupation rank of predicted earnings for individuals in a specific bin of actual within-occupation earnings. Panel (b) plots the 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.

various degrees and interactions across different occupations (Lazear, 2009). In this sense, XGBoost 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), 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.[13] Figure 4 shows the relationship between predicted and actual earnings of incumbents. Figure 4a is a plot of the within-

[13] Appendix Figure A.18 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.

Figure 5: 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.

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.[14] In addition to this, in Appendix Figure A.9 we plot the histogram of R^2 from the predictions, by occupation, which average to 0.093. In Figure 4, 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 5 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 occu-

[14]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.

pations differ substantially in the relative importance of skills, but also that a variety of skills are productive in each occupation. Looking first at cognitive skills, the skills with the highest relative importance in predicting income are verbal comprehension for life science professionals; technical understanding for engineers; inductive reasoning for computer scientists and programmers, and spatial ability for those that operate optical and electronic equipment. In each of these occupations, a range of other cognitive and non-cognitive skills are also important predictors. Among non-cognitive skills, psychological energy (i.e. focus and perseverance) is most important in predicting earnings of production managers; intensity (i.e. self motivation) for archivists and librarians; emotional stability (i.e. stress tolerance) for captains and pilots, and social maturity (i.e. extroversion) for finance and sales associates, such as real-estate agents.

A general concern regarding our methodology is that the measured skills, and consequently predicted earnings and occupational fit, might partly be a result of upbringing. If so, we may underestimate how much background factors affect outcomes, such as occupational choice and earnings. Importantly, to the extent that our results measure misallocation of talent, this is in terms of talent at the age of 18. Still, we have investigated this concern and concluded that such endogeneity of skills to parental background appears quantitatively limited. We study this in two ways. First, we leverage the fact that for a subset of our sample we have the skills measured in sixth grade, when children are aged 12 or 13. In Appendix A.3, 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.4, 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.5, 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 6. 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.6, we find that the two measures of occupational skill requirements yield similar results.

4.2 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: $Z(x, n) = V_n(x)$.[15] Individuals supply labor inelastically to the market within perfectly competitive firms. Labor is the only factor of production in a linear production function: $Y_n = A_n L_n$, where $L_n = \int_{i \in \Gamma^n} Z(x(i), n)\, di$, A_n represents aggregate productivity in occupation n, and Γ^n denotes the set of workers who choose occupation n. 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 specify utility in two parts. First, instead of assuming 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

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

goods produced by occupation n. They are subject to a budget constraint,

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

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).[16]

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

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

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

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

- *Supply equals demand in all occupations n:*

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

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

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

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

4.3 Estimation

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

$$g(c_1, ..., c_N) = \prod_n c_n^{\alpha_n} \quad \text{with} \sum_{n=1}^{N} \alpha_n = 1 \tag{2}$$

which gives the associated price index $P = \left(\frac{\prod_n P_n}{\prod_n \alpha_n}\right)^{\alpha_n}$. This formulation is convenient as, combined with the budget constraint (1), it implies that the optimal expenditure shares on each product is governed by its α coefficient:

$$\alpha_n = \frac{E_n}{E}, \ \forall n \in N \tag{3}$$

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 income $Y(x, n)$.[17] 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

$$u(f, n, x, i) = h(n, x) - b_n^f + \varepsilon_n(i) \tag{4}$$

[17] Deflating earnings by the price index yields $h(n, x) = Y(x, n)\left(\frac{\prod_n \alpha_n}{\prod_n P_n}\right)^{\alpha_n}$, which is linear in earnings.

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.[18]

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

$$b_n^f = m_n - \mathbb{I}_{G_f=G_n} d_{1,G_n} - \mathbb{I}_{g_f=g_n} d_{2,g_n} - \mathbb{I}_{f=n} d_{3,n} \tag{6}$$

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

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

[18] The PDF of the Type I EV distribution is $c(\varepsilon) = \kappa e^{-\kappa\varepsilon - e^{-\kappa\epsilon}}$, 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

$$\psi_n = Pr(\text{argmax}_n \quad u(f, k, x) = n) \tag{5a}$$

$$= \frac{e^{\kappa u(f,n,x)}}{\sum_n e^{\kappa u(f,n,x)}} \tag{5b}$$

fessional who earns 500,000 SEK per year is assumed to produce 500,000 units of legal services. The normalization has no effect on relative predicted earnings across individuals within occupations, which importantly is what matters for our results. Then, using the earnings predictions based on skills presented in Section 4.1, we obtain a productivity for every individual across all occupations.

