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OCCUPATIONAL CHOICE AND THE INTERGENERATIONAL MOBILITY OF WELFARE

Corina Boar
Danial Lashkari

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ABSTRACT

Based on responses in the General Social Survey, we construct an index that captures non-monetary qualities of occupations, such as respect, learning, and work hazards, relevant to the well-being of workers Using the Panel Study of Income Dynamics and National Longitudinal Survey of Youth data, we document that the children of richer US parents are more likely to select into occupations that rank higher in terms of this index. We rationalize this fact by introducing occupational choice with preferences over the intrinsic qualities of occupations into a standard theory of intergenerational mobility. Estimating the model allows us to infer the equivalent monetary compensation each worker receives from the intrinsic qualities of their chosen occupation. Earnings adjusted to reflect this additional compensation show substantially larger persistence of income from parents to children. Our model further predicts that the trends in the composition of labor demand in the US over the past three decades decreased intergenerational persistence, and also led to higher growth in the welfare of the average worker than that implied by observed earnings.

Corina Boar
Department of Economics
New York University
19 West 4th Street
New York, NY 10003
and NBER
corina.boar@gmail.com

Danial Lashkari
Boston College
Economics Department
Maloney Hall 343
140 Commonwealth Avenue
Chestnut Hill, MA 02467
United States
danial.lashkari@bc.edu

A data appendix is available at http://www.nber.org/data-appendix/w29381

1 Introduction

Modern economies aspire to offer individuals equal opportunities to build productive and fulfilling careers, regardless of the economic background they are born into. The most common measure of the success in realizing this promise is how well the monetary compensation individuals receive from their work is predictable based on the income of their parents (Black and Devereux, 2011). Despite this focus on monetary earnings, a long line of research in economics, sociology, and psychology highlighted the link between well-being and many *non*-monetary qualities of work, including the degree of autonomy and control, the variety and complexity of tasks, the opportunities for skill development, and the presence of physical hazard (e.g., Kohn and Schooler, 1973; Warr, 1990; Green, 2006; Hamermesh, 1999; Kalleberg, 2016). Focusing on career choice, for instance, individuals who choose occupations with higher non-monetary quality are remunerated in part through the higher value they receive from the intrinsic nature of their work throughout their lifetimes (Rosen, 1986). How does this non-monetary component of compensation vary with family economic background?

In this paper, we document that parental income is positively associated with the likelihood of choosing occupations that rank higher in terms of an index of *intrinsic* (non-monetary) quality of work.[1] That is, parental income predicts the non-monetary compensation that children receive from work. Thus, by solely relying on monetary compensation as a proxy for labor market outcomes, we may overestimate the degree of intergenerational mobility. We provide a model to quantify the size of the compensation that workers receive from intrinsic qualities of their occupations, and to account for its contribution to the measurement of intergenerational mobility.

To construct our proxy for the intrinsic quality of occupations, we follow a long tradition of survey-based indices of job quality.[2] We rely on the Quality of Work-life Module of the General Social Survey (GSS), collected from a representative sample of the US population, and consider seven questions covering different qualities highlighted in the literature. These questions assess social (respect at the workplace), physical (heavy lifting, hand movement), and intellectual (continuous learning, opportunity to develop new abilities) aspects of work, as well as those concerning autonomy and control (variety of tasks, need to work fast), and are all associated

[1] Here, we adopt a terminology that distinguishes the intrinsic qualities of an occupation, i.e., the rewarding characteristics tied to the nature of the job, from the extrinsic ones, e.g, the monetary wage or non-wage rewards received in return for performing the job (e.g., Kalleberg, 1977; Mottaz, 1985; Kalleberg, 2016).

[2] For attempts to organize and classify such indices, see de Bustillo et al. (2011) and Holman (2013). In addition to academic work, international organizations such as the International Labor Organization (ILO, 2013) and the OCED (Cazes et al., 2015) developed indicators that assess similar non-monetary aspects of job quality. Prior work in economics also used measures of job satisfaction to accounts for these aspects (Hamermesh, 2009).

with self-reported job satisfaction when controlling for extrinsic factors such as income and tenure. We project the responses to these questions to the occupation-level and combine them into a single index using principal component analysis. Our measure of intrinsic quality for each occupation is the value corresponding to the first principal component, which explains the majority of the variation in responses to all questions across occupations.

Using micro data from the Panel Study of Income Dynamics (PSID) and the National Longitudinal Survey of Youth 1997 (NLSY), we find a strong positive relationship between the intrinsic quality of the occupation chosen by each individual and the income of their parent, controlling for schooling and cohort fixed effects. This relationship robustly appears across different demographic groups in the data as a function of sex, race, schooling group, and cohort of birth.

We highlight at least two mechanisms to explain this fact. Our main mechanism, which we refer to as the *affordability channel*, captures the idea that larger monetary transfers from richer parents may allow their children to afford to choose higher quality occupations at the expense of possibly lower earnings.[3] We distinguish this from a second potential mechanism, the *earnings channel,* whereby the children of richer parents choose higher quality occupations because they earn more in those occupations. Using observed within-occupation variations in earnings across individuals, we find only limited evidence in favor of this channel, but are not able to rule it out completely due to the potential selection on unobservable talent across occupations.[4]

To make further progress, we construct a tractable model that accounts for these two mechanisms, allows for potential selection on unobservables, and can be directly fit to the data. The model assumes that preferences are separable in market consumption and the non-monetary quality of work. It accounts for the affordability channel since the monetary compensation that an individual attributes to a given level of intrinsic quality inversely depends on their marginal value of monetary resources. Thus, larger transfers from richer parents lower their children's marginal value of monetary resources, and raise the compensation they demand for giving up occupations with a high intrinsic quality. The equilibrium level of compensating differentials then sorts the children of rich parents into occupations with higher intrinsic qualities. The model also accounts for the earnings channel by allowing for a direct dependence of earnings on parental income that heterogeneously varies across occupations, in addition to an occupation-specific dependence on

[3] This mechanism is often invoked along with the anecdotal observation that many workers in creative occupations such as arts or design come from a rich background (e.g., Bui, 2014, March 18, 2017, Feb 9; Sussman, 2017, Feb 14).

[4] We further discuss a number of alternative mechanisms, such as stronger preference for quality among rich children, intergenerational transmission of occupational taste, or the role of parental transfers in mitigating earnings risk, and and provide suggestive evidence in the data that they may not play a substantial role in explaining our documented fact.

schooling attainment and unobserved talent.

The model generalizes the classical theory of intergenerational transmission of earnings and welfare (Becker and Tomes, 1979, 1986) and features overlapping generations of individuals who choose their occupation, and altruistically allocate wealth between own market consumption and transfers to their children, either directly or in the form of human capital investment. Before choosing their occupation, young adults receive independent taste shocks for each occupation. We discipline the mean of these shocks to be correlated with our proxies of intrinsic quality based on the GSS. We close the model by specifying a simple demand for occupational services, which allows us to endogenize occupational wages.

We derive closed form expressions for the conditional distribution of earnings, occupational choice, and schooling of each child given the income of their parents. We rely on this conditional distribution to perform a maximum likelihood estimation of the model based on parent-child pairs in the PSID data. The estimated parameters provide us with the full structure of the potential earnings of each individual given schooling, parental income, and inferred talent, across 54 occupations in the data. We show that, despite its parsimony, the model replicates the patterns of occupational choice and intergenerational mobility documented in the data. Moreover, it allows us to decompose the contribution of our two main channels to the relation between occupational quality and parental endowment, accounting for potential selection on unobservable talent. We again find that the affordability channel explains the lion's share of the relationship.

The model further allows us to derive measures of *compensated earnings* that include the additional compensation that each individual receives from the intrinsic quality of their occupation. We construct two different such measures depending on whether or not we include the conditional expected value of the idiosyncratic taste shocks. When we account for the intrinsic quality of occupations in our measure of persistence of earnings, we find substantially lower levels of mobility in welfare (between 15 and 35%). In addition, we find a higher degree of intergenerational persistence when including idiosyncratic taste shocks. This implies that richer children not only benefit from choosing occupations with higher intrinsic quality, but they also benefit from being able to choose occupations that better reflect their idiosyncratic tastes.

Finally, we revisit through the lens of our model the mobility implications of the trends in the occupational composition of the US labor force over the past three decades (Acemoglu and Autor, 2011). We first document that over this period the composition of the labor force has shifted towards occupations with higher intrinsic quality. We interpret these trends in conjunction with the rise in average earnings as reflecting shifts in occupational labor demand. The model then predicts that parental income becomes a less important determinant of selection into high intrinsic quality occupations, leading to a rise in the intergenerational mobility of earnings and welfare. The model also suggests that a non-trivial component of the rise in average welfare over the period stems from the rise in the workers' monetary valuation of the higher average intrinsic quality of occupations, and that the growth in our measures of compensated earnings may be more equally distributed across workers than the observed gains in earnings.

Prior Work Our paper builds on the large literature on intergenerational mobility. Earlier empirical contributions to this literature are summarized by Solon (1999) and Black and Devereux (2011). More recent work based on administrative data (Chetty et al., 2014a, 2017) has uncovered patterns that we can also replicate in our main data source, the PSID (see Appendix A.2). On the theoretical side, our model builds on the seminal model of Becker and Tomes (1979, 1986), who pioneered a view of intergenerational mobility through the lens of transmission of human capital (Heckman and Mosso, 2014; Mogstad, 2017). We maintain this parsimonious account of human capital transmission and introduce occupational choice with non-pecuniary intrinsic quality[5] in a framework that can be quantitatively disciplined by rich data on choices of children in a large set of occupations.[6]

Our results imply an imperfect mapping between the intergenerational mobility of income and welfare if individuals face tradeoffs between earnings and non-pecuniary aspects of occupations. This relates our paper to recent work that emphasizes how income or market consumption provides an imperfect proxy for welfare in the presence of other non-market factors that affect utility, such as leisure, home production, or mortality (Jones and Klenow, 2016; Aguiar et al., 2017; Boerma and Karabarbounis, 2021; Boppart and Ngai, 2021).

Our paper also relates to the literature on compensating differentials pioneered by Rosen (1986).[7] Complementing the hedonic approach in this literature (Mas and Pallais, 2017), recent work by Hall and Mueller (2018), Sorkin (2018), and Taber and Vejlin (2020) presents evidence on the non-monetary value of jobs and shows that job specific compensating differentials account for a large fraction of earnings variance within a firm. Relative to this literature, we emphasize the role of occupation-specific compensating differentials, complementing the work of Kaplan and Schulhofer-Wohl (2018), who document how changes in the distribution of occupations over

[5]For recent evidence on the central role of preferences for non-pecuniary aspects of occupations in the choice of college major and occupations, see Arcidiacono et al. (2020) and Patnaik et al. (2020).

[6]Lo Bello and Morchio (2019) also study the role of occupational choice on intergenerational mobility. However, they focus on how children rely on parental network to enhance their chances in frictional search for jobs.

[7]Prior microeconomic work has documented in different settings that individuals are willing to accept lower earnings in exchange for non-monetary qualities of jobs (e.g., Stern, 2004; Ariely et al., 2008; Sauermann and Cohen, 2010; Wiswall and Zafar, 2017).

time affected non-pecuniary costs and benefits of working.

Lastly, the focus on socioeconomic background and occupational choice relates our paper to Bell et al. (2018), who show the chances to become an inventor vary with parents' socioeconomic class, Hsieh et al. (2019), who find that obstacles to human capital accumulation for some demographic groups impact occupational choice and, in turn, economic growth, and to Halvorsen et al. (Forthcoming), who show that children of more affluent families pursue high-risk and high-return careers. Our hypothesis that growing up rich makes it more likely that children choose occupations with potentially lower earnings but high intrinsic quality is most similar to Luo and Mongey (2019). They show that higher student debt induces college graduates to accept jobs with higher wages and lower job satisfaction, which has implications for welfare in the context of student debt repayment policies.

2 Data and Facts

In this section we provide suggestive evidence that children from richer families are more likely to choose occupations with higher intrinsic quality, and show robustness to several considerations.

2.1 Data

We use data from the PSID and the GSS to conduct our empirical work. Appendices A.1 and A.3 discuss our variable construction and sample restrictions in detail. Here we briefly describe these data sources and the key variables we use.[8]

PSID. The PSID is a longitudinal survey of a representative sample of approximately 5,000 US households. We employ all surveys from 1968 to 2015. Our sample reflects the nationally representative core sample and sample extensions to better represent dynasties of recent immigrants. We match parents and children using the PSID Family Identification Mapping System and obtain a panel of parent-child pairs. Our analysis focuses on career choices, so we transform the panel into a cross-section with information on the occupation, education and lifetime earnings of parents and children, as well as the lifetime income and wealth of the parent.

In the cross-section, we define the occupation as the the most frequently held occupation between age 22 and 55 and consider an occupation classification with 54 occupations, listed in Table 8 in Appendix A.1. Education is defined as the highest level of education attained.

[8] In a robustness exercise we also use data from the National Longitudinal Survey of Yourth 1997 (NLSY), which we also describe in Appendix A.4.

Labor earnings in the cross-section are defined as the average earnings in the most frequently held occupation between age 22 and 55. Parental income and wealth in the cross-section are also defined as the average over parental family income and wealth between age 22 and 55. All monetary variables are evaluated at the same age and year. Lastly, we define parental endowment, a variable we use in the theoretical model, to be the sum of parental income and parental inherited wealth.[9] We use the PSID to study occupational choice by children as a function of parental income. In Appendix A.2 we show that standard measures of intergenerational mobility estimated using these data are consistent with those reported in Chetty et al. (2014b) based on administrative data, suggesting that the PSID is representative of the US population in terms of intergenerational mobiluty and is thus suited for the analysis in this paper.

GSS. The GSS is a survey that assesses attitudes, behaviors, and attributes of a representative sample of between 1,500 and 4,000 US residents. We use the Quality of Working Life module, administered in 2002, 2006, 2010 and 2014. This survey module is asked of respondents who are working and includes questions on hours worked, workload, worker autonomy, layoffs and job security, job satisfaction/stress, and worker well-being. We use a subset of these questions and principal component analysis (PCA) to create a measure of the intrinsic quality of occupations.

2.2 The Intrinsic Quality of Occupations

We begin by describing our measure of the intrinsic quality of occupations, which aims to capture the bundle of factors linked to worker well-being in the literature on job quality (e.g., Kohn and Schooler, 1973; Warr, 1990; Hamermesh, 1999; Green, 2006; Kalleberg, 2016). We rely on the GSS and therein focus on a number of survey questions that capture factors highlighted in this literature. In particular, we select seven questions that concern job characteristics related to the social (respect at the workplace), physical (little heavy lifting, little hand movement), and intellectual (continuous learning, opportunity to develop new skills) aspects of work, as well as those concerning autonomy and control (variety of tasks, no need to work fast).[10]

The characteristics above constitute dimensions along which the intrinsic nature of work may vary across occupations. To show that these variations indeed matter for the well-being of workers, we examine their association with the self-reported measure of job satisfaction in the survey.[11] We regress respondents' job satisfaction on their responses to the questions concerning

[9] We note that parental income and parental endowment are very strongly correlated. The slope coefficient of a linear regression of log parental income on log parental endowment is 1.002 (SE=0.007).

[10] Appendix A.3 discusses the exact wording of the GSS questions, as well as our treatment of the data.

[11] The question is: *"All in all, how satisfied would you say you are with your job?"*

each characteristic. The regressions additionally control for pontentially extrinsic factors such as respondent log income, log income interacted with the characteristic, hours worked, and tenure fixed effects,[12] and are performed separately in the sample of all respondents and those with income below and above the median. To make the coefficients comparable across different specifications, all variables are standardized.

Figure 1 shows the coefficients for each characteristic and its interaction with respondent income. First, we note that all job characteristics are positively associated with job satisfaction. That is, individuals who are treated with respect, do little hand movement, little heavy lifting, engage in continuous learning, have the opportunity to develop new skills, perform a variety of tasks, and do not need to work fast are likely to report higher degrees of job satisfaction. Second, this pattern does not depend on income, as is apparent from the near-zero coefficients on the interaction between the job characteristic and income. This point is further strengthened by the fact that all point estimates are fairly similar in the samples of individuals with income below and above the median.

Having shown that the seven job characteristics are indicative of worker satisfaction, we next define the intrinsic quality of an occupation to be the first principal component of the occupation-level variations in these characteristics.[13] To construct this measure, for each job characteristic, we estimate

$$resp_{it}^{d} = \boldsymbol{\zeta}^{d} \boldsymbol{X}_{it} + \widetilde{\upsilon}_{j}^{d} + \epsilon_{it}^{d}, \tag{1}$$

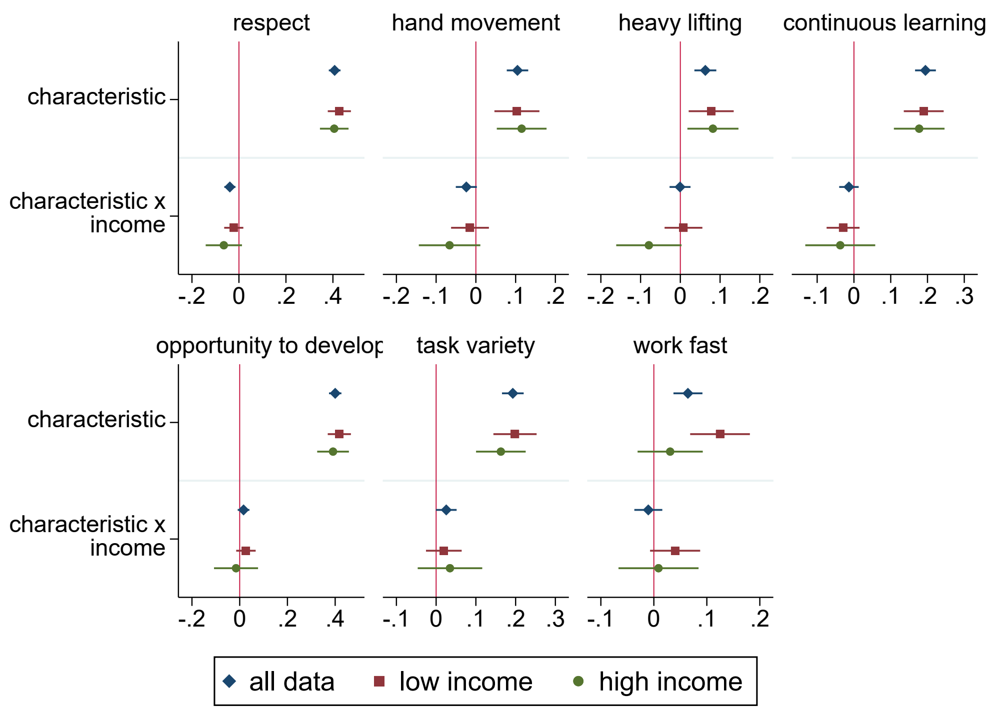
where $resp_{it}^{d}$ denotes the answer of respondent i in year t to the question about the job characteristic $d \in \{1, \ldots, 7\}$, $\widetilde{\upsilon}_{j}^{d}$ is an occupation-specific fixed effect, $\boldsymbol{X}_{it}$ is the vector of controls (log income, hours, and tenure fixed effects), and $\boldsymbol{\zeta}^{d}$ is the corresponding vector of coefficients. Our measure of the intrinsic quality of an occupation j, which we denote by ν_j, is an overall worklife quality index represented by the first principal component of all occupation characteristics $\widetilde{\upsilon}_{j}^{d}$. Table 4 in Appendix A.5.1 summarizes the results of the principal component analysis and shows that the occupation quality index loads positively on all characteristics and explains 51% of the total variance in the seven job characteristics. This suggests that a simple one-dimensional index captures the majority of variations in all our job characteristics across occupations.

Figure 2 displays the measured intrinsic quality by occupation, sorting occupations by the

[12] The fixed effects indicate whether the respondent has been at their job for less than one year, one year, 2-5 years, 6-10 years, 11-20 years or more than 20 years. Because the Quality of Worklife Module does not collect data on earnings, we use the total income of the respondent (earnings + other income) to proxy for work pay.

[13] This approach has also been used in spatial economics to measure the variations in amenities across cities (Diamond, 2016), and in trade to reduce the dimensionality of occupational tasks (Traiberman, 2019).