Given the aforementioned earnings predictions, and the resulting occupational choices, we estimate the costs $m = \{m_n\}_{n=1}^{N}$ to pin down each occupation's correct size. Finally, the discounts $d_1 = \{d_{1,G_n}\}_{G_n=1}^{2}$, $d_2 = \{d_{2,g_n}\}_{g_n=1}^{10}$, and $d_3 = \{d_{3,n}\}_{n=1}^{N}$ are identified from the number of occupational followers in excess of those caused by skills and entry costs. 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.[19] To calibrate the parameter κ, which governs the variance of preference shocks, we target the level of yearly aggregate earnings in SEK.

4.4 Model Fit

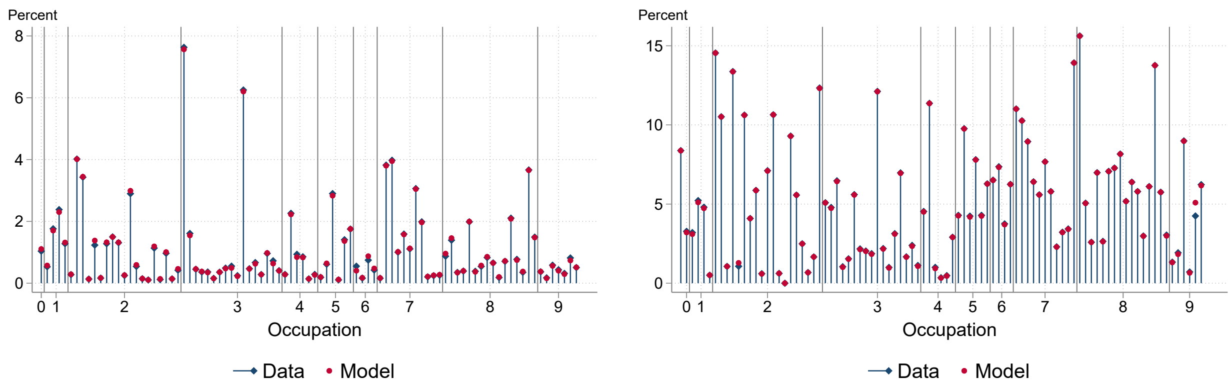
The model closely replicates the targeted moments: the share of sons who have fathers in white (blue) collar occupations and choose a white (blue) collar occupation themselves is 68.70 (59.86) percent in the data and 68.71 (59.85) percent in the model. We report the shares of sons who have an occupation in the same broad one-digit group as their father in Figure A.20 in Appendix F. Again, the model fits very closely to the data.

Figure 6 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

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

Figure 6: 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.

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 6 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 E. Importantly, the model closely replicates the expenditure shares observed in the data (as shown in Appendix Figure A.12), 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.14 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.

5 Estimation Results

5.1 Entry Costs and Discounts

Figure 7, panel (a), displays the costs of entering different occupations, as estimated by the model. We convert the entry costs and discounts into monetary values.[20] 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.[21] Panel (b) of Figure 7 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.[22]

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.

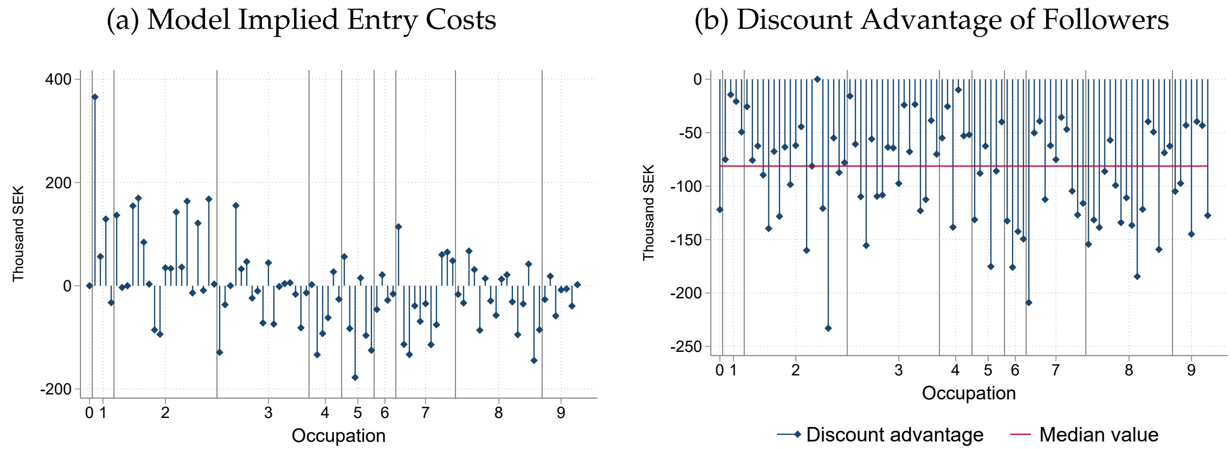
We interpret this reduced-form representation of discounts as capturing a broad set of parental influences—ranging from information and access to norms and expectations. Consequently, in the counterfactual exercises below, we remove the combined effect of all father-specific non-skill advantages, regardless of their source.

[20] 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.

[21] 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.

[22] 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 7: 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.

5.2 Interpreting the Entry Costs

To better understand what the estimated entry costs capture, we relate them to time costs of entering an occupation. For this exercise, we utilize data from the BLS Occupational Outlook Handbook of 2020.[23] The BLS reports the typical education and typical work experience in related occupations (in years) needed for entry into an occupation.[24] 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.

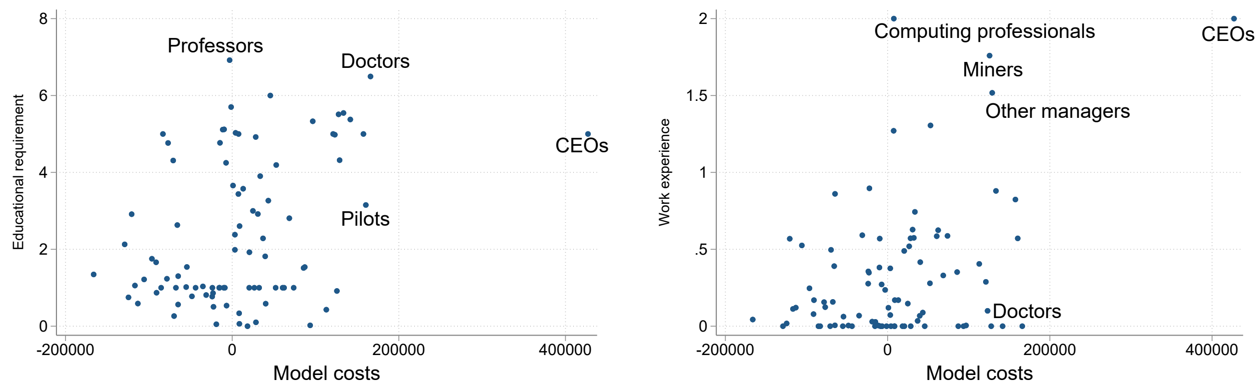
Figure 8, panel (a), plots the relationship between the model-estimated entry costs and the educational requirements, and panel (b) plots the relationship to work experience for different occupations. In both cases the costs estimated in our model calibration are

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

[24]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.6.1.

Figure 8: 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.

strongly positively correlated with these measures of occupation entry requirements. Our model estimates imply that CEOs, pilots, managers, and medical professionals face the highest entry costs. These professions require either higher education (e.g. health professionals), or a lot of work experience (e.g. CEOs, managers, and pilots).