Figure 1: Job Satisfaction and Job Characteristics

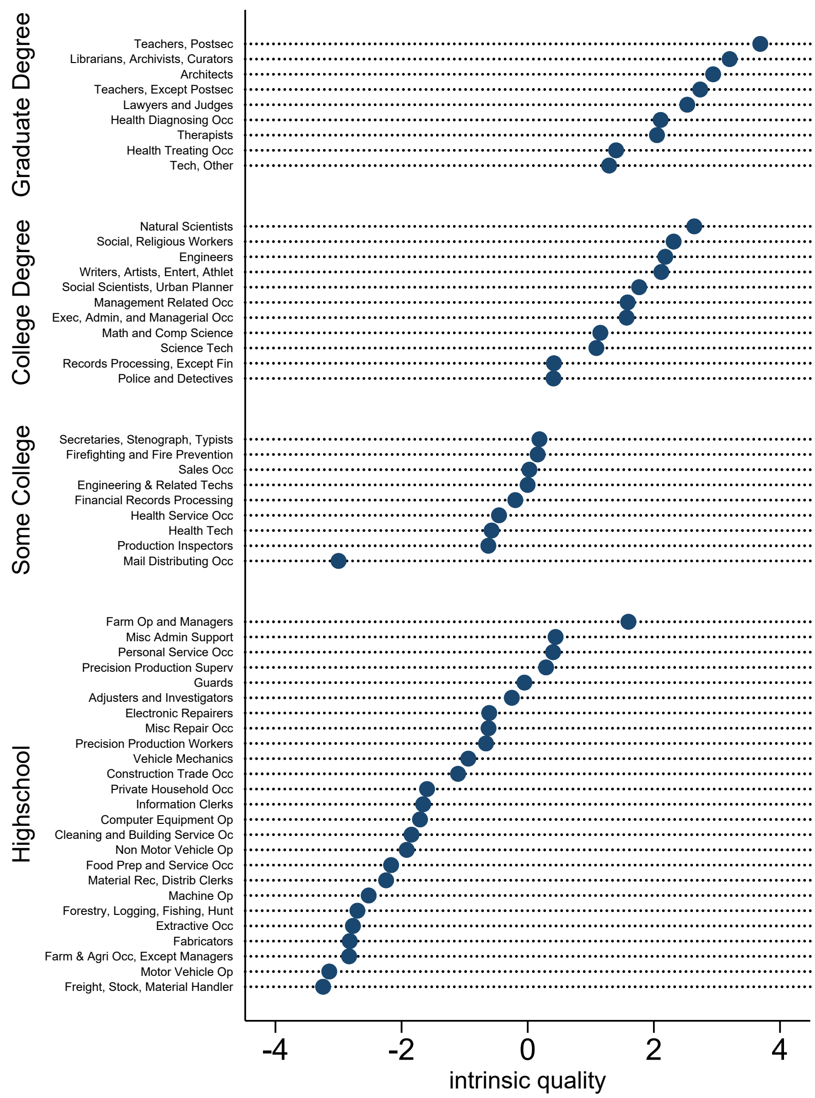


Notes: The figure reports point estimates and confidence intervals from regressing job satisfaction on each of the seven job characteristics we consider, controlling for income, tenure, hours worked and an interaction term between the job characteristic and income. Only the coefficients on job satisfaction and the interaction with income are reported. The specification is estimated on the entire sample, as well as on the sample with income below median (low income) and above median (high income).

most representative educational attainment. On average, occupations that require more education have higher intrinsic quality scores. There is, however, substantial heterogeneity between occupations even within education group. For instance, among occupations chosen mostly by highschool graduates, those with the lowest intrinsic quality are freight and material handlers and operators of motor vehicle, while farm managers and administrative support occupations have the highest quality. Among occupations chosen mostly with those with graduate degrees, technical jobs and health treating occupations have the lowest intrinsic qualities and postsecondary teachers and archivists and museum curators have the highest intrinsic quality. As anticipated by Figure 1, our measure of the intrinsic quality of occupations correlates positively with the generic measure of job satisfaction in the survey: the correlation is 0.524 (SE=0.118).

Figure 10b in Appendix A.5.2 shows how our measure of the intrinsic quality of occupations

Figure 2: Intrinsic Quality of Occupations



Notes: Dots are indices of intrinsic quality of occupations represented by the first principal component of seven occupation characteristics. Occupations are arranged based on the level of education attainment most representative of respondents with that occupation.

correlates with other characteristics of occupations studied in the literature (Autor and Dorn, 2013; Deming, 2017; Kaplan and Schulhofer-Wohl, 2018). Occupations with higher intrinsic quality have a higher content of abstract tasks, a lower content of manual and routine tasks, and require more social skills. In these occupations workers find work more meaningful, are in less pain, and feel less sad or tired when working, but feel more stressed.

2.3 Occupational Choice and Parental Income

In this section we document our key observation on a robust relationships between occupational choice, parental income, and the intrinsic quality of occupations.

2.3.1 Intrinsic Occupation Quality and Parental Income

We begin by showing simple statistics of how parental income relates to the intrinsic quality of the career chosen by children. Figure 3a displays a binscatter plot of the relationship between the intrinsic quality of the child's occupation and parental income, controlling for years of schooling and child cohort fixed effects. The positive relationship suggests that among children with the same education, those with richer parents choose careers with higher levels of intrinsic quality.

Motivated by the approximately linear nature of the relationship, Figure 3b presents the coefficients found by regressing the intrinsic quality of the child's occupation on log parental income, controlling again for years of schooling and child cohort fixed effects, for the entire data and for subsamples defined based on demographic group. The coefficient for the entire sample is 0.39 (SE=0.03) and robustly appears among children with different education, sex, race, and cohort groups. We view these results as suggesting that the relationship between parental income and the career choice of children is not driven by a particular demographic group.

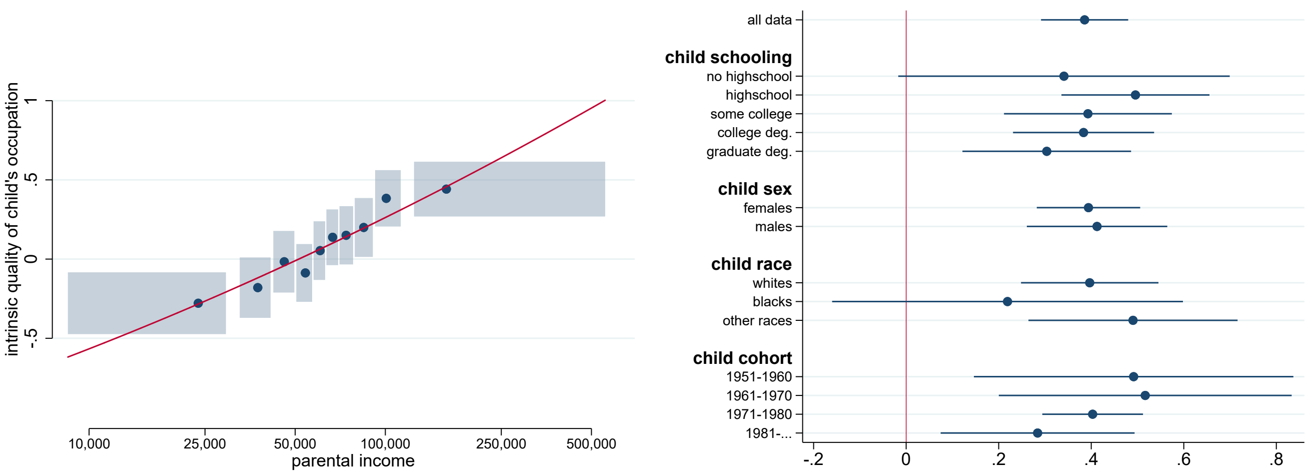
2.3.2 Potential Mechanisms

We next discuss potential mechanisms that can give rise to the positive correlation between parental income and the intrinsic quality of the child's occupation that we see in the data. Our structural model in Section 3 formalizes some of these mechanisms.

The Affordability Channel Our main mechanism, which we term the *affordabily channel*, captures the intuition that the children of rich parents can afford to choose high intrinsic quality occupations in spite of the potentially lower earnings they may offer. If children on average value the intrinsic quality of occupations, all else equal, high intrinsic quality occupations pay relatively lower wages in equilibrium. Because the children of rich parents are more likely to receive resources from their parents (McGarry, 1999), they attribute less value to this additional monetary compensation and instead sort into occupations with higher intrinsic qualities. The affordability channel describes a mechanism through which the inequality of opportunity stemming from different economic backgrounds can have consequences on welfare above and beyond those implied by earnings.

Figure 3: Intrinsic Quality of Occupations and Parental Income

(a) All Data (b) By Demographics



Notes: Panel (a) shows the relationship between parental income and the intrinsic quality of the child's occupation, controlling for children's years-of-schooling and birth-cohort fixed effects. The length of the boxes captures the number of observations in a given parental income bin. The height of the boxes is the confidence interval of the statistic for that bin. The solid line is a qudratic polynomial fit. Panel (b) plots coefficients on log parental income from linear regressions by demographic group of the intrinsic quality of the child's occupation on log parental income, controlling for the years of schooling and the birth cohort of the child.

The Earnings Channel A second mechanism that can generate the same pattern, which we term the *earnings channel*, is that children of rich parents choose high intrinsic quality occupations because they can earn more in those occupations. For example, children from a richer background might have access to a better quality education, a more extensive professional network (Kramarz and Skans, 2014), or have the chance to develop better social skills (Deming, 2017), all of which can differentially affect their potential earnings across occupations. If the returns to these attributes are higher exactly in the occupations with higher intrinsic quality, we cannot readily interpret higher likelihood of choosing those occupations as being driven by the non-monetary attributes.

We can use our data to examine the potential extent of the earnings channel. To measure potential earnings across all occupations, we estimate a flexible earnings equation that allows the earnings of the child in each occupation to depend on their parent's lifetime income and other covariates (years of schooling, age, gender and race) whose effect on earnings is allowed to vary by occupation.[14] We then use this earnings equation to predict potential earnings that children

[14]See Appendix A.6 for a formal discussion of the specification we estimate. We also experimented with an

in our sample would earn in each occupation. If the earnings channel is an important driver of our key fact in the data, controlling for the potential earnings of individuals across occupations would substantially lower the importance of parental income in explaining occupational choice.

To test this hypothesis, we estimate an *occupational choice elasticity* for each occupation, a measure of how much the likelihood of choosing that occupation depends on parental income, with and without controls for potential earnings. More specifically, we estimate logit models that allow the probability that a child i chooses occupation $o_i = j$ to depend on the logarithm of parental income, the educational attainment of child i (expressed in years of schooling), and the potential earnings across each occupation. Letting $\mathbb{P}(o_i = j)$ denote the unconditional probability that a child i chooses occupation $o_i = j$ and $\bar{y}$ denote lifetime parental income, we then define the elasticity of occupational choice with respect to parental income to be

$$\frac{\partial \ln \mathbb{P}(o_i = j)}{\partial \ln \bar{y}} = \beta_j^{\bar{y}} - \sum_{j'=1}^{54} \mathbb{P}(o_i = j')\, \beta_{j'}^{\bar{y}},$$

where $\beta_j^{\bar{y}}$ is the occupation-j-specific coefficient on log parental income.

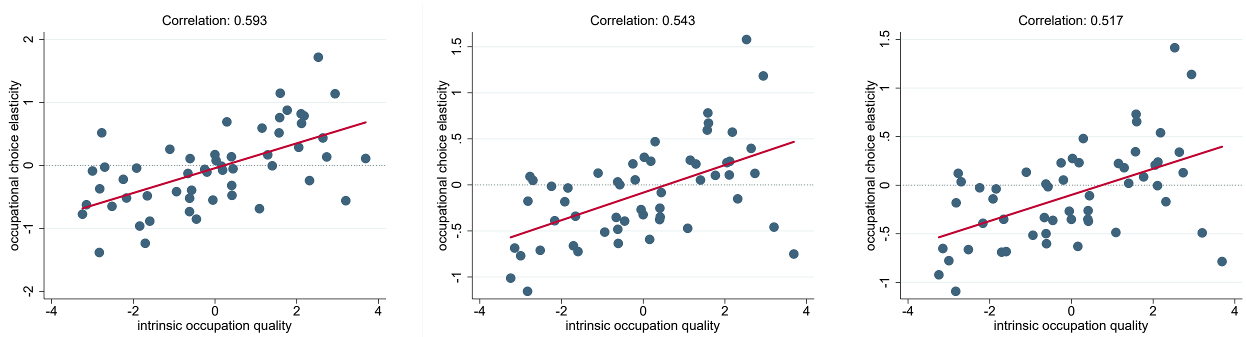
Figures 4a and 4b depict the correlation between the intrinsic quality of occupations and occupational choice elasticities, without and with controls for potential earnings, respectively. We find a large and positive correlation in both cases, equal to 0.59 (SE=0.11) and 0.54 (SE=0.12). This reflects that, even when controlling for the earnings channel, those occupations more likely to be chosen by children born into rich families also yield higher non-pecuniary qualities. We also note that variation in intrinsic occupation quality explains 35% and 30% of the variation in occupational choice elasticities without and with earnings controls, respectively.

Alternative Mechanisms In addition to our two leading explanations, there are additional mechanisms that could in principle drive the relationship between occupational quality and parental income. For instance, the children of rich parents may mechanically have a stronger preference for high intrinsic quality occupations. However, Figure 1 shows that this mechanism is unlikely to be an important driver of our fact since the strength of the relationship between our various job characteristics and job satistfaction does not depend on income. Moreover, when we measure the intrinsic quality of occupations in the samples of respondents in the GSS with annual income below and above the median we find a large correlation between the indices of occupation quality, equal to 0.769 (SE=0.090).

even more flexible earnings function that allows for second order terms of the continuous covariates, as well as interactions between covariates, all allowed to vary by occupation, and found similar results.

Figure 4: Occupational Choice Elasticities and the Intrinsic Quality of Occupations

(a) Benchmark (b) With Potential Earnings (c) (b) + Parent Occupation



Notes: Panel (a) shows the relationship between occupational choice elasticities (vertical axis) and the intrinsic quality of occupations (horizontal axis). Panel (b) shows the relationship between occupational choice elasticities estimated controlling for potential earnings and the intrinsic quality of occupations. Panel (c) shows the relationship between occupational choice elasticities estimated controlling for potential earnings and the occupation of the parent and the intrinsic quality of occupations.

Alternatively, in light of the well documented intergenerational persistence of occupational choice (Long and Ferrie 2013; Lo Bello and Morchio 2019), it is conceivable that the sorting of children into occupations reflects, in part, the transmission of taste for the occupation of one's parents (Doepke and Zilibotti, 2008, 2017). To account for this, we re-estimate occupational choice elasticities controlling not only for potential earnings across all occupations, as above, but also for a dummy variable that is equal to one if the parent works in that given occupation. Figure 4c shows that the correlation between occupational choice elasticities and the intrinsic quality of occupations equal to 0.52 (SE=0.083), and the intrinsic quality of occupations still explains 27% of the variation in occupational choice elasticities, compared to 35% in the benchmark.

Lastly, considerations involving earnings risk may play a role in driving our fact, but Table 5 in Appendix A.7 shows that intrinsic qualities correlate positively with occupational choice elasticities and continue to explain a sizable share of their variation when controlling for the degree of earnings risk across occupations.[15]

2.4 Additional Robustness

Figure 11 in Appendix D shows that our findings are robust to *(i)* an alternative measure of the intrinsic quality of occupations that considers only five of the job characteristics previously

[15] We proxy for the risk of occupations with measures of earnings dispersion using data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS).

considered, and *(ii)* a finer occupation classification with 80 occupations.

Finally, our results are also robust to estimating occupational choice elasticities with NLSY data. Appendix A.4 discusses the details of sample selection. Figure 12 in Appendix A.8 shows that PSID estimates of occupational choice elasticities correlate positively with those based on the NLSY. With respect to the correlation with the intrinsic quality of occupations, Figure 13 in Appendix A.8 shows that our main finding on the association between occupational intrinsic quality and parental income also holds in the NLSY data.

3 Model

Our model has an overlapping generations structure whereby in each period a generation of parents overlaps with one of children. We set up the model in two steps: we first characterize the occupational choice of a generation of children in Section 3.1 below, and then present the dynamics of the intergenerational transmission of economic status in Section 3.2. The first module constitutes the core of the theory and features both the affordability and earnings channels discussed in the previous section for explaining the relationship between parental income and the occupational quality of children.

3.1 Occupational Choice for A Generation of Children

Assume that the utility of a child i in a given cohort from choosing occupation $j \in \{1, \cdots, J\}$ is given by $u_{ij} = V\left(y_{ij}^{+}\right) + v_{ij}$, which is the sum of the value of the monetary resources y_{ij}^{+} available to the child in that occupation and the non-monetary value v_{ij} of choosing that occupation. Moreover, total endowment of the monetary resources $y_{ij}^{+} = b_i + e_{ij}$ is itself the sum of the (lifetime) earnings e_{ij} of the child in that occupation and the non-earnings monetary endowment b_i due to parental transfers to the child.

We assume that the non-monetary value of occupation j is given by $v_{ij} = \zeta\,\nu_j + \rho\,\epsilon_{ij}$, where ν_j denotes the intrinsic quality of occupation j and ϵ_{ij} an idiosyncratic taste shock that follows a zero-mean Type-I extreme-value distribution $\mathbb{P}_\epsilon$

$$\mathbb{P}_\epsilon(\epsilon) = \exp\left(-\exp\left(-\epsilon - \overline{\gamma}\right)\right), \tag{2}$$

where $\overline{\gamma} \equiv \int_{-\infty}^{\infty} u \exp(-u \exp(-u))du$ is the Euler-Mascheroni constant. The parameter ζ characterizes the weight of intrinsic qualities in the mean non-monetary value of occupations and the parameter ρ controls the dispersion of the occupation-specific taste shocks $\boldsymbol{\epsilon}$.[16] Consistent with our discussion in the previous section, our assumptions about the non-monetary value rule out a direct dependence of the children's preferences for different occupations on parental income.

Parental Endowment and Occupational Choice The simple setup above is sufficient to generate predictions about the dependence of occupational choice on parental endowment. The distribution of taste shocks implies that the probability of child i choosing occupation $o_i = j$ is[17]

$$\mathbb{P}\left(o_i = j\right) \propto \exp\left(\frac{1}{\rho}V\left(b_i + e_{ij}\right) + \frac{\zeta}{\rho}\nu_j\right). \tag{3}$$

Let y_i denote the parental endowment of child i, and consider two different occupations $j \in \{L, H\}$, a high-intrinsic quality occupation H and a low-intrinsic quality occupation L, such that $\Delta\nu \equiv \nu_H - \nu_L > 0$. In order for the child to be equally likely to choose the two occupations, the child demands some earnings compensation for the lower level of intrinsic quality she would enjoy in occupation L. Equation (3) implies that this *demanded compensation* $d_i \equiv e_{iL} - e_{iH}$ satisfies

$$V\left(b_i + e_{iH} + d_i\right) - V\left(b_i + e_{iH}\right) = \zeta\,\Delta\nu. \tag{4}$$

Consequently, the derivative of the demanded compensation with respect to parental endowment is given by

$$\frac{\partial d_i}{\partial y_i} = \left[\frac{V'\left(b_i + e_{iH}\right)}{V'\left(b_i + e_{iH} + d_i\right)} - 1\right]\left(\frac{\partial b_i}{\partial y_i} + \frac{\partial e_{iH}}{\partial y_i}\right), \tag{5}$$

which is positive valued whenever *(i)* the value of monetary endowment $V\left(\cdot\right)$ is concave and *(ii)* the total endowment $y^+_{iH} = b_i + e_{iH}$ of the child in occupation H rises in parental income.

Equation (5) shows the two alternative potential mechanisms driving the relationship between the intrinsic quality of child occupation and parental endowment. The earnings channel operates to the extent that the earnings e_{iH} in the high quality occupation rise in parental endowment. The affordability channel operates to the extent that the non-earnings endowment b_i due to parental transfers rises in parental endowment. In both cases, since the marginal value of every additional dollar in total monetary resources diminishes in total endowment, richer children demand larger compensations to be equally as likely to choose the occupation with a lower intrinsic quality.[18]

[16] We can motivate idiosyncratic taste shocks by assuming that each occupation j has a vector of qualities $\boldsymbol{x}_j$ valued by each child i as $\boldsymbol{\xi}_i'\boldsymbol{x}_j$, and that the coefficients $\boldsymbol{\xi}_i$ are distributed such that $\zeta\nu_j \equiv \mathbb{E}\left[\boldsymbol{\xi}_i'\boldsymbol{x}_j\right]$ with the expectation taken across children i's. The idiosyncratic taste shocks are then given by $\rho\epsilon_{ij} \equiv \boldsymbol{\xi}_i'\boldsymbol{x}_j - \mathbb{E}\left[\boldsymbol{\xi}_i'\boldsymbol{x}_j\right]$.

[17] See Lemma 1 in Appendix B.1.

[18] At its core, the argument relies on the assumption of separability between the monetary component and the

3.2 Mobility and Persistence Across Generations

Next, we embed our model of children's occupational choice in an overlapping model of intergenerational mobility. The additional components of the model serve three goals. First, they allow us to endogenize the dependence of the non-earnings endowment b_i on parental endowment y_i in Equation (5). Second, they endogenize occupation-specific wage rates through the labor market equilibrium, and thus allow us to study the effects of counterfactual changes in the environment on compensating differentials, occupational choice, and mobility. Third, by incorporating unobserved heterogeneity in occupation-specific ability, they allow us to account for the potential role of selection on earnings potentials.[19]

Each generation is comprised of a unit continuum and lives for two periods: childhood and adulthood (parenthood).[20] A parent with total endowment of y_i bears one child and chooses how to allocate her total endowment between own market consumption c_i and the resources to offer her child, in the form either of a human capital investment h_i or a direct transfer $b_i \geq 0$.[21] The parent drives utility $\log c_i$ from own consumption and from the expected future dynastic utility with a corresponding altruism weight $\beta < 1$, as in Barro (1974).

After the decisions on human capital investment and direct transfer are made, three components of uncertainty about the child's outcomes realize and the child chooses her own occupation o_i, as described in Section 3.1. First, the child receives an idiosyncratic human capital shock that leads to her observed schooling s_i based on a distribution $\mathbb{P}_s(\cdot|h_i)$ conditional on parental investment h_i. Second, the child receives an idiosyncratic talent shock u_i, drawn independently of other outcomes from a distribution $\mathbb{P}_u(\cdot)$. Finally, the child draws a J-dimensional vector $\boldsymbol{\epsilon} \equiv (\epsilon_j)$ of taste shocks across different occupations from the distribution $\mathbb{P}_\epsilon(\cdot)$ in Equation (2).

The earnings e_{ij} of the child i if she works in occupation j in her adulthood depend on her occupation-specific ability A_j and the occupation-specific wage rate per efficiency units of

taste for occupations, but not on the assumption that the child utility is a linear function of intrinsic quality. More generally, we can allow for a concave function of intrinsic quality ν_j, but we choose the linear specification for simplicity–it implies that occupational choice is invariant to uniform shifts in all intrinsic qualities.

[19] We abstracted from such selection in Section 2.3.2, where we relied on reduced-form estimates of earnings potentials.

[20] Throughout, we focus our attention on the stationary equilibria of our model and therefore do not include in our notation the dependence of the variables on the period to simplify the expressions.

[21] The latter assumption rules out the possibility of intergenerational debt markets in order to finance human capital investment, and is in line with the standard theories of intergenerational mobility (Becker and Tomes, 1986). Early empirical work questioned this assumption (see, e.g., Heckman and Mosso, 2014; Lee and Seshadri, 2019), but more recent work has reinforced the notion that borrowing constraints play an important role in shaping the patterns of educational attainment (Lochner and Monge-Naranjo, 2012, 2016; Hai and Heckman, 2017).

ability w_j. We allow the occupation-specific abilities to be functions of schooling, talent, and the endowment of the parent as $e_{ij} \equiv e_j(s_i, u_i, y_i) = w_j A_j(s_i, u_i, y_i)$.[22] The dependency of occupation-specific ability on parental endowment y_i accounts for potential channels for the direct intergenerational persistence of income, including the persistence of ability or the effects of parental endowment on social skills and professional networks.

The Value of Monetary Endowment Consider a child with talent u_i, schooling attainment s_i, and taste shocks $\boldsymbol{\epsilon}_i$ who receives parental transfers b_i. As we saw Section 3.1, the utility she will enjoy in her adulthood period after choosing her occupation is given by

$$V^+(s_i, u_i, \boldsymbol{\epsilon}_i, b_i, y_i) \equiv \max_j \; V(b_i + e_j(s_i, u_i, y_i)) + \zeta \, \nu_j + \rho \, \epsilon_{ij}. \tag{6}$$

The intergenerational structure introduced here allows us to characterize the monetary component $V(y_i)$ of the welfare of an adult parent with total endowment y_i as

$$V(y_i) \equiv \max_{c,h,b} \log c + \beta \, \mathbb{E}_{s,u}\left[\mathbb{E}_{\boldsymbol{\epsilon}}\left[V^+(s, u, \boldsymbol{\epsilon}, b, y_i) \,|s, u \right] \middle| h \right], \tag{7}$$

$$y_i \geq c + \frac{b}{1+r} + \varphi(h), \tag{8}$$

where $\varphi(\cdot)$ is a function that characterizes the cost for different levels of human capital investment h, and r is the real rate of interest from one period to the next. The parent values the expected utility of the child $\mathbb{E}[V^+]$, defined by Equation (6), and accordingly decides on human capital investment h and direct transfer b depending on the available endowment y. Given our distributional assumption on the taste shocks $\boldsymbol{\epsilon}$, we can write the expected utility of a child with schooling s, talent u, and parental endowment y in Equation (7) as [23]

$$\overline{V}^+(s_i, u_i, y_i) \equiv \mathbb{E}_{\boldsymbol{\epsilon}}\left[V^+ | s_i, u_i, y_i \right] = \rho \log \left(\sum_{j=1}^{J} e^{\frac{\zeta \nu_j}{\rho}} \; \exp\left[\tfrac{1}{\rho} V\left(b^*(y_i) + e_j(s_i, u_i, y_i) \right) \right] \right), \tag{9}$$

where $b^*(\cdot)$ corresponds to the transfer policy implied by Equation (7).

Parents and children in a given period take the future paths of occupation-specific wages,

[22] We can equivalently restate our model as a Roy model by assuming a multi-dimensional ability vector $\boldsymbol{a}_i \in \mathbb{R}^J$ such that the earnings of child i in occupation j satisfies $e_{ij} = w_j a_{ij}$. Conditional on schooling attainment s_i and parental endowment y_i, the remaining variation in occupation-specific ability is given by the dependence of each function $A_j(\cdot)$ on child's talent u_i.

[23] See Lemma 2 in Appendix B.1.

interest rate, and schooling costs as given, and make decisions regarding consumption, transfers, schooling investments and occupational choice.[24]

Production and Occupational Labor Demand We endogenize the vector of occupation-specific wages $\boldsymbol{w}$ by assuming that competitive firms operate a Cobb-Douglas technology $X \equiv K^{\chi}L^{1-\chi}$ that combines capital K and a composite L of different types of labor. The stock of capital K constitutes, in part, the asset used by parents for intergenerational transfers. We do not clear the asset market and assume that the interest rate r is exogenous and equal to the rental rate of capital. The composite L is a CES aggregator of different occupations, given by

$$L \equiv \left(\sum_{j=1}^{J} \Psi_j^{\frac{1}{\psi}} \left(Z_j L_j\right)^{\frac{1-\psi}{\psi}} \right)^{\frac{\psi}{1-\psi}}, \tag{10}$$

where ψ is the elasticity of substitution in occupational labor demand, Ψ_j is an occupational demand shifter, and Z_j and L_j denote the productivity and the total efficiency units employed in occupation j.[25] We normalize the price of final goods to unity, implying $1 = \left(\frac{r}{\chi}\right)^{\chi} \left(\frac{W}{1-\chi}\right)^{1-\chi}$, where W is the price index corresponding to the CES aggregator in Equation (10). The labor demand for occupation j is then given by

$$w_j L_j = (1-\chi)\, X \, \frac{w_j L_j}{\sum_{j'} w_{j'} L_{j'}} = (1-\chi)\, X\, \Psi_j \left(\frac{w_j}{Z_j W}\right)^{1-\psi}. \tag{11}$$

We further assume an education sector, in which competitive institutions transform final goods to human capital investment services according to the production function $h \equiv \varphi^{-1}(x)$. This implies the cost function for human capital investment $\varphi(\cdot)$ in Equation (8).

Equilibrium Intergenerational Mobility The stationary equilibrium features a distribution of endowments for the adults in each generation $F_y(y)$, and a corresponding conditional distribution of child earnings $F_e(e|y)$ given parental endowment y. As we discuss below, the first distribution determines the occupational labor supply function, while the latter accounts for the drivers of intergenerational persistence of earnings and income.[26]

[24] Due to perfect altruism, we can show that the problem laid out above provides a recursive solution to a sequential formulation of the dynastic intertemporal problem. See Appendix B.1.

[25] All the results of the paper, as well as the quantitative exercises presented, further extend to any specification of labor demand with a general aggregator of the form $L = \mathcal{L}\left(Z_1 L_1, \cdots, Z_J L_J\right)$.

[26] Appendix B.2 characterizes these distributions and discusses the different channels for the persistence of earnings, income, and welfare in the model.

The policy functions $b^*(\cdot)$ and $h^*(\cdot)$ that solve the Bellman equation (7) allow us to find the conditional occupational choices of the children. As in Equation (3), the probability that a child with schooling s_i, talent u_i, and of a parent with endowment y_i chooses occupation j is given by

$$\mu_j(s_i, u_i, y_i) \equiv \mathbb{P}(o_i = j) = \frac{e^{\zeta \nu_j/\rho} \exp\left[\frac{1}{\rho} V\left(b^*(y_i) + w_j A_j(s_i, u_i, y_i)\right)\right]}{\sum_{j'=1}^{J} e^{\zeta \nu_{j'}/\rho} \exp\left[\frac{1}{\rho} V\left(b^*(y_i) + w_{j'} A_{j'}(s_i, u_i, y_i)\right)\right]}. \tag{12}$$

Given wages $\boldsymbol{w} \equiv (w_j)$, the supply of occupation-specific efficiency units of labor satisfies

$$w_j L_j = \int_0^\infty \mathbb{E}_{s,u}\left[e_j(s,u,y)\, \mu_j(s,u,y) \,|\, h^*(y)\right] dF_y(y). \tag{13}$$

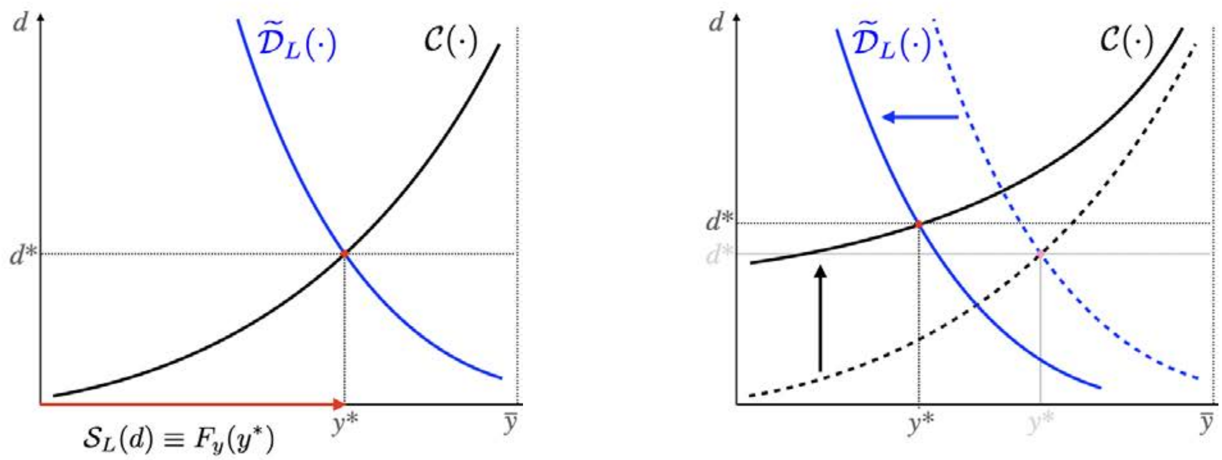
Equating the supply function above with the labor demand Equation (11) yields $J-1$ constraints on the vector of wage rates $\boldsymbol{w}$. The wage index is then given by $W = (1-\chi)(r/\chi)^{\chi}$, which yields an additional constraint on the vector of wage rates $\boldsymbol{w}$. Having determined the wage rate, we can find the aggregate labor supply L by summing Equation (13) across all occupations.

The model features three potential channels for the dependence of child earnings on parental income, captured by the distribution $F_e(e|y)$. First, an increasing human capital investment policy function $h^*(y)$ implies that the children of richer parents are expected to acquire higher levels of schooling and higher earnings if the ability function $A_j(s,u,y)$ is increasing in schooling attainment s. Second, the children of rich parents may be endowed by other social, cognitive, or non-cognitive skills that are not captured by schooling, or by networks and connections that help them succeed in given occupations. Such channels are captured by a potentially increasing dependence of the ability function $A_j(s,u,y)$ on parental endowment y, leading to positive associations between parental endowment and child earnings. The third and final channel stems from the patterns of occupational choice, as captured by the dependence of the occupational choice probabilities in Equation (12) on parental endowment y. This dependence may affect the sorting of children with different levels of schooling attainment and talent across occupations with varying returns to these characteristics, contributing to the dependence of earnings on parental endowment for otherwise similar children.

The Affordability Channel in Equilibrium Figure 5a provides a visual representation of how the demanded compensation defined in Equation (4) and the occupational labor demand together determine equilibrium compensating differentials. To focus on the core mechanism, the figure considers a simplified setting with only two occupations $j \in \{L, H\}$ where differences in parental endowment are the only relevant source of heterogeneity among workers, i.e.,

Figure 5: Demanded Compensation and Compensating Differentials

(a) Benchmark (b) Shifted Labor Demand



Notes: Panel (a) represents the determination of equilibrium compensationg differentials in a special case of the model with $\rho \to 0$, where the only source of heterogeneity among workers is parental endowment. The curve $\mathcal{C}$ characterizes the demanded compensation as a function of parental endowment and the curve $\widetilde{\mathcal{D}}$ shows a monotonic transformation of relative occupational labor demand (see text for details). The equilibrium compensating differentials d^* intersects the two curves, and the supply of labor for the low-intrinsc quality occupation is given by the sorting condition $y < y^*$. Panel (b) represents the change in equilibrium compensating differentials in moving from the benchmark to the model with shifts in labor demand.

$A_j(s,u,y) \equiv A_j$ and $\rho = 0$. Since earnings do not depend on parental endowment, the earnings channel does not operate in this simplified environment.

The curve $d = \mathcal{C}(y)$ shows the demanded compensation $d \equiv e_L - e_H = w_L A_L - w_H A_H$ that makes an individual indifferent between the two occupations as a function of parental endowment. Children with parental endowment $y < \mathcal{C}^{-1}(d)$ choose occupation L, implying the sorting of the children of poorer parents into occupation with the lower intrinsic quality. The labor supply of occupation L is given by $\mathcal{S}_L(d) \equiv F_y(\mathcal{C}^{-1}(d))$. Accordingly, if we define a monotonic transformation $\widetilde{\mathcal{D}}_L(\cdot) \equiv F_y^{-1}(\mathcal{D}_L(\cdot))$ of the labor demand $\mathcal{D}_L(\cdot)$ for occupation L, the equilibrium compensating differentials d^* is the intersection of the demanded compensation curve $\mathcal{C}$ and the transformed labor demand curve $\widetilde{\mathcal{D}}_L$.

The logic of sorting based on parental endowment presented here continues to operate under the richer setting that includes heterogeneity in idiosyncratic occupational taste ($\rho > 0$), occupational ability (dependence of A_j on s, u, and y), and multiple occupations.

4 Model Estimation

In this section, we discuss our approach to estimating the parameters of the model and present the results. As we will see, the model yields a simple characterization of the data generating process and thus lends itself to a maximum likelihood estimation strategy.

4.1 Maximum-Likelihood Estimation

A period in the model corresponds to a generation, which we assume spans 30 years. Prior to the estimation, we calibrate two parameters based on existing work: the exogenous interest rate r and the altruism parameter β. We set r equal to 2.21% per year, as in Kaplan and Violante (2014), and β equal to 0.5, a value that is within the range of estimates in the literature.[27]

Our PSID sample is composed of $4,637$ parent-child observations. For each pair i, we observe the earnings e_i, occupation o_i, schooling s_i of the child, and parental endowment y_i. Schooling in the data takes one of the five values: no high-school degree, high-school degree, some college, college degree, graduate degree. Correspondingly, we set this variable to take values $s_i \in \{0, \cdots, 4\}$. The occupations in the data are the 54 groups listed in Table 8 in Appendix A.1.

Functional Form Assumptions We assume a log-linear specification for the ability function A_j that leads to the following form for the earnings function

$$\log e_j\left(s, u, y\right) \equiv \log\left[w_j A_j\left(s, u, y\right)\right] = \alpha_j + \kappa_j s + \theta_j u + \delta_j \log y. \tag{14}$$

The constant term α_j absorbs the logarithm of wage rate per efficiency unit of occupational ability, as well as a constant occupation-specific shifter for the logarithm of occupation-specific ability function A_j. Thus, this term is an endogenous variable. Exogenous parameters κ_j and θ_j capture the returns to education and talent in occupation-specific ability, respectively. Finally, the exogenous parameter δ_j accounts for the earnings channel, which includes all potential mechanisms through which parental endowment may directly impact occupation-specific ability.[28]

As for the remainder of the model, we assume that the underlying distribution of talent is standard normal $\mathbb{P}(u) = \mathcal{N}(0; 1)$ and that schooling attainment conditional on human capital

[27]For example, the altruism parameter is 0.2 in Boar (2020), 0.51 in Nishiyama (2002) and 0.69 in Barczyk and Kredler (2017).

[28]In the corresponding Roy model, the idiosyncratic vector of abilities $\boldsymbol{a}_i$ (such that $e_{ij} = w_j a_{ij}$) has a multivariate log-normal distribution characterized by expected values $\mathbb{E}\left[\log a_{ij} | s_i, y_i\right] = \alpha_j - \log w_j + \kappa_j s_i + \delta_j \log y_i$ and covariances $\mathbb{C}\left[\log a_{ij}, \log a_{ij'} | s_i, y_i\right] = \theta_j \theta_{j'}$. See footnote 22.

investment is drawn from a truncated and discretized Gaussian distribution

$$\mathbb{P}_{s|h}\left(s|h\right) \equiv \frac{\exp\left(-\frac{1}{2}\left(\frac{s-h}{\vartheta}\right)^{2}\right)}{\sum_{s'=0}^{4}\exp\left(-\frac{1}{2}\left(\frac{s'-h}{\vartheta}\right)^{2}\right)}. \tag{15}$$

For the human capital investment cost function $\varphi(h)$, we assume a continuous and piecewise linear function defined over $h \in [0,4]$. We parameterize the cost function with a vector $\boldsymbol{\varphi} \equiv (\varphi_1, \cdots, \varphi_4)$, such that φ_k corresponds to the slope of the function between $k-1$ and k.

Let $\boldsymbol{\varsigma} \equiv (\rho, \zeta, \vartheta, \boldsymbol{\varphi}, \boldsymbol{\alpha}, \boldsymbol{\kappa}, \boldsymbol{\delta}, \boldsymbol{\theta})$ denote all the model parameters to be estimated, and let $\boldsymbol{d} \equiv (e_i, o_i, s_i, y_i)_{i=1}^{N}$ denote the data described above. Using Equation (14), we can infer the unobserved talent of the individual given the model parameters according to

$$u_i = \mathcal{U}\left(e_i, o_i, s_i, y_i; \boldsymbol{\varsigma}\right) \equiv \frac{1}{\theta_{o_i}}\left[\log e_i - \left(\alpha_{o_i} + \kappa_{o_i} s_i + \delta_{o_i} \log y_i\right)\right]. \tag{16}$$

This allows us to write down the joint probability of data $\boldsymbol{d}$ conditional on parental income. Appendix C.1 provides the full expression for the log-likelihood function and Appendix C.2 presents the details of the algorithm that we use to solve the corresponding maximization problem.

In addition to our benchmark model, we also re-estimate the model without intrinsic qualities, i.e., setting $\nu_j \equiv 0$ for all occupations. We will use the resulting estimates to contrast the predictions of the benchmark model against the same model without intrinsic qualities.

4.2 Estimation Results

Table 1a reports the estimated preference parameters ζ and ρ. The weight ζ on the intrinsic quality is positive, suggesting that individuals value the non-material aspects of work. A small value of ρ implies a large average elasticity of occupational choice to earnings, suggesting that the model accounts for the sensitivity of individuals to the variations in earnings across occupation. The table also presents the parameters of the cost function for human capital investment, and the standard deviation of the distribution of schooling attainment conditional on human capital investment ϑ. The education cost parameters imply a convex form for the monetary costs of parental investment in their children's human capital, reflecting that in the data children from rich families have, on average, higher levels of educational attainment. However, there is substantial heterogeneity in this relationship, reflected in the sizable estimate of ϑ.

Table 1b reports the correlations between the estimated parameters of the earnings function

Table 1: Estimation Results

(a) Preference and Education Parameters

Parameter		Value
weight on occ. intrinsic quality	ζ	0.025 (0.015)
dispersion in occ. taste shocks	ρ	0.053 (0.011)
education cost	φ_1	92.6 (4.552)
	φ_2	2113.6 (138.864)
	φ_3	908.2 (66.565)
	φ_4	1730.5 (129.137)
dispersion in schooling shocks	ϑ	1.627 (0.168)

Notes: Table entries show the estimated model parameters. Standard errors for each parameter, computed based on re-estimating the model for 25 bootstrapped samples, are in the parentheses.