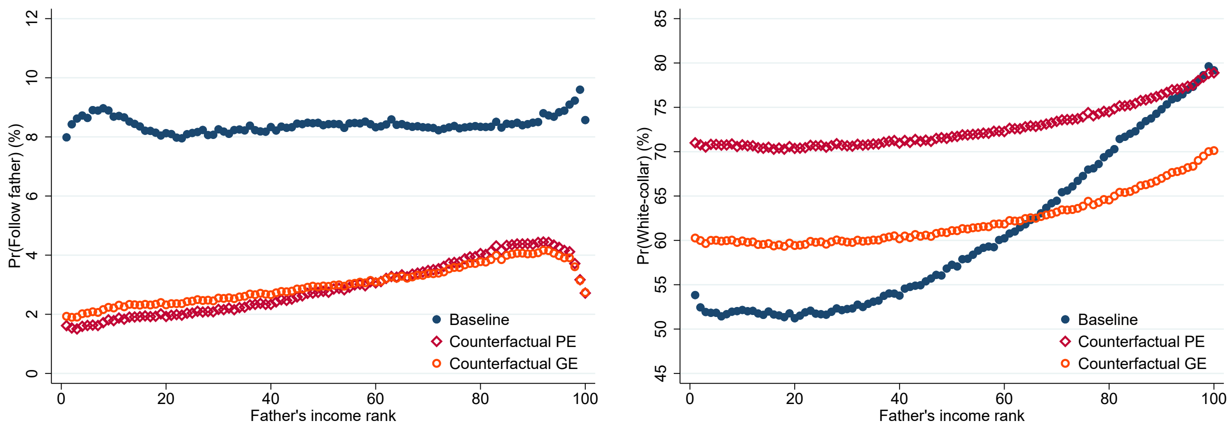
6 Counterfactual Analysis

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.

Figure 9: 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.

6.1 Effects on Occupational Choice and Occupational Following

Figure 9 shows the effect of the removal of the discount on occupational choices.[25] Panel (a) shows, for the baseline model, the strong tendency for sons to pursue the occupation of their fathers. As summarized in Table 1, this averages at 8.4 percent. Still, there is a greater propensity to follow among sons of the lowest- and highest-income fathers. The orange circles plot the counterfactual follower share when discounts are removed. The results are striking: occupational following drops by more than half, down to 3.0 percent on average. This drop is considerably more pronounced among sons of lower-income fathers, whereas sons of fathers in the top quintile of their earnings distribution are roughly twice as likely to follow their fathers when selecting into occupations only based on skills than sons of fathers in the bottom quintile. At the very top, however, the pattern reverses.

Panel (b) in Figure 9 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

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

Table 1: Counterfactual Model Results

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

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

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 9.

A natural concern is that this large drop in occupational following in the counterfactual economy results from unobserved occupation-specific skills inherited from fathers. That is, that fathers possess certain skills that give them a comparative advantage in their occupation, which they pass on to their sons. Omitting these skills from the model exaggerates the skill mismatch of their sons and the counterfactual drop in following. We address this concern in Appendix A.5 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.21 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.

6.2 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 10 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 10 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.