(b) Estimated Earnings Function

	ν	α	κ	δ	θ
ν	1				
α	-0.75 (0.09)	1			
κ	0.91 (0.06)	-0.81 (0.08)	1		
δ	-0.70 (0.10)	0.26 (0.13)	-0.68 (0.10)	1	
θ	0.47 (0.12)	-0.61 (0.11)	0.50 (0.12)	-0.33 (0.13)	1

Notes: Table entries are correlation coefficients between occupation specific parameters of the earnings function and the intrinsic quality of occupations. Standard errors of the correlation coefficient are in parentheses.

and the intrinsic quality of occupations.[29] These correlation patterns suggest that *(i)* occupations with higher intrinsic qualities display lower fixed components of earnings and lower returns to parental endowment, but higher returns to schooling and talent, *(ii)* occupations with lower fixed components of earnings exhibit higher returns to schooling and talent, implying a tradeoff between occupations with high fixed components of earnings and with high returns, and *(iii)* occupations with higher returns to education also exhibit high returns to talent.

Our maximum likelihood estimation strategy fits the model to the joint distribution of all observed data without emphasizing specific moments of interest. However, we can show that the estimated model indeed fits the empirical relationships most relevant to our theory. In particular, Appendix C.3.1 shows that the predicted policy function $b^* (y)$ for transfers is increasing in parental endowment y, in line with the prior empirical evidence and the condition needed for the affordability mechanism in Equation (5). Moreover, we show in Appendix C.3.2 that the magnitude of intergenerational transfers implied by this policy function is in line with the available

[29] See Table 10 in Appendix E.2 for a full list of the estimated parameters.

empirical evidence. Therein, we additionally show that the estimated model also reproduces a number of moments capturing the observed patterns of educational attainment and occupational choice as a function of parental endowment.

In the remainder of this section, we specifically focus on the success of the model in accounting for the two most important moments of interest: first, the relationship between intrinsic occupation quality and the occupational choice of rich and poor children, as discussed in the motivating facts in Section 2.3, and second, the observed persistence of earnings in the data.

4.3 Parental Endowment and Occupational Choice

We first study the predictions of the estimated model regarding the relationship between children's occupational choice and parental endowment. We define the expected intrinsic quality of individual i in the data implied by the model as[30]

$$\overline{\nu}_i^+ \equiv \mathbb{E}_{\epsilon}\left[\nu_{o_i}|s_i, u_i, y_i\right] = \sum_j \mathbb{P}\left(o_i = j\right)\, \nu_j, \tag{17}$$

where unobserved talent u_i is inferred for individual i from Equation (16) and where the probabilities of occupational choice $\mathbb{P}\left(o_i = j\right)$ are given by Equation (3). We can now revisit our key fact about the relation between parental endowment and child occupational quality through the lens of the model. Figure 6a shows a binscatter plot of this relationship when controlling for education group fixed effects. We find the conditional expectation of occupational choice shows a positive relationship with parental endowment that closely resembles that observed in the actual occupational choices in the data in Figure 3a. The first row of Figure 6b shows that the estimated coefficient for log parental endowment in a linear regression of the expected intrinsic occupational quality $\overline{\nu}_i^+$ that includes education group fixed effects is 0.25 ($SE = 0.07$), close to the coefficient of 0.31 ($SE = 0.04$) found based on observed occupational choices in the data.

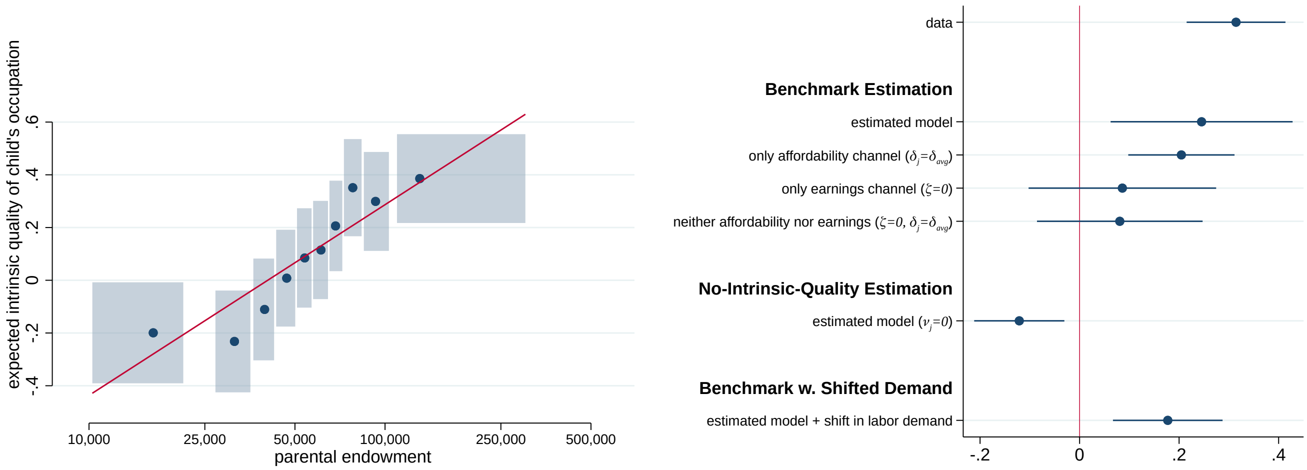
We next examine the contributions of our two leading channels of interest, affordability and earnings, to the predicted relationship between expected occupational quality and parental endowment in the estimated model. Recall that the earnings channel is driven by the (potentially) direct relationship between earnings and parental endowment across occupations. The estimated model captures this channel through the variations in parameters δ_j in Equation (14) across occupations. To isolate the affordability channel, we remove the contribution of the earnings

[30] We can show that the expected intrinsic quality is equal to the derivative of the expected utility of the child with respect to the preference weight of intrinsic qualities ζ that is, $\overline{\nu}_i^+ \equiv \partial \log \overline{V}_i^+ / \partial \zeta$ where the child's expected utility $\overline{V}_i^+$ is given by Equation (9).

Figure 6: Expected Intrinsic Quality of Occupations and Parental Endowment in the Model

(a) Benchmark Model

(b) Model Variants



Notes: Panel (a) shows the relationship between parental endowment and the expected intrinsic quality of the child's occupation $\bar{v}_i^+$, controlling for children's education group fixed effects. The length of the boxes captures the number of observations in a given parental income bin. The height of the boxes is the confidence interval of the statistic for that bin. The solid line is a linear fit. Panel (b) plots coefficients on log parental endowment from linear regressions by demographic group of the intrinsic quality of the child's occupation on log parental income, controlling for children's education group fixed effects.

channel by eliminating the cross-occupation variations in these parameters and setting all of them to the average value across occupations ($\delta_j \equiv \delta_{avg}$ for all j). We then use the resulting earnings function to recompute expected occupational qualities from Equation (17) with adjusted values for earnings across occupations e_{ij} for each individual i. Figure 6b shows that removing the earnings channel in this way only mildly reduces the relationship between occupational quality and parental endowment leading to a coefficient of 0.20 ($SE = 0.04$) on log parental endowment.

To isolate the role of the earnings channel we remove the preference for intrinsic quality ($\zeta = 0$). In this case, children do not have any preferences toward high quality occupations and the variations in the probabilities of occupational choice are entirely driven by differences in earnings across occupations. Figure 6b shows that removing the affordability channel substantially weakens the relation between expected occupational quality and parental endowment, leading to a coefficient of 0.09 ($SE = 0.07$) on log parental endowment in a linear regression including education group fixed effects. This coefficient is only marginally larger than that the corresponding coefficient of 0.08 ($SE = 0.06$) found by removing both channels from the benchmark estimated model ($\zeta = 0$ and $\delta_j \equiv \delta_{avg}$ for all j). Neither coefficient is significantly different from zero. Figure 6b further shows that the model estimated without preference for occupational quality in fact leads to a negative relationship between occupational quality and parental endowment. Thus, we conclude that the affordability channel is responsible for most of the relationship between occupational quality and parental endowment as predicted by the estimated model.

Demanded Compensation and Compensating Differentials We can further use the estimated model to showcase the workings of the affordability channel. In Section 3.2, we provided an account of this channel through the combination of *(i)* demanded compensation, i.e., the amount needed to convince each child to switch to occupations with lower intrinsic quality, and *(ii)* the equilibrium level of compensating differentials. We can now illustrate the demanded compensation by computing for each child i in the PSID data the compensation d_i required to render the child indifferent between remaining in their current occupation and moving to an occupation with intrinsic quality that is $\Delta\nu$ lower than the intrinsic quality of the current occupation. Specifically, d_i is such that

$$V\left(b^*\left(y_i\right)+e_i+d_i\right)-V\left(b^*\left(y_i\right)+e_i\right)=\zeta\Delta\nu, \tag{18}$$

where $\Delta\nu$ is set to equal the difference between the 75^{th} and the 25^{th} percentile of the distribution of intrinsic qualities. Figure 7 shows that, consistent with the prediction of the theory, this compensation is increasing in parental endowment. It represents, on average 10% of earnings in the region of the parental endowment space where the most mass is, but can be as high as 25%, on average, for children of rich parents.

The dependence of demanded compensation on parental endowment and the equilibrium compensating differentials together lead to sorting of the children of rich parents to high quality occupations. In Appendix D.2, we offer two alternative strategies for uncovering the magnitude of the equilibrium compensating differentials as a function of occupational intrinsic quality. We show that the model predicts sizable compensating differentials both at the micro level, that is, in terms of the earnings across occupations most likely to be considered by each individual, and at the macro level, that is, in terms of the equilibrium wage rates across all occupations.

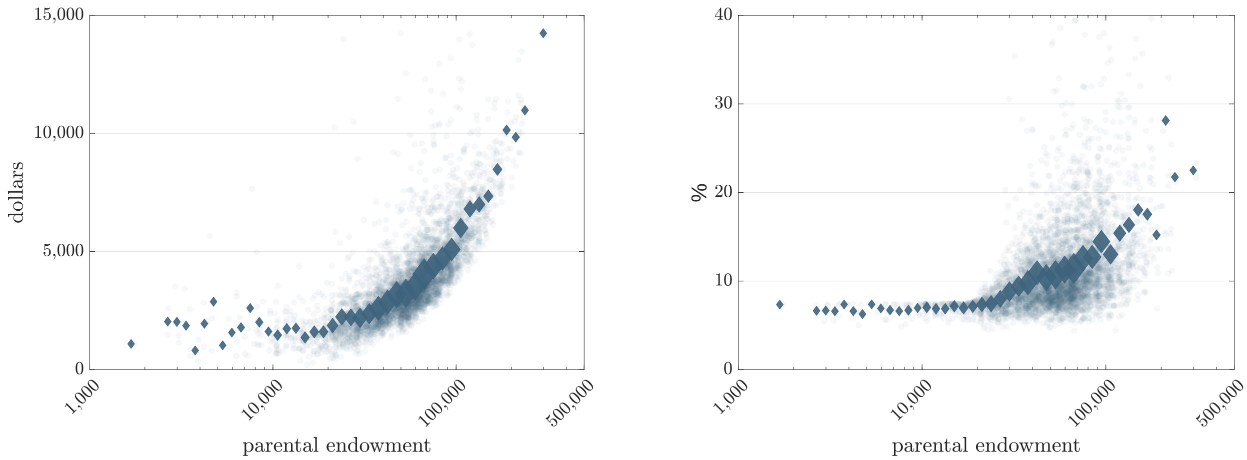
4.4 Intergenerational Income Mobility in the Estimated Model

We next examine the degree of intergenerational mobility of earnings under the estimated model. In addition to occupational choice, the model includes two additional sources of heterogeneity in earnings: schooling and talent. In our analysis in Section 4.3, we relied on the observed schooling

Figure 7: Earnings Compensation and Parental Endowment

(a) Compensation in Dollars

(b) Compensation as Share of Earnings



Notes: The figure shows the compensation required to make children indifferent between their current occupation and an occupation with an intrinsic quality that is $\Delta\nu$ lower, as function of the parental endowment. The compensation is expressed in 1996 US dollars in Panel (a) and as a percentage of earnings in Panel (b). $\Delta\nu$ is equal to the difference between the 75^{th} and the 25^{th} percentile of the distribution of intrinsic qualities.

s_i and the inferred talent u_i of each child in the data to compute expected occupational quality. To incorporate the model-predicted heterogeneity in these two variables in our analysis, we take the following strategy. For each observed parent-child pair i in the data, we take the parental endowment y_i as given and draw unobserved talent u_i for the child from the distribution $\mathbb{P}(u_i)$ assumed under the model. We then re-draw educational attainment s_i, occupational choice o_i, and earnings e_i for each child in the data based on the conditional distribution implied by the model. We generate 10,000 instances of such re-sampled datasets and study different proxies for intergenerational mobility across different datasets created as such.[31]

Table 2 contrasts the measures of intergenerational mobility in our PSID sample against their respective average in the re-sampled datasets based on our estimated model following the procedure discussed above. We calculate four such measures. The first is the intergenerational elasticity between parental endowment and the child's earnings, and is defined as the slope coefficient of a regression of log-child earnings on log-parental endowment (Black and Devereux,

[31]We also use this alternative approach to revisit the predictions of the model for the relation between occupational quality and parental endowment. In particular, Figure 19a in Appendix D.1 shows the distribution of the coefficient on log parental endowment in a linear regression of occupational quality across the 10,000 re-sampled datasets under the benchmark model and that estimated without preference for occupational quality. We find results similar to those found based on the approach in Section 4.3.

Table 2: Intergenerational Mobility

	Data	Model
Intergenerational elasticity	0.339	0.272 (0.005)
Rank-rank slope	0.356	0.258 (0.005)
Share at higher decile than parents	0.432	0.439 (0.003)
Covariance log e and log y	0.119	0.095 (0.002)

Notes: The model moments are averages over 10,000 samples generated from the model. The standard deviation of each measured in across the samples are reported in the parentheses. In each sample we redraw schooling attainment, occupational choice and earnings for each child.

2011). The second is the rank-rank slope between parental endowment and child earnings. Letting $r_{y,i} \in [0,1]$ denote the parent i's rank in the distribution of parental endowment and $r_{e,i} \in [0,1]$ denote their child's rank in the distribution of children earnings, the rank-rank slope is defined as the slope coefficient of a regression of $r_{e,i}$ on $r_{y,i}$. The third is the share of children who are in a higher decile of the child earnings distribution than their parents are in the parental endowment distribution. The fourth is the covariance between log-child earnings on log-parental endowment. As the table shows, the model, despite its parsimony, is able to reproduce between 72 and 100% of the intergenerational persistence in the data. In Appendix C.4, we discuss the drivers of persistence of earnings in the model.

5 Mobility of Welfare and the Intrinsic Quality of Occupations

In this section, we study the implications of the model for intergenerational mobility in terms of welfare proxies that include both the monetary and non-monetary aspects of labor outcomes.

5.1 Welfare and Compensated Earnings

The most comprehensive measure of welfare in the model is V^+ in Equation (6), which accounts for both the monetary and non-monetary components of welfare. However, in order to compare our measure of mobility of welfare with the standard measures that rely on monetary values such as income, we need to transform the welfare measure V^+ into a money metric. We also face an additional challenge in that we do not observe the idiosyncratic occupation-specific taste shocks, which constitute one component of the non-monetary value.

To tackle the latter challenge, we take two alternative strategies. The first relies on the observation that, given parental endowment y_i, talent u_i, schooling s_i, and occupation o_i of children, the conditional cumulative distribution function of V^+ is independent of the ex-post occupation of the child, and is given by[32]

$$F_v\left(v^+|s_i,u_i,y_i\right) \equiv \mathbb{P}\left(V^+ < v^+|s_i,u_i,y_i,o_i\right) = \exp\left[-\exp\left(-\frac{v^+ - \overline{V}^+(s_i,u_i,y_i)}{\rho} - \overline{\gamma}\right)\right], \quad (19)$$

where the Euler-Mascheroni constant $\overline{\gamma}$ is defined as in Equation (2) and $\overline{V}^+(s,u,y)$ satisfies Equation (9) and gives the conditional expectation of V^+. This result implies that, conditional on the tuple (s_i,u_i,y_i), the residual inequality of welfare generated by heterogeneity in idiosyncratic occupation-specific taste shocks is the same regardless of the ex-post occupation. In other words, if we know the tuple (s_i,u_i,y_i) for a given individual in the model, we can characterize the welfare of the individual subject to an additional shock that has the same distribution for everyone. Recall from Equation (16) that we can infer the talent of each child in the data given their observed earnings, schooling, parental endowment, and occupational choice. Thus, we can infer the expected welfare $\overline{V}_i^+ \equiv \mathbb{E}_{\boldsymbol{\epsilon}}\left[V^+|e_i,o_i,s_i,y_i\right]$ of each child i observed in our data by substituting for unobserved talent u_i from Equation (16) into the expression from Equation (9).

The second strategy simply abstracts from the idiosyncratic shock component of welfare V^+ and evaluates the two components corresponding to the market consumption and the intrinsic quality of occupation[33]

$$\widetilde{V}_i^+ \equiv V\left(b^*(y_i) + e_i\right) + \zeta\,\nu_{o_i}. \quad (20)$$

Noting that $\overline{V}_i^+ - \widetilde{V}_i^+ \equiv \rho\mathbb{E}_{\boldsymbol{\epsilon}}\left[\epsilon_{o_i}|e_i,o_i,s_i,y_i\right]$, the two measures above allow us to separate the contribution of intrinsic qualities and taste shocks in forming our welfare proxy.

In order to translate the two measures of welfare above into monetary values, we rely on the concept of *compensating variation*. We perform a hypothetical exercise in which each child i is moved from their observed occupation o_i to a common benchmark occupation, which we

[32]See Lemma 3 in Appendix B.1. Appendix B.2 uses this result to derive the distribution of child welfare conditional on parental endowment.

[33]The two measures are highly correlated in our data. A regression of $\widetilde{V}_i^+$ on $\overline{V}_i^+$ in our sample leads to a coefficient of 0.9995 ($SE = 0.001$).

choose to be the one with the lowest level of intrinsic quality $\underline{\nu}$ (without any additional taste shocks). We then compute the compensating variation that makes each child indifferent between remaining in their original occupation o_i and moving to this alternative benchmark occupation.

Consider the expected utility measure $\overline{V}_i^+$ defined above. The corresponding compensation $\overline{d}_i$ for this measure satisfies

$$V\left(b^*\left(y_i\right)+e_i+\overline{d}_i\right)+\zeta\underline{\nu}=\overline{V}_i^+, \tag{21}$$

where in the left hand side of the equation we have used the fact that the expected taste shock for the child under the benchmark occupation is zero. Similarly, for the second measure $\widetilde{V}_i^+$ defined in Equation (20), we can define the compensation $\widetilde{d}_i$ such that it satisfies

$$V\left(b^*\left(y_i\right)+e_i+\widetilde{d}_i\right)-V\left(b^*\left(y_i\right)+e_i\right)=\zeta\left(\nu_{o_i}-\underline{\nu}\right). \tag{22}$$

We then define two measures of *compensated earnings* $\overline{ce}_i$ and $\widetilde{ce}_i$ as

$$\overline{ce}_i\equiv e_i+\overline{d}_i, \qquad \widetilde{ce}_i\equiv e_i+\widetilde{d}_i, \tag{23}$$

to be the measures of earnings that account for the contribution of intrinsic occupational quality to the welfare of the worker.

5.2 Mobility of Compensated Earnings

The procedure discussed above allows us to compute the compensated earnings for each child in the data, given uncompensated (observed) earnings, schooling attainment, occupational choice, and parental endowment. We find the ranks $r_{\overline{ce},i}$ and $r_{\widetilde{ce},i}\in[0,1]$ of the child in the respective distributions of compensated earnings for the two measures of compensated earnings defined in Equations (23). To examine the implications of the model regarding the intergenerational mobility of income versus welfare, we compare rank-rank slopes between parental endowment and the realized and compensated earnings of the child.