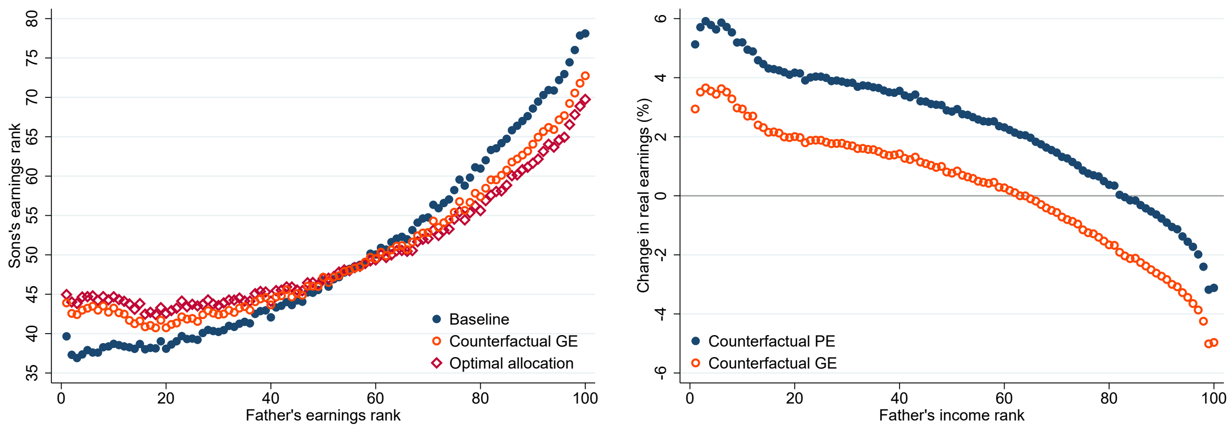
Among sons of fathers in the bottom quintile, annual earnings increase by 2.8 percent on average, while among sons of fathers in the top quintile earnings fall by 3 percent. In partial equilibrium the average change in earnings is larger than after prices have adjusted, both due to larger earnings increases among sons from poorer backgrounds and smaller earnings declines among those of richer fathers. As reported in Figure 9, 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

Figure 10: 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.

on the change in this deviation. We estimate that parental background accounts for 25.7 percent of the observed earnings persistence.[26] The remainder accounted for by skills.[27] These results are consistent with prior work documenting strong intergenerational correlation in both cognitive and non-cognitive skills (e.g. Björklund and Jäntti, 2012; Grönqvist, Öckert, and Vlachos, 2017). 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.

[26]The change in mobility is defined as the proportional reduction in the distance from perfect mobility (rank = 50) when moving from the baseline (β_{BL}) to the general-equilibrium counterfactual (β_{GE}): $\Delta\text{Mobility} = 1 - \frac{|50-\beta_{GE}|}{|50-\beta_{BL}|}$.

[27]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.

6.3 Effects on Aggregate Earnings

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

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.19). 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.[28] 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.22, 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.

6.4 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

[28]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.

a certain number of workers in each occupation, and that this number is unaffected by our re-sorting.[29] Under this assumption, we reassign individuals to occupations such that aggregate earnings are maximized, subject only to the occupation size constraints.[30]

Output under the optimal—or earnings-maximizing—allocation is 7 percent higher than it is in the baseline model. Next, we plot, in Figure 10 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.

6.5 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.[31]

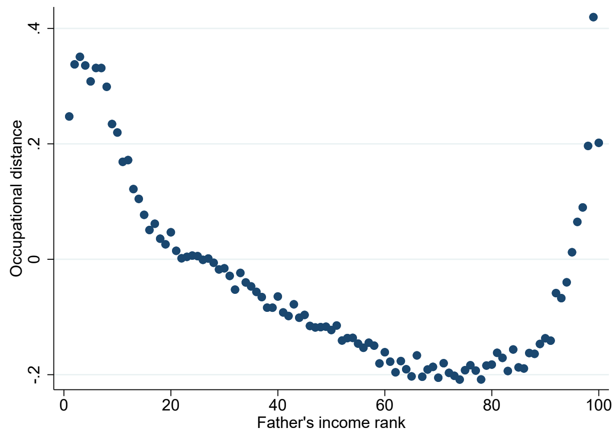
Figure 11 plots the average skill distance moved across the father's income distribution. Skill distances are standardized within the population by their mean and standard deviation. There is systematically more misallocation among sons of lower-income fathers

[29] 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.

[30] 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.

[31] 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.6 and A.7 provide details on the data used and the measure.

Figure 11: 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.

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 10 that when discounts are removed, sons of lowest-income fathers earn higher incomes while sons of the highest-income fathers experience an earnings decline. Together with Figure 11, 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.

7 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.