The first row of Table 3 summarizes these rank-rank slopes. Accounting for the intrinsic quality of occupations lowers intergenerational mobility relative to what is predicted by earnings alone. Specifically, the rank-rank slope between parental endowment and compensated earnings $\widetilde{ce}$ ($\overline{ce}$) of the child is 16% (35%) larger than that between parental endowment and the realized earnings of the child.[34] The fact that the measure of compensated earnings that accounts for

[34] If, instead, we consider the hypothetical exercise of moving each child i from their observed occupation o_i to a common benchmark occupation that is the one at the 25^{th} percentile of the intrinsic quality distribution we

both the intrinsic quality of occupations and for the idiosyncratic shocks ($\overline{ce}$) implies lower levels of mobility than the measure of compensated earnings that only accounts for the intrinsic quality of occupations ($\widetilde{ce}$) has an important implication. In particular, we learn that richer children not only benefit from choosing occupations with higher intrinsic quality, but *they also benefit from being able to choose occupations that better reflect their idiosyncratic taste.*

Overall, these results suggest that failing to account for differences in the quality of worklife across occupations leads us to overestimate the degree of mobility of opportunity and welfare.

Expected Mobility under the Model In the exercise above, we evaluated the degree of intergenerational persistence for the individuals in the PSID sample, taking the observed schooling and inferred talent as given in the data. However, in order to evaluate the effects of any changes in the environment on mobility, we need to compare the expected degrees of mobility predicted in the model, given the endogenous responses of schooling and and occupational choice. To build measures of expected mobility and persistence as a benchmark for these comparisons, we follow the strategy introduced in Section 4.4 and re-sample 10,000 datasets, re-drawing schooling, talent, occupational choice, and earnings for each individual conditional on their observed parental endowment. We do this separately under the benchmark model, as well as *(i)* under the model estimated without intrinsic qualities, and *(ii)* the benchmark estimated model with removed intrinsic qualities.

Table 3 presents the results for the three models in the first three rows of the second block. In line with the results based on the observed data, the benchmark model predicts that the mobility is on average the highest in terms of uncompensated earnings, and the lowest in terms of the compensated measure accounting for both intrinsic qualities and taste shocks. Under the two cases with no variations in intrinsic qualities, the mobility of uncompensated earnings is slightly lower than that in the data.[35] More importantly, the mobility in terms of the compensated measure $\widetilde{ce}$, which accounts for the intrinsic quality of occupations, falls under the benchmark model relative to the mobility of the uncompensated earnings. The two models without intrinsic qualities, mechanically, lead to the same predictions about mobility for the uncompensated earnings and this measure of uncompensated earnings. Finally, in all models, the mobility is lower in terms of the compensated measure $\overline{ce}$, that additionally accounts for idiosyncratic taste shocks, compared to the mobility of the uncompensated earnings.

obtain $r_{\widetilde{ce}} = 0.39$ and $r_{\overline{ce}} = 0.47$, so that the intergenerational mobility of compensated earnings is, respectively, 8% and 31% lower than the intergenerational mobility of realized earnings.

[35]See Appendix C.4.2 for a discussion of the drivers of the change in the mobility of uncompensated earnings compared to the benchmark.

Table 3: Mobility of Uncompensated and Compensated Earnings under the Model

Rank-rank slope of endowment y and	Earnings	Compensated earnings, $\widetilde{ce}$	Compensated earnings, $\overline{ce}$
		Observed data	
Benchmark	0.356 (0.021)	0.411 (0.022)	0.480 (0.024)
		Resampled data	
Benchmark	0.260 (0.005)	0.332 (0.005)	0.442 (0.005)
Estimated w/o Intrinsic Qualities	0.279 (0.006)	0.279 (0.006)	0.428 (0.005)
Benchmark w. Removed Intrinsic Qualities	0.269 (0.006)	0.269 (0.006)	0.396 (0.005)
Shifts in Labor Demand	0.210 (0.006)	0.267 (0.006)	0.362 (0.005)

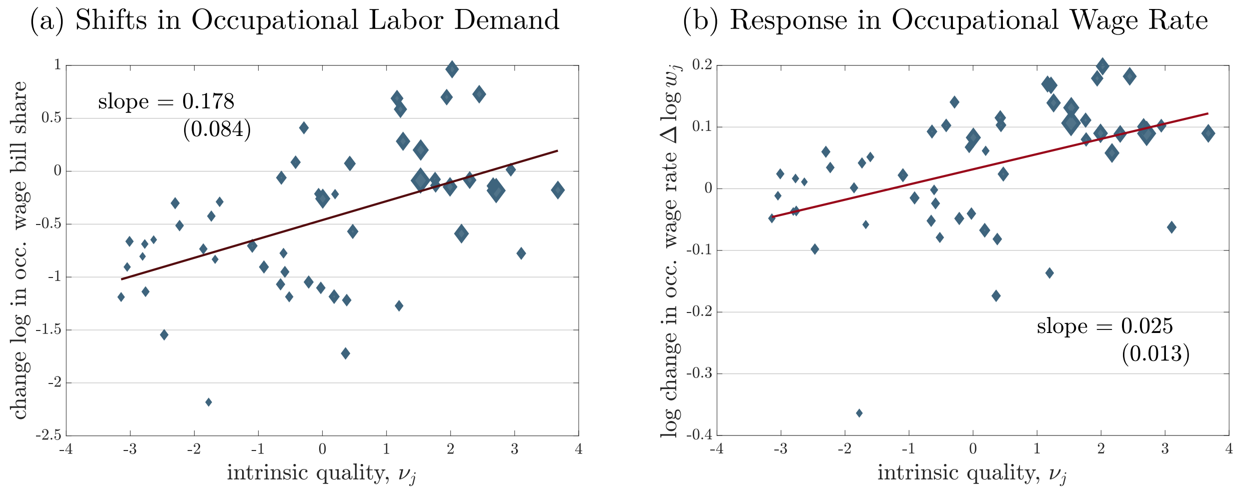
Notes: Table entries are rank-rank slopes between parental endowment and child observed and compensated earnings. The statistics in the panel *Observed data* are based on the PSID data and the standard errors are computed across individuals. The statistics in the panel *Resampled data* are based on the re-sampled datasets according to the strategy described in Section 4.4. Standard errors are computed across re-sampled datasets.

6 Trends in Occupational Labor Demand

A large literature has documented substantial shifts in the occupational composition of the labor force in the US, including an expansion of occupations that require non-routine, abstract and social skills, and a shrinkage of those that are intensive in routine tasks (Autor et al., 2006, Acemoglu and Autor, 2011, Jaimovich and Siu, 2012, Autor and Dorn, 2013). Following the approach common in this literature, we use data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) to calculate, for each occupation, the change in the wage bill share over three decades. We restrict attention to workers with age between 16 and 64 and we calculate, for each occupation, the average wage bill share between 1980 and 1985 and between 2010 and 2015.[36] Figure 8a shows a substantial rise in the share of occupations with high intrinsic quality: the slope of the linear fit suggests that an increase of one standard deviation in the intrinsic quality of occupations has been associated with a rise in

[36]Our measure of wages is annual pre-tax wage and salary income from the previous calendar year. We drop observations with topcoded wage and salary income.

Figure 8: Shifts in Occupational Labor Demand



Notes: Panel (a) shows the change in the log occupational labor demand from the 1980–1985 average to the 2010–2015 average, as a function of the occupational intrinsic qualities ν_j. Panel (b) plots the predictions of models with and without variations in the intrinsic qualit for the change in the log occupational wage rates $\alpha_j^d - \alpha_j$, where d represents the environment reflecting the trends in occupational labor demand. The area of each diamond is proportional to the total wage bill for that occupation, and the two lines show a linear fit.

the wage bill of approximately 40%. In this section, we examine the implications of this fact for the welfare of workers, in terms of intergenerational mobility, inequality, and earnings growth.

Figure 5b provides an intuitive account of the rise in the compensating differentials as a result of the shift in labor demand. This shift moves the transformed demand curve $\widetilde{\mathcal{D}}_L$ to the left, since the demand for low-intrinsic quality occupations falls. In the absence of any supply response, this would lead to a fall in the compensating differentials, and a modest expansion of the labor supply of the high intrinsic-quality occupations toward the children of relatively poorer parents.

However, the model implies an additional general equilibrium response in occupational labor supply. Recall from Equation (4) that the shape of the demanded compensation curve $\mathcal{C}(\cdot)$ is driven by the dependence of the marginal value function on the sum of parental transfers and earnings. Since the shift in the demand curve $\widetilde{\mathcal{D}}_L$ leads to a response in occupational earnings, we need to account for the full general equilibrium structure to determine the predictions of the model with regard to compensating differentials and occupational choice.

To account for this general equilibrium effect, we consider moving from the benchmark environment to one with occupational wage bill shares corresponding to the changes observed in the CPS data from 1980s to 2010s. In addition, we assume a change in total wage bill $\sum_j w_j L_j$ corresponding to the 17.2% growth over the same period, as reported by the Bureau of Labor

Statistics (BLS). We let d denote this variation in the environment.[37] Equalizing occupational labor supply and demand in Equation (13) then allows us to solve for fixed components of the earnings function $\boldsymbol{\alpha}^d$ that characterize the new occupational wage rates w_j, as well as the corresponding value function V^d and stationary distribution of endowments F_y^d.

Comparing the fixed components of the earnings function $\boldsymbol{\alpha}^d$ with those under the benchmark estimated model, Figure 8b shows the response of occupational wages to the shifts in occupational labor demand. The model predicts that rise in demand for occupations with high intrinsic quality translates into higher earnings for occupations with higher intrinsic quality.[38] Note, in addition, that the mean occupational wage rate also rises by approximately 2.5%, to account for the component of the shift in labor demand capturing the growth in average earnings.

The endogenous response of wages in the model combines the changes in both labor demand and labor supply in general equilibrium. As we just discussed, the latter is in part driven by the endogenous response of demanded compensation. In Appendix D.3, we show evidence that in our quantitative exercise the demanded compensation rises in response to our labor demand shock. This is because the rise in mean earnings makes high quality occupations more affordable for everyone, particularly among the children of poorer parents whose monetary resources are more strongly tied to their own earnings. We further show that the upward shifts in demanded compensation are large enough to raise the compensating differentials, in line with the stylized account of Figure 5b.

6.1 Response in Occupational Choice and Mobility

Next, we examine the effect of the shifts in occupational labor demand on the relationship between parental endowment and the likelihood of choosing occupations with high intrinsic qualities, following the same strategy as in Section 4.3. Using Equation (17) to compute the expected occupational quality for each individual in the data under the model with shifted labor demand, we again run a linear regression of this expected quality on log parental endowment, controlling for education group fixed effects. We find an estimated coefficient of 0.18 ($SE = 0.04$) that suggests a weaker relationship between the occupational quality of the children and the parental endowment of the parent as the result of the shifts in labor demand (see the last row

[37] We refer to this change in the environment as a shift in occupational labor demand, but in our model such a shift can be rationalized as a combination of shifts in occupational technologies Z_{jt} or demand shifters Ψ_{jt}.

[38] In particular, the linear fit in the figure implies that a standard deviation increase in the intrinsic quality of occupation is predicted to lead to a rise in wage rates of approximately 4.7%.

of Figure 6b).[39] Interestingly enough, this result appears in line with the gradual decline in the point estimates corresponding to this coefficient for the later cohorts of birth in the data, as can be seen in Figure 3b. However, due to the size of the standard errors, we cannot clearly establish the statistical significance of such a trend in the data.

Turning to intergenerational mobility, the last row of Table 3 shows the effect on the persistence of earnings, proxied by the average rank-rank slope of a child's earnings on parental endowment in 10,000 datasets re-sampled based the model with shifted labor demand. We find that the persistence in terms of realized earnings falls compared to the benchmark model. The main driver of this rise in mobility of earnings is the rise in the expected returns to schooling as the children of poorer parents switch to occupations with high intrinsic qualities that also offer higher returns to schooling κ.[40]

The mobility in terms of compensated earnings $\widetilde{ce}_i$ and $\overline{ce}_i$ also rises. To understand the drivers of the changes, let us first examine the case of the $\widetilde{ce}_i$ measure. Two distinct forces shape the contribution of the compensation $\widetilde{d}_i$ from Equation (22) to the mobility in terms of $\widetilde{ce}_i$ as a measure of compensated earnings: *(i)* the dependence of occupational intrinsic qualities ν_{o_i} on parental endowment y_i and *(ii)* the dependence of own endowment $b^*(y_i) + e_i$ on parental endowment y_i. Both components in fact show the weakening of the intergenerational link: the former as seen in the last row of Figure 6b and the latter as seen in Table 3. Together, these two forces lead to a rise in the mobility of welfare: the children of poor parents shift to occupations with higher intrinsic quality and also the value that these children attribute to this intrinsic quality rises as they become relatively richer. The overall effect is a fall in the correlation between compensation $\widetilde{d}_i$ and parental endowment y_i, which in turn leads to the patterns in Table 3. The case of $\overline{ce}_i$ follows a similar logic.

6.2 Growth in Compensated Earnings

As we saw, the trends in labor demand have shifted the composition of the labor force toward occupations with higher intrinsic quality. Since workers value this rise in the intrinsic occupational quality in ways that are not reflected in their earnings, the observed rise in workers' earnings

[39] Once again, this finding is robust to re-sampling the schooling and the talent variables based on the conditional probabilities implied by the model. Figure 19b in Appendix D.1 compares the relationship between occupational quality and parental endowment in 10,000 re-sampled dataset under the benchmark model and that with shifts in labor demand.

[40] See Table 1b for the correlations between different parameters of the earnings function and the intrinsic qualities across occupations. See Appendix C.4.3 for a discussion of the drivers of the change in the mobility of uncompensated earnings compared to the benchmark.

does not fully capture all welfare-relevant aspects of their job market outcomes.

We use our model to calculate the growth in compensated earnings, which accounts for the contribution of intrinsic quality and idiosyncratic taste for occupations to worker welfare. Recall that given the normalization of the total population to unity, the growth in average earnings in the model corresponds to the change in the value of $\mathbb{E}\left[e\right] \equiv \sum_j w_j L_j$ given by Equation (13) in moving from the benchmark to the shifted labor demand. We can define a measure of average compensated earnings corresponding to each of the two measures introduced in Section 5.1 as

$$\mathbb{E}\left[ce\right] \equiv \sum_j \int_0^\infty \mathbb{E}_{s,u}\left[\left(e_j\left(s,u,y\right) + d_j\left(s,u,y\right)\right)\mu_j\left(s,u,y\right) \mid h^*(y)\right] dF_y\left(y\right), \tag{24}$$

where $d_j\left(s,u,y\right)$ either satisfies Equation (22) or Equation (21). As before, the first case compensates individuals only for the intrinsic quality of their respective occupation, and the second for the additional value of their conditional expected idiosyncratic taste shock.

The growth in the average earnings from shifting labor demand is 17.1%. The corresponding growth in the measures $\mathbb{E}\left[\widetilde{ce}\right]$ and $\mathbb{E}\left[\overline{ce}\right]$ defined in Equation (24) is 19.2% and 17.7%, respectively. Thus, accounting for the role of taste for occupation *raises* our estimates of growth by 0.6 to 2.1 percentage points over a baseline of around 17 percentage points, or around 4-12 percent of the measured growth. The intuition for this upward correction is straightforward: the economy has shifted labor toward occupations that workers enjoy more. Therefore, a larger share of worker compensation comes from the intrinsic qualities occupations, leading to an underestimation of growth in worker welfare if we merely rely on observed earnings.

In Appendix D.4, we show that the small size of the gap between the growth in terms of uncompensated and compensated earnings masks much heterogeneity across different earnings groups. In particular, we find that the growth in compensated earnings is much larger compared to uncompensated earnings for lower quantiles of earnings. Whereas the growth in terms of uncompensated earnings is biased toward high earnings groups, the growth in compensated earnings is much more equally distributed across groups. Thus, we conclude that accounting for the effect of the welfare effects of the intrinsic quality of occupations and the shifts in the occupational composition of the labor force has an *equalizing effect* on our measures of earnings growth across income groups.

7 Conclusion

In this paper, we use micro data from the Panel Study of Income Dynamics (PSID), the National Longitudinal Survey of Youth 1997 (NLSY) and the General Social Survey (GSS) to document that children of rich parents are more likely to choose occupations with a higher intrinsic quality. The intrinsic quality of an occupation captures welfare-relevant aspects of the occupation that go beyond earnings. We proxy this by the first principal component of a bundle of job amenities that the average worker values and that are implicitly priced in the market in the form of compensating differentials. We find a positive correlation between parental income and intrinsic occupation quality that is robust across datasets, occupation classifications and measures of intrinsic occupation quality. Such a correlation arises if children of rich parents choose high intrinsic quality occupations because they can afford to do so – the affordability channel, or because they can earn more in those occupations – the earnings channel.

We then construct and estimate a quantitative model of intergenerational mobility and occupational choice to explain this fact and to study its implications. The model predicts that the affordability channel explains most of the observed correlation. Under standard assumptions on utility, in the model the marginal value of earnings is lower for children of rich parents, as these parents are able to make larger monetary transfers. Consequently, rich children demand a higher earnings compensation than poor children for working in low intrinsic quality occupations.

We use to model to asign a monetary value to the intrinsic quality of occupations and revisit standard measures of intergenerational mobility. We find that accounting for this non-monetary component of welfare generates substantially higher persistence of earnings across generations, leading us to conclude that relying on observed earnings alone overestimates the degree of intergenerational mobility of opportunity.

Finally, we examine the impact of trends in occupational labor demand on earnings and welfare growth, and on the intergenerational mobility and inequality of earnings and welfare. We find that the observed earnings growth is accompanied by an even higher growth in welfare as a larger share of worker compensation reflects the intrinsic quality of occupations. Additionally, the intergenerational mobility of earnings and welfare rises and the growth in welfare over the period is more equally distributed across workers than the observed gains in earnings.

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Online Appendix

A Data Appendix

A.1 PSID Data and Sample Selection

We use all waves of the PSID from 1968 to 2015. To match parents and children we use the PSID Family Identification Mapping System, resulting in a panel of parent-child pairs. We drop pairs for which the age difference between parents and children in less than 15 years and larger than 65 years, as well as pairs with missing occupation of the child in all years. We transform the panel of parent-child pairs into a cross-section of parent-child pairs with the following variables:

1. *Occupation*: defined, for both parents and children, as the most frequently held occupation between age 22 and age 55. To study occupational choice and characteristics of occupations, we map detailed (and changing) occupation classifications in the PSID into 54 occupations, listed in Table 8 in Appendix E.1. We initially map occupation codes to a balanced panel of occupations using the crosswalk from Autor and Dorn (2013); Autor (2015); Dorn (2009). We then further aggregate these occupations based on the number of observations in each occupation cell and the similarity of tasks across occupations. In robustness exercises, we also consider a finer occupation classification, with the 80 occupation groups listed in Table 9 in Appendix E.1.

2. *Education*: defined, for both parents and children, as the highest level of education attained.

3. *Earnings*: defined, for both parents and children, as the average earnings in the most frequently held occupation between age 22 and 55. Our earnings measure reflects wages and salaries, inclusive of bonus payments. Prior to constructing earnings in the cross-section, in the panel we remove age and time trends by projecting earnings on a quadratic age term, a quadratic time trend and an interaction term between age and year, all of which are allowed to vary by occupation. We then evaluate earnings at age 40 and in year 2000, to ensure comparability across years when averaging over time. The earnings variable in the cross-section is then obtained by averaging over the earnings in the most frequently held occupation. Since the earnings variable thus constructed nets out age and time effects, in all subsequent regressions we do not control for age and time. Although we do not explicitly control for cohort fixed effects, we verify ex-post that the earnings variable is relatively stable across cohorts of parents and children.

We make a few additional remarks that apply to this, as well as other variables in the analysis. First, earnings, as well as all other nominal variables used in the analysis are expressed in 1996 US dollars. Second, earnings of the parent refer to the sum between the earnings of the father and the earnings of the mother. Third, the parent's age, occupation, and education refer to those pertaining to the head of the parent household, which is usually the father.

4. *Parental income*: defined as the average of the parent's family income between age 22 and 55. Our income measure equals the sum of taxable income, transfers and social security income of all members of the family unit. As with earnings, we first remove age and time trends by projecting family income on a quadratic age term, a quadratic time trend and an interaction term between age and year, all of which are allowed to vary by occupation. We allow these to vary by occupation as labor earnings is a component of family income. We then evaluate family income at the age of 40 and in year 2000, to ensure comparability across years when averaging over time, and do not control for age or time in any subsequent regression that uses this variable. Here too we verify ex-post that the parental income variable is relatively stable across cohorts of parents.

5. *Parental endowment*: defined as the sum between parental earnings and annualized parental inherited wealth. Parental earnings are constructed as described above. As for parental inherited wealth, PSID only collected information on household wealth in 1984, 1989, 1994 and every other year since 1999. To bypass this data limitation we pursue the following imputation procedure. Let a_{it} denote the wealth of household i in year t, and x_{it} denote a vector of observable characteristics of household i in year t that includes earnings, family income, full sets of dummies for age, race, family size, marital status, years of schooling, and calendar year. We first estimate the following cross-validation lasso model

$$\min_{\theta} \sum \left(a_{it} - x_{it}'\theta\right)^2 + \lambda \left\|\theta\right\|_1 ,$$

where θ is a vector of parameters and λ is the penalty level, both to be estimated. The penalty level λ is chosen by cross-validation in order to optimize out-of-sample prediction performance. We consider a 5-fold cross-validation, which means that the the data is split into 5 parts and the estimator is trained on all but the k^{th} fold and then validated on the k^{th} fold, iterating over $k = 1, \dots, 5$. We then use the estimate of θ, which we denoted by $\hat{\theta}$,to impute wealth, when missing, according to $\hat{a}_{it} = x_{it}'\hat{\theta}$. We note that for the observations with non-missing wealth, projecting observed wealth a_{it} on imputed wealth $\hat{a}_{it}$ yields a slope of 1.135 with a standard error of 0.009 and an R^2 of 0.31.

We define wealth in the cross-section as the average of parent's wealth between age 22 and 55. As before, to ensure comparability across time, we first project wealth on a quadratic age term, a quadratic time trend and an interaction term between age and calendar year and evaluate wealth at age 40 and in year 2000.

Lastly, letting $\hat{a}_i$ denote parental wealth and $\hat{e}_i$ denote parental earnings in the cross-section, both constructed as discussed above, we defined parental endowment y_i as

$$y_i = \hat{e}_i + \frac{\hat{a}_i \times 0.638}{30},$$

where $\hat{a}_i$ is multiplied by a factor of 0.638 to account for the fact that approximately 63.8% of wealth is inherited (Gale and Scholz, 1994) and then divided by 30 to account for the fact that in the model a period is 30 years. We note that parental income and parental endowment are very strongly correlated. The slope coefficient of a linear regression of log parental income on log parental endowment is 1.002 (SE=0.007).

A.2 Intergenerational Mobility in PSID

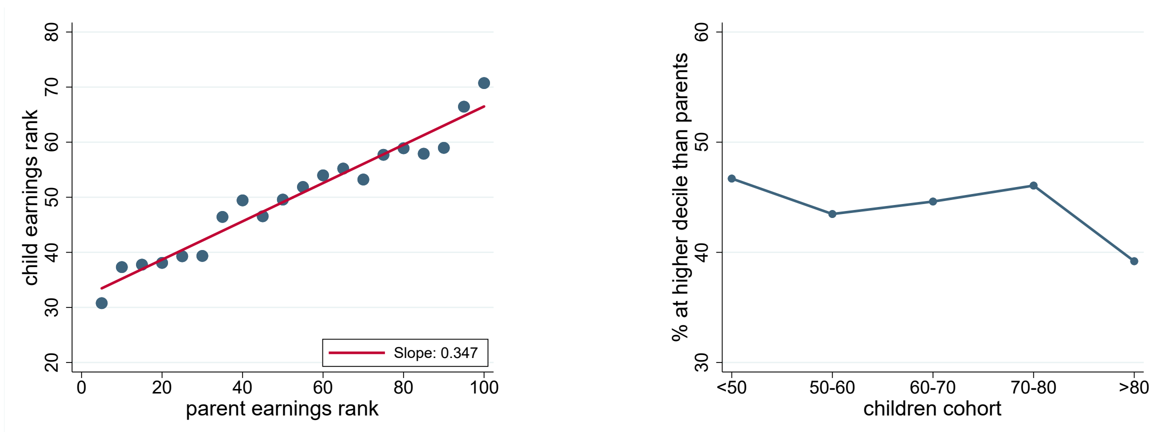
We briefly revisit the patterns of intergenerational mobility in the US using the PSID data. We compare our results with those reported by Chetty et al. (2014a) using de-identified federal income tax records to establish that the PSID is suitable for the study of intergenerational mobility.

The measure of intergenerational mobility we consider is in the tradition of Solon (1999), Dahl and DeLeire (2008), Black and Devereux (2011), Chetty et al. (2014a), and reflects the relative outcomes of children from different parental backgrounds. The specific measure of relative mobility we employ is the *rank-rank slope*, the slope coefficient of a regression of the child's position in the earnings distribution on the position of their parent in the distribution. Parent and child earnings ranks are calculated relative to their corresponding birth cohort.

We estimate a rank-rank slope equal to 0.35, meaning that a 10 percentile point increase in parent's earnings rank is associated with a 3.5 percentile point increase in the child's earnings rank. It is important to note that the rank-rank slope estimated with the PSID data is almost identical to the value 0.34 reported in Chetty et al. (2014a) based on administrative data. This suggests that the PSID is representative of the US population in terms of intergenerational

Figure 9: Intergenerational Mobility of Earnings in PSID Data

(a) Rank-Rank Correlations (b) Probability of Move to Higher Decile



Notes: Panel (a) plots the mean child rank within each parent earnings bin. There are 20 bins. Panel (b) displays the fraction of children born in the cohort on the X-axis who are in a higher decile of the lifetime earnings distribution than their parents.

mobility and is thus suited for the analysis in this paper.

We also calculate a measure of absolute intergenerational mobility, namely the fraction of children who move to a higher earnings decile than their parents. On average, 43% of children move to a higher decile of the lifetime earnings distribution than their parents. This fraction is however declining over time, consistent with the findings of Chetty et al. (2014a) and Chetty et al. (2017). Figure 9a and Figure 9b below offer a depiction of these statistics. Figure 9a displays the mean child earnings rank for 20 parent earnings bins. Figure 9b displays the evolution of the fraction of children who move to a higher earnings decile than their parents for five birth cohorts of children: pre-1950, 1951-1960, 1961-1970, 1971-1980, post-1980.

A.3 General Social Survey

The GSS is a survey that assesses attitudes, behaviors, and attributes of a representative sample of US residents. The survey began in 1972, collecting information on a sample between 1,500 and 4,000 respondents. We use seven topics/questions from the Quality of Working Life module, administered in 2002, 2006, 2010 and 2014. These topics/questions are: *(i)* At the place where I work, I am treated with respect, *(ii)* Does your job regularly require you to perform repetitive or forceful hand movements or involved awkward postures?, *(iii)* Does your job require you to do repeated lifting, pushing, pulling or bending?, *(iv)* My job requires that I keep learning new things, *(v)* I have an opportunity to develop my own special abilities, *(vi)* I get to do a number of different things on my job, and *(vii)* My job requires that I work very fast. We recode answers to topics/questions *(i)*, *(iv)*-*(vii)* to range from 1-Strongly disagree, 2-Disagree, 3-Agree to 4-Strongly agree and answers to topics/questions *(ii)* and *(iii)* to 1-Yes and 2-No. We standardize these answers so that the value of the response $resp_{it}^{d}$ across individuals i and time t for each question d.

A.4 NLSY Data and Sample Selection

The NLSY97 is a longitudinal survey of a nationally representative sample of approximately 9,000 youths who were between 12 and 16 years old as of December 31, 1996. The first round of interviews took place in 1997, when both the youths and their parents were interviewed. In subsequent years, the youths were interviewed annually until 2011 and biennially since then. We use the NLSY to complement our PSID analysis of occupational choice as a function of parental income. As with the PSID, we transform the panel into a cross-section with information on the occupation, education and earnings of the children, as well as the lifetime income of parents.

We apply the same procedure as with the PSID for transforming the panel data into a cross-section. Specifically, we define the occupation of the child as the most frequently held occupation between age 22 and age 36, the maximum age in the NLSY sample. We define education as the highest level of education attained and labor earnings as the average earnings in the most frequently held occupation between age 22 and 36, net of age and time effects that are allowed to vary by occupation. Between 1997 and 2003 the survey collected information on the income of the parent. We define parental income in the cross-section as the average over parental family income over this period, net of time effects.

We make use of all the waves of the NLSY 1997. We transform the panel into a cross-section following, as closely as possible, the procedure applied to the PSID data. The result cross-section contains the following variables:

1. *Occupation*: defined as the most frequently held occupation between age 22 and age 36. The oldest respondents in the NLSY 1997 are 36.

2. *Education*: defined as the highest level of education attained.

3. *Earnings*: defined as the average earnings in the most frequently held occupation between age 22 and 36. Prior to constructing earnings in the cross-section, in the panel we remove age and time trends by projecting earnings on a quadratic age term, a quadratic time

trend and an interaction term between age and year, all of which are allowed to vary by occupation. We then evaluate earnings at age 30 and in year 2010, to ensure comparability across years when averaging over time. We evaluate earnings at a different age and in a different year than in the PSID data because the NLSY sample covers a more recent period than the PSID. The earnings variable in the cross-section is then obtained by averaging over the earnings in the most frequently held occupation. Since the earnings variable thus constructed nets out age and time effects, in all regressions that use this variable we do not control for age and time.

4. *Parental income*: defined as the average of the parent's family income collected in the survey. We first remove time trends by projecting parental income on a quadratic time trend. We then evaluate family income in year 2010.

A.5 Further Details on the Measure of Intrinsic Quality

A.5.1 Principal Component Analysis

Table 4 lists the occupation characteristics we consider in our measure of the intrinsic quality of occupations, the loading factors from our principal component analysis and the variance that remains unexplained in each characteristic.

A.5.2 Intrinsic Quality and Other Occupational Characteristics

Figure 10b shows how our measure of the intrinsic quality of occupations correlates with other characteristics of occupations. First, we use six dimensions of feelings about work collected in the American Time Use Survey in 2010, 2012 and 2013. Respondents were asked how meaningful they find their work, how happy, sad, and tired they are while working and how much stress and pain they experience. Following Kaplan and Schulhofer-Wohl (2018) and our treatment of the GSS variables, we project the responses on a vector of covariates that includes the logarithm of weekly earnings and hours, a quadratic age polynomial, dummies for education (high-school or less, some college, college degree or more), race (Black, white, other), and gender, as well as on occupation fixed effects. We then correlate the occupation fixed effects with the intrinsic quality of occupations. Second, we consider the measures of abstract, routine and manual task content of occupations by Autor and Dorn (2013), based on the Dictionary of Occupational Titles, and the measure of social skill intensity of occupations by Deming (2017), based on O*NET.

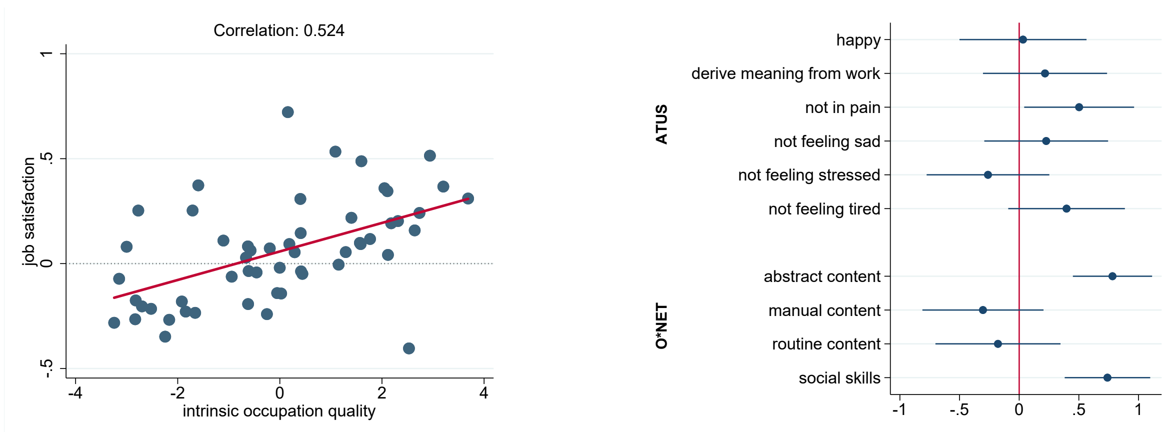
Table 4: Principal Component Analysis for Occupation Characteristics

Occupation characteristic	Loading	Unexplained variance
Social		
Treated with respect	0.38	0.49
Physical		
Little hand movement	0.41	0.40
Little heavy lifting	0.36	0.52
Intellectual		
Keep learning new things	0.47	0.21
Opportunity to develop abilities	0.41	0.40
Autonomy and control		
Do numerous different things	0.40	0.43
Do not need to work fast	0.11	0.95

Figure 10: Intrinsic Quality of Occupations and Other Occupation Characteristics

(a) Job Satisfaction

(b) Other Characteristics of Occupations



Notes: Panel (a) shows the relationship between the intrinsic quality of occupations (horizontal axis) and a general index of job satisfaction (vertical axis). Panel (b) plots correlation coefficients between the intrinsic quality of occupations and other characteristics of occupations.

A.6 Estimating Potential Earnings

We examine the extent to which parental income increasses the efficiency of children in different occupations by estimating the following specification

Table 5: Occupational Choice Elasticities, Risk and the Intrinsic Quality of Occupations

	(1)	(2)	(3)
Intrinsic quality, ν	0.197	0.183	0.188
	(0.037)	(0.038)	(0.039)
Coeff. of variation log earnings		-3.101	-2.570
		(2.383)	(3.396)
Constant	-0.043	0.183	0.319
	(0.069)	(0.307)	(0.286)
Controls	–	No	Yes
R^2	0.352	0.372	0.359

Notes: The table shows the intercept, the slope coefficients and the R-squared of a regression of occupational choice elasticities on the intrisic quality of occupations (column 1) and the coefficient of variation of log earnings by occupation (columns 2 and 3).

$$\ln e_{ij} = \alpha_{1j} \ln \bar{y}_i + \tilde{\boldsymbol{X}}_i' \boldsymbol{\alpha}_j + \delta_j + \epsilon_{ij},$$

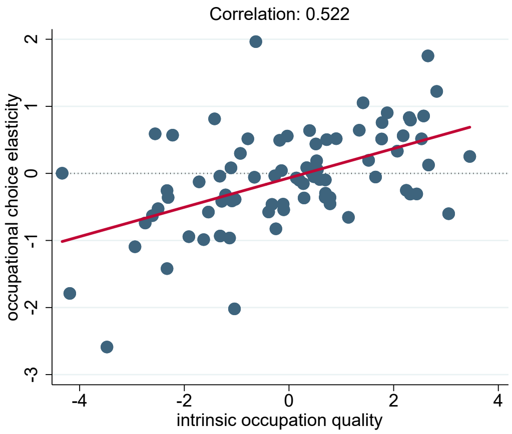
where e_{ij} are the annual earnings of child i working in occupation j, $\bar{y}_i$ is their parent's lifetime income, $\tilde{\boldsymbol{X}}_i$ is a vector of covariates including years of schooling, age, gender, and race whose effect on earnings is allowed to vary by occupation, and δ_j are occupation fixed effects. The coefficients of interest are α_{1j}, which capture the effect of parental income on occupational efficiency. The correlation between α_{1j}, the elasticity of earnings with respect to parental income, and v_j, the intrinsic quality of occupations, is small (-0.047) and not statistically significant (SE=0.139).

A.7 Earnings Risk and Occupational Choice

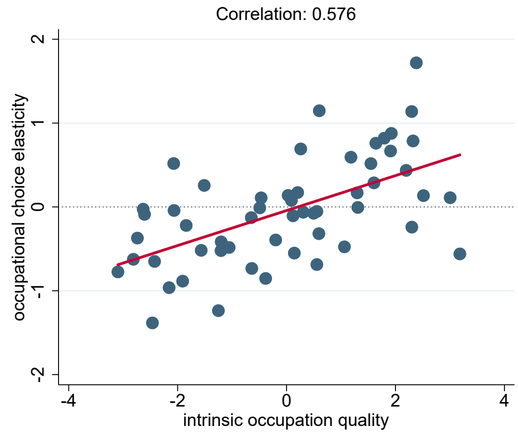
Table 5 examines whether controlling for the risk of occupations alters the relationship between occupational choice elasticities and intrinsic qualities. Column (1) reports results from projecting occupational choice elasticities on the intrinsic qualities of occupations. Columns (2) and (3) add to this projection a control for the coefficient of variation of log earnings by occupation, measured as the ratio between the standard deviation and the average log earnings by occupation. In column (2) the coefficient of variation of log earnings by occupation is calculated based on the pooled sample of the 1976-2017 waves of the Annual Social and Economic Supplement (ASEC) of the CPS. In column (3) the coefficient of variation of log earnings by occupation is calculated controlling for age (16-25, 26-35, 36-45, 46-55, 56-64), sex, race (white, Black, other) and year.

Figure 11: Occupational Choice Elasticities and The Intrinsic Quality of Occupations, Robustness

(a) Alternative Occupation Classification



(b) PCA 5 Job Characteristics



Notes: The left panel is based on an occupation classification with 80 occupation groups. In the right panel the intrinsic quality of occupations is estimating by applying the PCA on 5 job characteristics. The standard error of the correlation coefficient in the left panel is 0.097 and that of the correlation coefficient in the right panel is 0.113.

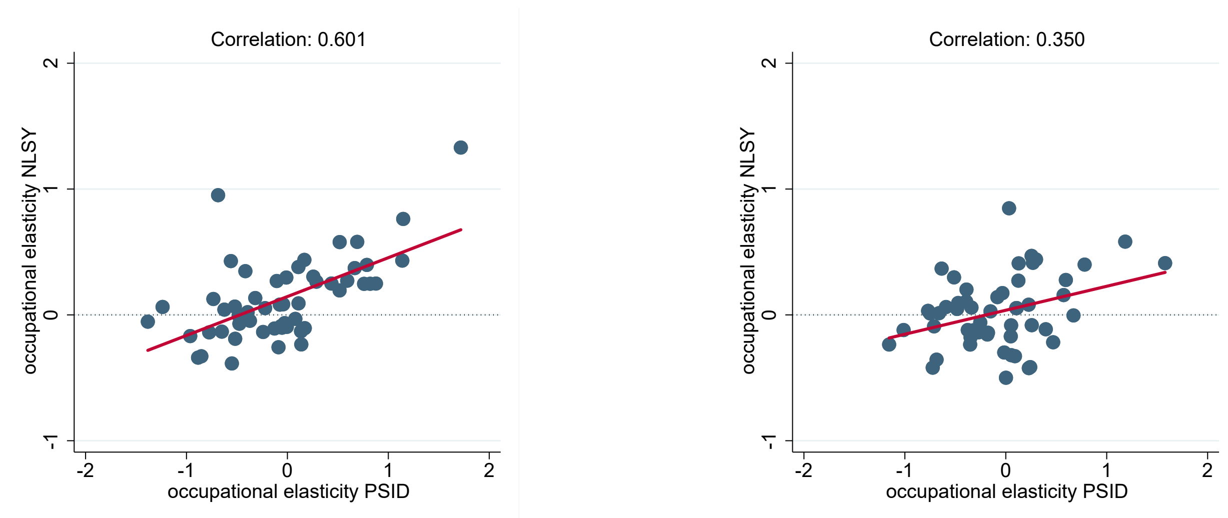
A.8 Additional Robustness Exercises

Figure 11 displays the relationship between occupational choice elasticities estimated with the PSID data and the intrinsic quality of occupations under two alternative specifications. In the left panel, occupational choice elasticities and the intrinsic quality of occupations are estimated for the 80 occupation groups in Table 9. In the right panel, we maintain the occupation classification with 54 groups in Table 8, but define the intrinsic quality of occupations to be the first principal component of 5 job characteristics only: treated with respect, little hand movement, little heavy lifting, keep learning new things, do numerous different things. In both cases, the correlation remains positive, high (0.52 and 0.58, respectively) and statistically significant.

Figure 12 displays the correlation between elasticities estimated with the PSID and NLSY data. Figure 13 displays the relationship between occupational choice elasticities estimated with the NLSY data and the intrinsic quality of occupations.

Figure 12: Occupational Choice Elasticities, PSID vs NLSY

(a) Without Earnings Controls (b) Controlling for Potential Earnings



Notes: The left panel depicts the benchmark occupational choice elasticities. The right panel depicts the occupational choice elasticities estimated controlling for potential earnings in all occupations. The standard error of the correlation in the left panel is 0.111 and that of the correlation in the right panel is 0.131.