7.1 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.[32] Our identification strategy exploits the variation in employment change within fathers' occupations across cohorts of sons. We estimate this with:

$$y_{int} = \alpha_n + \beta \Delta emp_{int} + \delta_t + \boldsymbol{X}_i'\gamma + \varepsilon_{int} \tag{7}$$

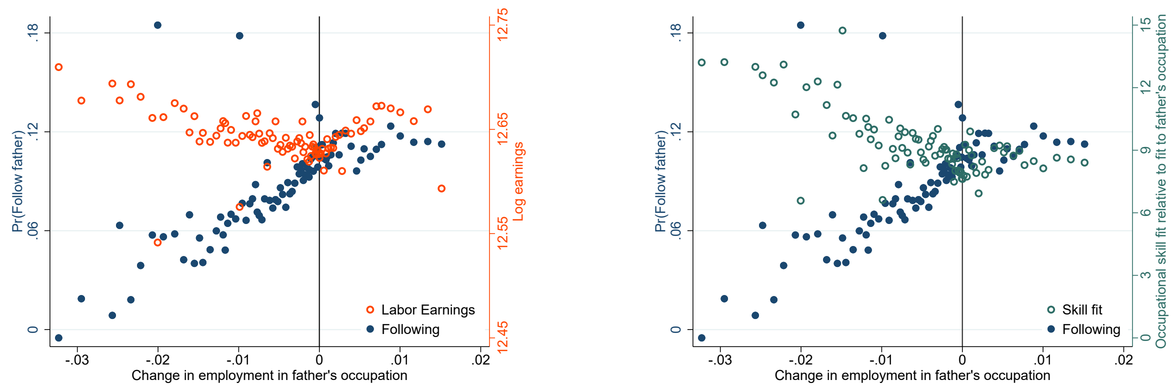
where y_{int} is the outcome of interest, e.g., the propensity of individual i to follow his father into occupation n, α_n are father's occupation fixed effects, Δemp_{nt} is the change in employment in the father's occupation, δ_t are year-at-prime-age (i.e. birth cohort) fixed effects, and $\boldsymbol{X}_i$ 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 12, panel (a), provides a graphical representation of regression (7). First, in blue, it plots a binned scatter of the propensity to follow and the change in the employment share in the father's occupation, Δemp_{nt}. Here, we control for father's occupation and cohort fixed effects, as well as demographic controls. In line with our hypothesis, a decline in the father's employment coincides with a reduction in occupational following. We present the corresponding regression estimates in Table 2. In the first stage regression, the estimate of β is 2.5, implying that a 1 percentage point decline in employment in father's occupation

[32]As we document in Appendix Figure A.23, 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 12: 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 (7). 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.

as share of total employment leads to a reduction in occupational following by 2.5 percentage points. Second, in orange, Figure 12 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

$$y_{int} = \alpha_n + \theta follow_{int} + \delta_t + \boldsymbol{X}_i'\gamma + \varepsilon_{int} \tag{8}$$

where an indicator for following, $follow_{int}$, is instrumented by the employment change in father's occupation, Δemp_{int}. Presented in Table 2, the IV estimate is -0.55, suggesting that sons who do not pursue their father's occupation as a result of an employment decline in that occupation earn roughly 50 percent more than they otherwise would. This indicates that sons who are induced to enter occupations other than their father's, enter occupations to which they are better matched and therefore receive higher returns on their skills. Figure 12, 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

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 (7). 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

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.[33] Table 2 presents estimated effects of following on earnings predicted by skills, showing that sons enter occupations where their skills earn a substantially higher return.

Naturally, these IV estimates only capture the causal effect of following on earnings under the exclusion restriction that an employment decline in a father's occupation affects future earnings of sons only through occupational choice. While this is a strong assumption, one would expect that other direct effects of a decline in father's occupation, such as reduced employment or earnings of fathers, would lead to a *decrease* rather than increase in son's earnings in adulthood. In line with this, Hilger (2016) finds that parental layoffs during a child's teen years or early adulthood affect their early career earnings negatively,

[33]Appendix Figure 12 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.

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.