B Model Appendix

B.1 Proofs and Derivations

Sequential Formulation of the Problem of Generation t The problem laid out in Section 3.2 corresponds to the recursive formulation of the the following sequential problem faced by each generation t:

$$\max_{\left(c_{t'},j_{t'},b_{t'+1},h_{t'+1}\right)_{t'=t}^{\infty}} \mathbb{E}_t \left[\sum_{t'=t}^{\infty} \beta^{\tau-t} \left(\log c_\tau + \zeta \nu_{j_\tau} + \epsilon_{j_\tau \tau} \right) \right],$$

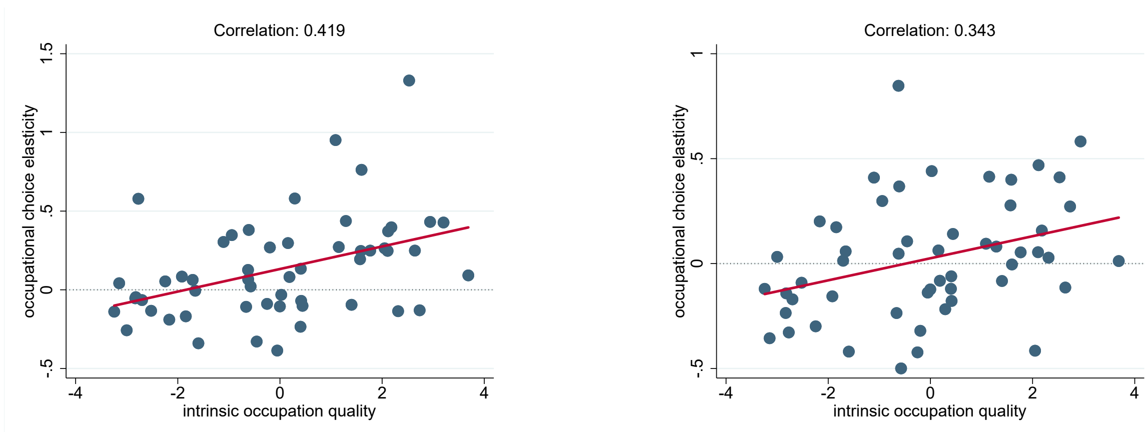
$$y_{t'} \geq c_{t'} + \frac{b_{t'+1}}{1+r_{t'}} + \varphi_{t'}(h_{t'+1}), \qquad t' \geq t,$$

$$y_{t'} = b_{t'} + e_{j_{t'}t'}\left(s_{t'}, u_{t'}, y_{t'-1}\right),$$

facing a sequence of *i.i.d.* shocks $(\boldsymbol{\epsilon}_{t'})_{t'=t}^{\infty}$, s_t, and u_t. The timing of the decisions are such that individuals in period t choose their own occupation and consumption j_t and c_t, and the investments b_{t+1} and h_{t+1} given the histories of the outcomes of their dynastic line. However, as the recursive formulation above shows, the relevant aspect of their ancestoral history can be

Figure 13: Occupational Choice Elasticities and the Intrinsic Quality of Occupations, NLSY

(a) Without Earnings Controls (b) Controlling for Potential Earnings



Notes: Panel (a) shows the relationship between occupational choice elasticities (vertical axis) and the intrinsic quality of occupations (horizontal axis). Panel (b) shows the relationship between occupational choice elasticities estimated controlling for potential earnings and the intrinsic quality of occupations. The standard error of the correlation coefficient in the left panel is 0.126 and that of the correlation coefficient in the right panel is 0.132.

captured by the total income of their parents y_{t-1} (and the corresponding investment decisions b_t and h_t).

Lemma 1. *The probabilities of occupational choice under a stationary distribution are given by Equation (3) (and also Equation (12)).*

Proof. Let $\boldsymbol{\epsilon} \equiv (\epsilon_j)_{j=1}^{J}$ be a tuple of *i.i.d.* random variables distributed according to a zero mean, with the cumulative distribution function

$$F(x) \equiv \mathbb{P}(\epsilon_j \leq x) = \prod_{j=1}^{J} \exp(-\exp(-x - \overline{\gamma})),$$

where $\overline{\gamma} \equiv \int_{-\infty}^{\infty} u \exp(-u \exp(-u))du$ is the Euler-Mascheroni constant. Let $\vartheta_{ij} \equiv V\left(y_{ij}^{+}\right) + \zeta\, \nu_j$. The probability of choosing occupation j for a child with schooling s, talent u, parental transfer b, and parental income y is given by

$$\begin{aligned}
\mathbb{P}\left(o_i = j\right) &\equiv \mathbb{P}\left(j = \operatorname*{argmax}_{j'} \vartheta_{ij'}\right), \\
&= \int_{-\infty}^{\infty} F'\left(\epsilon_j\right) \times \prod_{j' \neq j} \mathbb{P}\left(\epsilon_{j'} \leq \epsilon_j + \tfrac{1}{\rho}\left(\vartheta_{ij} - \vartheta_{ij'}\right)\right) d\epsilon_j,
\end{aligned}$$

$$
\begin{aligned}
&= \int_{-\infty}^{\infty} \exp\left(-\epsilon_j - \overline{\gamma}\right) \exp\left(-e^{-\epsilon_j - \overline{\gamma}}\right) \\
&\qquad \times \prod_{j' \neq j} \exp\left(-e^{-\left(\epsilon_j + \frac{1}{\rho}\left(\vartheta_{ij} - \vartheta_{ij'}\right)\right) - \overline{\gamma}}\right) d\epsilon_j, \\
&= \int_{-\infty}^{\infty} \exp\left(-\epsilon_j - \overline{\gamma}\right) \exp\left(-e^{-\epsilon_j - \overline{\gamma}}\left(1 + \sum_{j' \neq j} e^{-\frac{1}{\rho}\left(\vartheta_{ij} - \vartheta_{ij'}\right)}\right)\right) d\epsilon_j, \\
&= \frac{1}{1 + \sum_{j' \neq j} e^{-\frac{1}{\rho}\left(\vartheta_{ij} - \vartheta_{ij'}\right)}} \int_0^{\infty} \exp\left(-x\right) dx, \\
&= \frac{e^{\frac{1}{\rho}\vartheta_{ij}}}{\sum_{j'} e^{\frac{1}{\rho}\vartheta_{ij'}}},
\end{aligned}
$$

where in the last equality, we have used the change of variables $x \equiv e^{-\epsilon_j - \overline{\gamma}}\left(1 + \sum_{j' \neq j} e^{-\frac{1}{\rho}\left(\vartheta_{ij} - \vartheta_{ij'}\right)}\right)$. $\square$

Lemma 2. *The expected utility of children in Equation (7) is given by Equation (9).*

Proof. We use the same notation as in the proof of Lemma 1 above. Consider a child with schooling s_i, talent u_i, parental transfer b_i, and parental income y, and let $\vartheta_{ij} \equiv V\left(b_i + e_j\left(s_i, u_i, y_i\right)\right) + \zeta\, \nu_j$,to simplify the expressions. The probability that the expected adult utility of this child is below v is given by

$$
\begin{aligned}
F_v(v) &\equiv \mathbb{P}\left[V^+\left(s_i, u_i, \boldsymbol{\epsilon}_i, b_i, y_i\right) < v\right], \\
&= \mathbb{P}\left[\max_j \; \vartheta_{ij} + \rho\, \epsilon_{ij} < v\right], \\
&= \prod_{j=1}^{J} \mathbb{P}\left(\epsilon_{ij} \leq \tfrac{1}{\rho}\left(v - \vartheta_{ij}\right)\right), \\
&= \prod_{j=1}^{J} F\left(\tfrac{1}{\rho}\left(v - \vartheta_{ij}\right)\right), \\
&= \prod_{j=1}^{J} \exp\left(-\exp\left(-\tfrac{1}{\rho}\left(v - \vartheta_{ij}\right) - \overline{\gamma}\right)\right), \\
&= \exp\left(-\exp\left[-\tfrac{1}{\rho}v + \log\left(\sum_{j=1}^{J} e^{\frac{1}{\rho}\vartheta_{ij}}\right) - \overline{\gamma}\right]\right).
\end{aligned}
$$

This allows us to calculate

$$
\begin{aligned}
\mathbb{E}_{\boldsymbol{\epsilon}}\left[V^{+}\left(s_i, u_i, \boldsymbol{\epsilon}_i, b_i, y_i\right)\right] &= \tfrac{1}{\rho}\sum_{j=1}^{J}\int_{-\infty}^{\infty} v\, f\left(\tfrac{1}{\rho}\left(v-\vartheta_{ij}\right)\right)\prod_{j'\neq j} F\left(\tfrac{1}{\rho}\left(v-\vartheta_{ij}\right)\right) dv, \\
&= \tfrac{1}{\rho}\sum_{j=1}^{J}\int_{-\infty}^{\infty} v\, e^{-\frac{1}{\rho}(v-\vartheta_{ij})-\overline{\gamma}} \prod_{j'=1}^{J}\exp\left(-\exp(-\tfrac{1}{\rho}\left(v-\vartheta_{ij'}\right)-\overline{\gamma})\right) dv, \\
&= \tfrac{1}{\rho}\int_{-\infty}^{\infty} v\left(e^{-\frac{1}{\rho}v-\overline{\gamma}}\sum_{j=1}^{J} e^{\frac{1}{\rho}\vartheta_{ij}}\right)\exp\left(e^{-\frac{1}{\rho}v-\overline{\gamma}}\sum_{j'=1}^{J} e^{\frac{1}{\rho}\vartheta_{ij'}}\right) dv.
\end{aligned}
$$

Defining $x_i \equiv \frac{1}{\rho}v+\overline{\gamma}-\log\sum_{j'=1}^{J} e^{\frac{1}{\rho}\vartheta_{ij'}}$, we find:

$$
\begin{aligned}
\mathbb{E}_{\boldsymbol{\epsilon}}\left[V^{+}\left(s_i, u_i, \boldsymbol{\epsilon}_i, b_i, y_i\right)\right] &= \rho\sum_{j=1}^{J}\int_{-\infty}^{\infty}\left(x_i-\overline{\gamma}+\log\sum_{j'=1}^{J}\exp\left(\tfrac{1}{\rho}\vartheta_{ij'}\right)\right)\exp\left(-x_i\right)\exp\left(\exp\left(-x_i\right)\right) dx_i, \\
&= \rho\,\log\sum_{j'=1}^{J}\exp\left(\tfrac{1}{\rho}\vartheta_{ij'}\right).
\end{aligned}
$$

□

Lemma 3. *For a stationary equilibrium, define V^+ as in Equation (6). We then have $\mathbb{P}\left(V^+ < v|y,s,u,j\right) = \mathbb{P}\left(V^+ < v|y,s,u\right)$, where we have defined the distribution of utility conditional on the selected occupation j as*

$$
\mathbb{P}\left(V^+ < v|y,s,u,j\right) \equiv \mathbb{P}\left(V^+ < v \,\middle|\, y,s,u,\; j = \underset{j'}{\mathit{argmax}}\, V\left(b+e_{j'}\left(s,u,y\right)\right)+\zeta\,\nu_{j'}+\rho\,\epsilon_{j'}\right).
$$

Proof. We use the same notation as in the proof of Lemma 1 above. The distribution of utilities, conditional on a given occupation j is given by:

$$
\begin{aligned}
F_v\left(v|j\right) &\equiv \mathbb{P}\left(V^{+}\left(s,u,\boldsymbol{\epsilon},b,y\right) < v|\, j = \underset{j'}{\operatorname{argmax}}\ \vartheta_{j'}+\rho\,\epsilon_{j'}\right), \\
&= \frac{\mathbb{P}\left(V^{+}\left(s,u,\boldsymbol{\epsilon},b,y\right) < v\,,\; j = \underset{j'}{\operatorname{argmax}}\ \vartheta_{j'}+\rho\,\epsilon_{j'}\right)}{\mathbb{P}\left(j = \underset{j'}{\operatorname{argmax}}\ \vartheta_{j'}+\rho\,\epsilon_{j'}\right)}, \\
&= \frac{1}{\mu_j}\times\int_{-\infty}^{\frac{1}{\rho}(v-\vartheta_{jt})} F'\left(\epsilon_j\right)\times\prod_{j'\neq j}\mathbb{P}\left(\epsilon_{j'}\leq\epsilon_j+\tfrac{1}{\rho}\left(\vartheta_j-\vartheta_{j'}\right)\right) d\epsilon_j,
\end{aligned}
$$

$$
\begin{aligned}
&= \frac{1}{\mu_j} \int_{-\infty}^{\frac{1}{\rho}(v-\vartheta_{jt})} \exp\left(-\epsilon_j - \overline{\gamma}\right) \exp\left(-e^{-\epsilon_j - \overline{\gamma}} \left(1 + \sum_{j' \neq j} e^{-\frac{1}{\rho}\left(\vartheta_j - \vartheta_{j'}\right)} \right) \right) d\epsilon_j, \\
&= \frac{1}{\mu_j} \times \frac{1}{1 + \sum_{j' \neq j} e^{-\frac{1}{\rho}\left(\vartheta_j - \vartheta_{j'}\right)}} \int_{e^{-\frac{1}{\rho}(v-\vartheta_{jt})-\overline{\gamma}}\left(1+\sum_{j'\neq j} e^{-\frac{1}{\rho}\left(\vartheta_j-\vartheta_{j'}\right)}\right)}^{\infty} \exp\left(-x\right) dx, \\
&= \exp\left(-e^{-\frac{1}{\rho}v - \overline{\gamma}} \left(\sum_j e^{\frac{1}{\rho}\vartheta_j} \right) \right), \\
&= F_v(v),
\end{aligned}
$$

where, again, in the fifth equality we have used the change of variables

$$
x \equiv e^{-\epsilon_j - \overline{\gamma}} \left(1 + \sum_{j' \neq j} e^{-\frac{1}{\rho}\left(\vartheta_j - \vartheta_{j'}\right)} \right).
$$

□

Lemma 4. *The joint distribution of the observed data based on the model is given by*

$$
\mathbb{P}\left(\boldsymbol{d};\boldsymbol{\varsigma}\right) = \prod_{i=1}^{N} \left\{ \frac{\exp\left[\frac{\zeta}{\rho}\nu_{o_i} + \frac{1}{\rho}V\left(b^*\left(y_i\right) + e_{o_i}\left(s_i, \mathcal{U}\left(e_i, s_i, o_i, y_i; \boldsymbol{\varsigma}\right), y_i\right)\right)\right]}{\sum_j \exp\left[\frac{\zeta}{\rho}\nu_j + \frac{1}{\rho}V\left(b^*\left(y_i\right) + e_j\left(s, \mathcal{U}\left(e_i, s_i, o_i, y_i; \boldsymbol{\varsigma}\right), y\right)\right)\right]} \right.
$$
$$
\left. \times \frac{1}{\sqrt{2\pi\, \theta_{o_i}^2}} \exp\left(-\frac{1}{2}\mathcal{U}\left(e_i, s_i, o_i, y_i; \boldsymbol{\varsigma}\right)^2 \right) \times \frac{\exp\left(-\frac{1}{2}\left(\frac{s_i - h^*(y_i)}{\vartheta}\right)^2\right)}{\sum_{s'=0}^{4} \exp\left(-\frac{1}{2}\left(\frac{s' - h^*(y_i)}{\vartheta}\right)^2\right)} \right\}, \tag{25}
$$

where $\mathcal{U}\left(e_i, s_i, o_i, y_i; \boldsymbol{\varsigma}\right)$ *is defined by Equation (16).*

Proof. The observations are independent, thus we have $\mathbb{P}\left(\boldsymbol{d};\boldsymbol{\varsigma}\right) = \prod_i \mathbb{P}\left(e_i, o_i, s_i | y_i\right)$. Based on the model, we have:

$$
\begin{aligned}
\mathbb{P}\left(e_i, o_i, s_i | y_i\right) &= \mathbb{E}_{u_i}\left[\mathbb{P}\left(e_i, o_i, y_i, s_i, u_i\right)\right], \\
&= \int \mathbb{P}\left(o_i | y_i, s_i, u_i\right) \delta\left(e_i - \left(\alpha_{o_i} + \kappa_{o_i} s_i + \delta_{o_i} y_i + \theta_{o_i} u_i\right)\right) \mathbb{P}\left(u_i\right) \mathbb{P}\left(s_i | y_i\right) du_i, \\
&= \mathbb{P}\left(s_i | y_i\right) \int \mathbb{P}\left(o_i | y_i, s_i, u_i\right) \delta\left(e_i - \left(\alpha_{o_i} + \kappa_{o_i} s_i + \delta_{o_i} y_i + \theta_{o_i} u_i\right)\right) \frac{e^{-u_i^2/2}}{\sqrt{2\pi}} du_i, \\
&= \mathbb{P}\left(s_i | y_i\right) \int \mathbb{P}\left(o_i | y_i, s_i, \frac{x}{\theta_{o_i}}\right) \delta\left(e_i - \left(\alpha_{o_i} + \kappa_{o_i} s_i + \delta_{o_i} y_i\right) - x\right) \frac{e^{-x^2/2\theta_{o_i}^2}}{\sqrt{2\pi}} \frac{dx}{\theta_{o_i}},
\end{aligned}
$$

$$= \mathbb{P}_{s|h}\left(s_i|h^*\left(y_i\right)\right)\mathbb{P}\left(o_i|y_i, s_i, \frac{e_i - \left(\alpha_{o_i} + \kappa_{o_i}s_i + \delta y_i\right)}{\theta_{o_i}}\right)\frac{e^{-\left(e_i-\left(\alpha_{o_i}+\kappa_{o_i}s_i+\delta y_i\right)\right)^2/2\theta_{o_i}^2}}{\sqrt{2\pi}\theta_{o_i}},$$

where we have perform the change of variables $x \equiv u_i/\theta_{o_i}$ in the fourth equality. Equation (25) immediately follows. □

B.2 The Stationary Distribution of Endowment and Intergenerational Mobility

Assume that the earnings function $e_j(s, \cdot, y)$ is monotonically increasing in talent u for all occupations and define a corresponding inverse of the earnings function $\widetilde{E}_j^{-1}(\cdot; s, y)$ as

$$u \equiv \widetilde{E}_j^{-1}(e_j(s, u, y); s, y).$$

We can write the cdf for the earnings of the children of parents with endowment y as

$$F_e\left(e|y\right) = \mathbb{E}_s\left[F_e(e|s, y)\,\middle|\, h^*(y)\right], \tag{26}$$

where we have defined the cdf $F_e(e|s, y)$ of the earnings of children with schooling s and parental endowment y as

$$F_e(e|s, y) \equiv \sum_{j=1}^{J}\int^{\widetilde{E}_j^{-1}(e;s,y)} \mu_j\left(s, u, y\right)\, d\mathbb{P}_u(u), \tag{27}$$

where the conditional occupational choice function μ_j satisfies Equation (12). Equation (27) accounts for two distinct effects of the parental endowment on child earnings. The first effect is that higher parental endowment may raise the earnings within the occupation. This is reflected in the upper bound on the integral. The second effect is that parental endowment shapes the patterns of occupational choice and is reflected through the dependence of the term μ_j on parental endowment. Finally, Equation (26) accounts for the effect of parental investment in human capital on the distribution of earnings.

Given the conditional distribution of earnings, it is easy to see that the stationary cdf of total endowment y has to satisfy the following fixed point condition

$$F_y\left(y^+\right) = \int_0^\infty F_e(y^+ - b^*(y)|y)\, dF_y(y), \tag{28}$$

where the conditional distribution of earnings $F_e(\cdot|y)$ satisfies Equations (26) and (27). The dispersion in total endowment is shaped by two distinct forces: the dependence of child earnings on parental total income $F_e(\cdot|y)$ as well as the direct parental transfer policy $b^*(y)$.

Mobility of Welfare We can further characterize the dependence of the welfare of the child on the parental endowment as

$$F_v\left(v^+|y\right) = \mathbb{E}_{s,u}\left[F_v\left(v^+|s,u,y\right) | \, h^*(y)\right], \tag{29}$$

where $F_v\left(v^+|y\right)$ satisfies Equation (19). Equation (29) additionally accounts for the contribution of parental endowment to the welfare of the children through its effect on schooling attainment. Conditional on attained schooling, Equation (19) shows the welfare effect of parental endowment through its direct effect on earnings and its indirect effect on the patterns of occupation choice. Finally, the long-run stationary distribution of welfare in the model immediately follows from Equation (29) as $F_v(v) \equiv \int F_v(v|y)\, dF_y(y)$.

C Estimation Appendix

C.1 Log-Likelihood Function

The maximum-likelihood estimation problem corresponds to that of maximizing the following the log-likelihood function

$$\begin{aligned}
\mathcal{L}\left(\boldsymbol{d};\boldsymbol{\varsigma}\right) \equiv& \sum_{i=1}^{N} \log \mathbb{P}\left(e_i, o_i, s_i | y_i\right), \\
=& \frac{\zeta}{\rho}\left(\sum_{i=1}^{N} \nu_{o_i}\right) + \frac{1}{\rho}\sum_{i=1}^{N} V\left(b^*\left(y_i\right) + e_j\left(s_i, y_i, \mathcal{U}\left(e_i, o_i, s_i, y_i; \boldsymbol{\varsigma}\right)\right)\right) \\
& - \sum_i \log\left(\sum_j \exp\left[\frac{\zeta}{\rho}\nu_j + \frac{1}{\rho}V\left(b^*\left(y_i\right) + e_j\left(s_i, y_i, \mathcal{U}\left(e_i, o_i, s_i, y_i; \boldsymbol{\varsigma}\right)\right)\right)\right]\right) \\
& - \frac{1}{2}\sum_i \mathcal{U}\left(e_i, o_i; \boldsymbol{\varsigma}\right)^2 - \tfrac{1}{2}\sum_i \log\theta_{o_i} \\
& - \frac{1}{2}\sum_i\left(\frac{s_i - h^*\left(y_i\right)}{\vartheta}\right)^2 - \sum_i \log\sum_{s'=0}^{4}\exp\left(-\frac{1}{2}\left(\frac{s' - h^*\left(y_i\right)}{\vartheta}\right)^2\right).
\end{aligned} \tag{30}$$

The second and third lines of Equation (30) characterize the conditional distribution of occupational choice, given schooling, earnings, and parental endowment. The fourth and fifth lines characterize the conditional distribution of talent and schooling, given parental endowment. We find the set of parameters $\boldsymbol{\varsigma}$ maximizing the log likelihood function above for the observed data. For the derivation, see Lemma 4 in Appendix B.