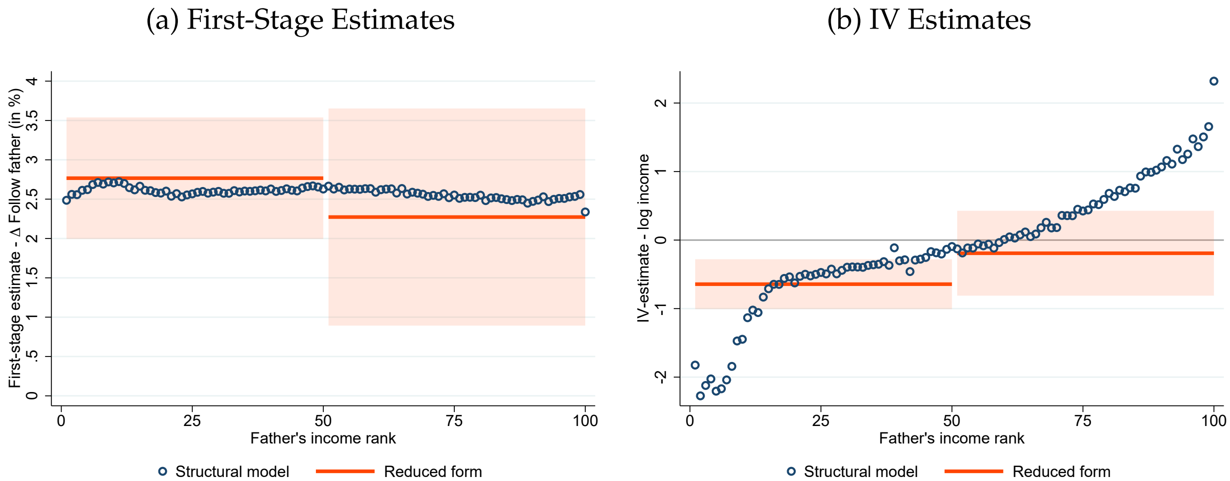
7.2 Estimates Using Data Generated by the Structural Model

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 13, panel (a), plots the first-stage estimates based on the model, showing how the following probability changes in response to an increase in discounts equivalent to 30,000 SEK, for sons across their father's earnings distribution. An increase in the discounts raises following probability almost uniformly but with somewhat larger responses among sons of lower income fathers. For comparison, the figure adds the quasi-experimental first-stage estimates exploiting the change in employment in father's occupation, splitting the sample in half by father's earnings. As the figure documents, these first-stage estimates show a similar pattern. Panel (b) plots the IV estimates based on the structural model and the corresponding quasi-experimental estimates. The IV estimates are -0.097 on average, implying that following leads to 10 percent lower earnings. However, the estimates are highly

Figure 13: 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.

heterogeneous. Among sons of fathers earning below the median, following leads to a 75 percent reduction in earnings. Among sons of fathers earning above the median, following leads to a 55 percent increase in earnings. The figure also includes the comparable quasi-experimental estimates. The two sets of estimates are qualitatively and quantitatively in line, especially the estimates for sons of low-income fathers, for which the reduced-form estimates imply that following leads to 64 percent decrease in earnings.[34]

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

[34]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.

8 Conclusion

We show that the strong tendency of children to choose the same occupations as their parents has negative consequences for intergenerational income mobility. We use individual-level data on cognitive and non-cognitive skills of men 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 income mobility increases by almost a third. Moreover, we estimate that a quarter of the observed intergenerational income persistence among sons can be explained by the influence of their fathers' occupational background.

Our results likely represent a lower bound on the aggregate consequences of talent misallocation. First, due to data limitations, our analysis focuses on men. Yet, as we show, while sons are more likely to follow in their fathers' occupations, daughters tend to follow their mothers. If historical barriers to entry have been higher for women, the associated misallocation costs could be even larger than our estimates suggest. Second, reallocation may have dynamic effects on output. Prior work shows that family background shapes who becomes an inventor (Bell et al., 2019). Redirecting talented individuals toward innovative activities could thus increase both individual earnings and long-run economic growth. Incorporating these dimensions—gender differences and dynamic effects on output and income—is beyond the scope of this paper but represents an important avenue for future research.

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