C.2 Details of the Estimation Procedure

Initialization with 14 Occupations. We initialize the values of parameters in our main estimation based on a preliminary estimation stage using a less granular classification of the occupations observed in the data at the level of 14 occupation codes to reduce the dimensionality of the problem at the initialization stage. We further simplify the parameter search at this stage by setting the return to parental endowment to zero, i.e., $\boldsymbol{\delta} \equiv \mathbf{0}$.

In turn, we initialize the values of parameters of the restricted model in this first stage estimation by applying the following strategy. First, note that Equations (14) and (12) together imply that the conditional expected log earnings of children based on the model satisfies

$$\mathbb{E}\left[\log\left(e\right)\Big| j, s, y\right] = \alpha_j + \kappa_j \log s + \delta_j \log y + \theta_j \underbrace{\frac{\int u \times \mu_j\left(s, u, y\right) d\mathbb{P}(u)}{\int \mu_j\left(s, u, y\right) d\mathbb{P}(u)}}_{\equiv \overline{u}_j(s,y)}, \tag{31}$$

where $\overline{u}_j\left(s, y\right)$ stands for the conditional expectation of talent given parental endowment, schooling, and occupational choice. This term controls for the effect of selection on unobservable talent and shows why we cannot uncover the occupation-specific returns to schooling and parental endowment based on a simple regression of log earnings on the latter. We can similarly derive the conditional variance of log earnings as

$$\mathbb{V}\left[\log\left(e\right)\Big| j, s, y\right] = \theta_j^2 \frac{\int \left(u - \overline{u}_j\left(s, y\right)\right)^2 \times \mu_j\left(s, u, y\right) d\mathbb{P}(u)}{\int \mu_j\left(s, u, y\right) d\mathbb{P}(u)}. \tag{32}$$

Intuitively, the presence of a strong dispersion in log earnings in a given occupation conditional on schooling and parental income suggests a strong degree of return to talent in that occupation.

We consider a set of bins for the values of parental endowment $Y = \left\{\bar{y}^1, \bar{y}^2, \bar{y}^3, \bar{y}^4, \bar{y}^5\right\}$ and map each observed parental endowment in the data to one of the bins, setting $\bar{y}_i \equiv \arg\min_{\bar{y} \in Y} \Big| \log y_i - \bar{y} \Big|$. Inspired by Equations (31) and (32), we find an initial estimate for the coordinates of returns to schooling $\boldsymbol{\kappa}$ by relying on an observation-weighted least-squares regression of log earnings $\widehat{\mathbb{E}}\Big[\log e\Big|j,s,\bar{y}\Big]$ on schooling s while attempting to control for the selection term by $\widehat{\mathbb{V}}\Big[\log\, e\Big|j,s,\bar{y}\Big]^{1/2}$. Using the resulting estimates, we recover initial guesses for occupation-specific fixed earnings and returns to talent $(\boldsymbol{\alpha},\boldsymbol{\theta})$ as

$$\alpha_j^{(0)} = \frac{\sum_{s,\bar{y}}\Big(\widehat{\mathbb{E}}\Big[\log\, e\Big|j,s,\bar{y}\Big]-\kappa\, s\Big)\,\#(j,s,\bar{y})}{\sum_{s,\bar{y}}\#(j,s,\bar{y})},$$

$$\theta_j^{(0)} = \sqrt{\frac{\sum_{s,\bar{y}}\widehat{\mathbb{V}}\Big[\log\, e\Big|j,s,\bar{y}\Big]\,\#(j,s,\bar{y})}{\sum_{s,\bar{y}}\#(j,s,\bar{y})}}.$$

The procedure above yields our initial guesses for the parameters of the earnings function. For the remaining parameters, we pick the following initial guesses. In practice, we parameterize the cost function $\varphi(\cdot)$ for human capital investments with a vector $(\widetilde{\varphi}_1,\widetilde{\varphi}_2,\widetilde{\varphi}_3,\widetilde{\varphi}_4)$ such that $\varphi_k\equiv\exp(\widetilde{\varphi}_k)$ gives the slope of the cost function in the interval $h\in[k-1,k]$. We consider a convex form characterized by $\widetilde{\boldsymbol{\phi}}=(5,6,7,8)$. Finally, we initialize the remaining parameters, i.e., the dispersion of idiosyncratic taste shocks ρ, the weight of intrinsic valuations ζ, and the dispersion of schooling shocks ϑ all at unity.

Optimization with 14 Occupations. We perform the maximization of the log likelihood objective function in two stages. In the first stage, we perform an iterative, block-wise scheme, in which we iterate over maximizing the objective function only over one of the following three partitions of the model parameters (keeping all other components at their current levels): 1) the taste parameters (ζ,ρ), 2) the human capital cost parameters $(\widetilde{\boldsymbol{\phi}},\vartheta)$,[41] and 3) the parameters of the earnings function $(\boldsymbol{\alpha},\boldsymbol{\kappa},\boldsymbol{\theta},\boldsymbol{\delta})$.[42] After a few rounds of this block-wise optimization, we then perform a joint maximization of the objective function over the entire parameter space using a SQP-type algorithm.

Initialization and Optimization with 54 Occupations. We use the estimates found on the data with 14 occupational codes to initialize the parameters of the model for the main data with 54 occupational codes. We rely on a crosswalk between the two levels to initialize all the parameters of the earnings function at the 54-occupation level that belong to the same

[41] In practice, we found overall improvements in the final objective function when in the rounds updating the education parameter block we initially over-weight the terms in the objective function that correspond to the conditional distribution of schooling attainment given parental endowments.

[42] Since we rely on a discretization of the state space to solve the Bellman equation, the numerical evaluation of the gradients and the Jacobians of the objective function often leads to discontinuities. In order to smooth out these discontinuities, we steer the optimization routine by providing initially large-step approximations to the gradients and gradually lowering the step-size for the evaluation of the gradients.

14-occupation level code with the values estimated in the first stage for the latter. We then apply another iterative, block-wise optimization scheme similar to the one discussed above across the implied 14 blocks of occupational codes. For each block, we separately update the parameters of the earnings function corresponding to the occupations within each of the 14-occupation codes. After a few rounds of applying this block-wise strategy, we follow the same strategy as that discussed above for the 14-code level to gradually extend the search to the joint space including other model parameters. We finally introduce the returns to parental endowment parameters $\boldsymbol{\delta}$, before applying a final round of joint optimization in the space of all model parameters.[43]

C.3 Additional Estimation Results

C.3.1 Policy Functions

Figure 14 displays the policy functions for education investment $h^*(y)$ and direct transfers $b^*(y)$. As Panel (a) of the figure shows, both direct transfers and education investment are increasing in parental endowment. Panel (b) shows that poor parents transfer resources to their children mainly by investing in their human capital. In contrast, rich parents devote a larger share of their endowment to direct transfers. We note that the apparent non-monotonicity in the policy function for the share of endowment spent on children's education simply reflects the discrete nature of our education groups. That this share is decreasing in parental endowment at high levels of parental endowment is a consequence of the fact that in the PSID data we only observe the number of years of schooling and cannot distinguish more refined aspects of schooling attainment such as the major or the quality of college education.

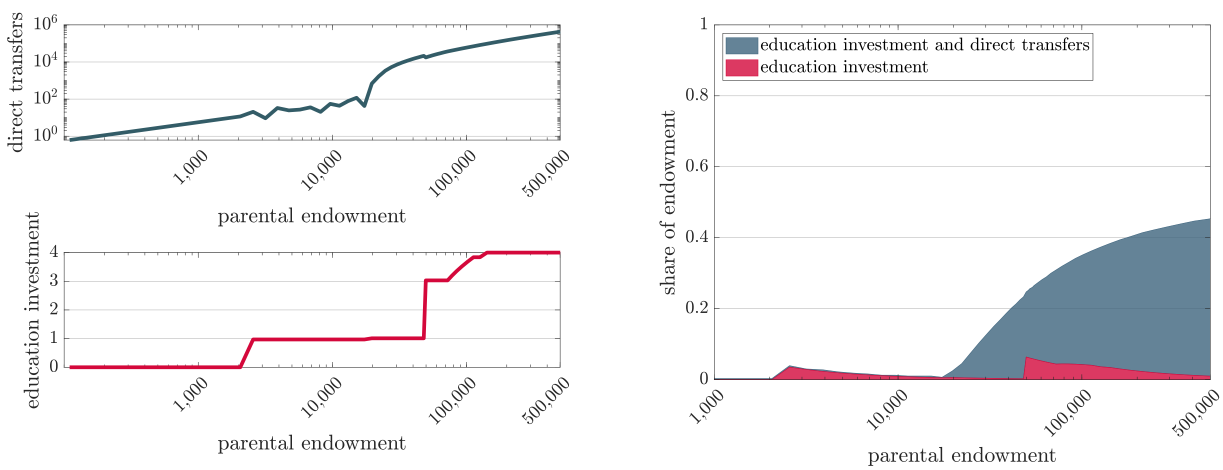
That the transfer policy function is increasing in parental endowment is in line with the condition needed for the affordability mechanism in Equation (5). Moreover, it is also in line with qualitative patterns regarding intergenerational transfers in survey data, which we discuss next. A number of issues that we outline below make quantitative comparisons difficult, so we emphasize the qualitative fit.

National Longitudinal Survey of Youth 1997 (NLSY97) We rely on the dataset on inter-vivos transfers constructed by Abbott et al. (2019) using information from the "Income" and "College Experience" sections of the NLSY97. The authors construct two measures of inter-vivos transfers, one that accounts only for direct transfers to children and one that in addition

[43]We initialize the values of these returns parameters as the slopes corresponding to auxiliary regressions of $\theta_j u_i$ on y_i for all i such that $o_i = j$.

Figure 14: Investment in Education and Direct Transfers

(a) $b^*(y)$ and $h^*(y)$ (b) Policy Functions as Share of Endowment



Notes: Panel (a) shows the policy functions for direct transfers (top) and education investment (bottom). Panel (b) shows direct transfers and education investment as share of parental endowment.

to direct transfers also includes an implicit transfer corresponding to the value of rent.

Two aspects of the data complicate the comparison with the model implied transfer function. First, the data only accounts for inter-vivos transfers, while the model implied transfer function $b^*(y_i)$ includes both inter-vivos transfers and inheritance. Second, the NLSY97 sample of children receiving transfers is younger than our model counterpart, with ages between 16 and 22. In light of this, we emphasize the qualitative patterns present in the data on the monotonicity of transfers with respect to parental monetary resources.

We split parents in the NLSY97 sample in four quartiles of parental net worth (as reported by the parent) and calculate, for each quartile, the average inter-vivos transfer. Inter-vivos transfers are increasing in parental net worth. Specifically, average transfers by parental net worth quartile (expressed in 1996 US dollars) are, respectively: \$773, \$965, \$1,034, \$1,504. Adjusted to include the rent equivalent, average transfers by parental net worth quartile are, respectively: \$3,920, \$4,050, \$4,373, \$5,021.

Health and Retirement Study (HRS) and Asset and Health Dynamics Study (AHEAD)
McGarry (1999) uses data from HRS and AHEAD to study how the propensity of making and inter-vivos transfer of leaving a bequest varies with the characteristics of the parents and children. The HRS surveys individuals both from 1931 to 1941 and the AHEAD surveys individuals

born in 1923 or earlier. In contrast, the average parent in our PSID sample was born in 1943. The HRS and AHEAD surveys started in 1992 and 1993, respectively, when respondents were 51-61 years old in the HRS and 70 and over in AHEAD, so the sample of parents reporting information on transfers in these datasets is older than our model counterpart.

Respondents were asked about transfers of \$500 or more made to children in the previous year, as well as about their intentions regarging bequest. In Table 3 McGarry (1999) reports that wealthier and higher income parents are more likely to have made a inter-vivos transfer, in line with our model. Specifically, moving from the lowest to the highest income quartile increases the probability of a transfer by 20 to 26 percentage points, depending on the data source. The probability of making a bequest also increases in parental income and wealth, although the magnitudes are not reported in the paper.

C.3.2 Model Fit to Other Moments of Interest

Parental Endowment and Intergenerational Transfers We next compare the prediction of our model regarding transfers as a function of parental endowment with their empirical counterpart. Our estimated model implies that aggregate transfers represent 49.1% of aggregate parental endowment. We use two data moments to calculate its empirical counterpart. First, according to Table 4 in Gale and Scholz (1994), intergenerational transfers (inter-vivos transfers, bequests and college expenses) represent 63.8% of aggregate wealth. This number falls to 51.8% if college expenses are not included in intergenerational transfers. We denote this ratio by $\frac{B}{W}$. Second, Kuhn and Rios-Rull (2020) report an earnings to wealth ratio of 13.9%.[44] Denoting this by $\frac{E}{W}$, we can the calculate the transfer to endowment ratio is the data as

$$\frac{B}{Y} = \frac{\frac{B}{W}}{\frac{E+W}{W}} = \frac{\frac{B}{W}}{\frac{E}{W}+1},$$

which is equal to 0.560 if we include college expenses in intergenerational transfers and 0.455 if we do not. Both are close to the model implied ratio of 0.491.

Parental Endowment, Schooling Attainment and Occupational Choice Table 6 compares the predictions of the model regarding children's schooling attainment as a function of parental endowment with the corresponding patterns in the data. Consistent with the data, children of poor parents (i.e. those with log parental endowment below the median) in the model are

[44]This is the average earnings to wealth ratio from 1989 to 2019, which is also equal to the earnings to wealth ratio in 2001. Our model is estimated with data evaluated in the year 2000.

more likely not to graduate from high-school or to only obtain a high-school degree. Conversely, children of rich parents have a higher educational attainment and are more likely to obtain a college or a graduate degree.

Table 7 assesses the model's performance in terms of predicting the dependence of occupational choice on parental endowment and schooling attainment. To that end, the table reports correlation coefficients between occupational choice probabilities conditional on parental endowment and schooling predicted by the model and their counterpart in the PSID data. These correlation coefficients are positive and large, suggesting that the model is able to capture which occupations are more likely to be chosen by children with a given educational attainment and parental endowment.

C.4 The Decomposition of Persistence in Earnings

We next provide a decomposition that characterizes the channels through which the model generates intergenerational persistence. Our model offers a simple characterization for the last measure in Table 2, i.e., the covariance between child earnings and parental endowment y. Let $\mathbb{C}_{ey}(\log e, \log y)$ denote the covariance between log earnings and log parental endowment:

$$\mathbb{C}_{ey}(\log e, \log y) = \mathbb{E}_{ey}\left[\log e \ (\log y - \mathbb{E}_y[\log y])\right],$$

Table 6: Schooling Attainment Conditional on Parental Endowment

	Data		Model	
	Poor parent	Rich parent	Poor parent	Rich parent
No high-school	0.05	0.01	0.21	0.02
High-school	0.42	0.18	0.24	0.07
Some college	0.27	0.23	0.23	0.19
College degree	0.16	0.33	0.19	0.33
Graduate degree	0.10	0.25	0.13	0.40

Notes: Table entries are probabilities of obtaining a given schooling attainment (rows) conditional on parental endowment. Poor parents are those with log parental endwoment below the median. Rich parents are those with log parental endowment above the median.

Table 7: Occupational Choice Conditional on Parental Endowment and Schooling

Corr(data,model)	Poor parent	Rich parent
No high-school	0.68	0.27
High-school	0.85	0.76
Some college	0.64	0.14
College degree	0.64	0.57
Graduate degree	0.81	0.76

Notes: Table entries are correlation coefficients between occupational choice probabilities conditional on parental endowment and schooling predicted by the model and their counterpart in the PSID data. Poor parents are those with parental endwoment below the median. Rich parents are those with log parental endowment above the median.

$$= \mathbb{E}_y \left[\mathbb{E}_e[\log e\, |y] \, \left(\log y - \mathbb{E}_y[\log y] \right) \right].$$

We can decompose the conditional expectation of the earnings of children given parental endowment to different components stemming from the dependence of the schooling and occupational choices of the former on the endowment of the latter. To build toward this decomposition, let us first define the conditional joint probability of occupational choice, talent, and schooling given parental endowment as

$$\mathbb{P}\left(j, s, u|y\right) \equiv \mu_j(s, u, y)\, \mathbb{P}_u(u)\, \mathbb{P}_{s|h}(s|h^*(y)), \tag{33}$$

where the conditional probabilities of occupational choice are given by Equation (12). Using this joint distribution, and with slight abuse of notation, we can define a number of marginal conditional distributions. For instance, the conditional distribution of occupational choice given parental endowment is given by $\mathbb{P}(j|y) \equiv \int \sum_s \mathbb{P}\left(j, s, u|y\right) du$ and the conditional distribution of schooling given parental endowment is $\mathbb{P}(s|y) \equiv \int \sum_j \mathbb{P}\left(j, s, u|y\right) du = \mathbb{P}_{s|h}(s|h^*(y))$.

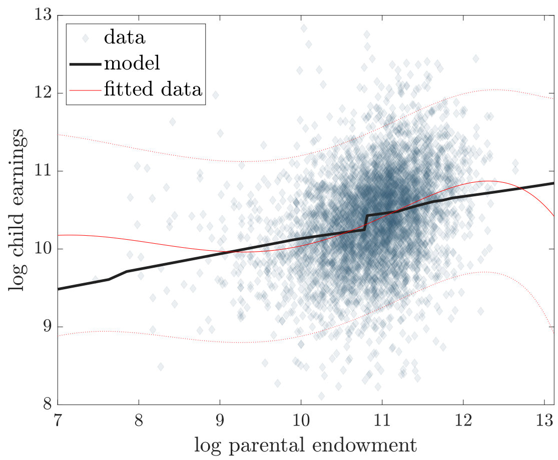
Based on the definitions above, Equation (14) implies that we can write the expected value of child earnings conditional on parental endowment as

$$\mathbb{E}_e[\log e|\, y] = \overline{\alpha}(y) + \overline{\kappa}(y)\, \overline{s}(y) + \overline{\delta}(y)\, \log y + \mathbb{C}_{js}\left(\kappa_j, s|\, y\right) + \mathbb{C}_{ju}\left(\theta_j, u|\, y\right), \tag{34}$$

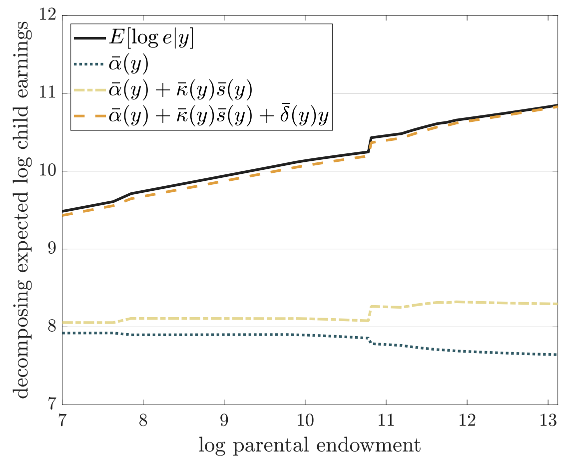
where we have defined the expected values of the parameters of the earnings function conditional on parental income y, e.g., $\overline{\alpha}(y) \equiv \mathbb{E}_j\left[\alpha_j|y\right] \equiv \sum_j \alpha_j \mathbb{P}(j|y)$, and similarly for $\overline{\delta}(y)$ and $\overline{\kappa}(y)$.

Figure 15: Child Earning vs. Parental Endowment

(a) Data vs. Model



(b) Decomposition



Notes: Panel (a) compares the relationship between log earning and log parental endowment across child-parent pairs in the data. The red lines show a 3-degree polynomial fit and the corresponding 95% confidence bands. The solid black line shows $\mathbb{E}_e[\log e|y]$ implied by the model. Panel (b) decomposes the conditional expected log earnings of the children given parental endowment to different components based on Equation (34).

Similarly, we have defined the expected level of schooling conditional on parental income as $\bar{s}(y) \equiv \mathbb{E}_s[s|y] = \sum_s s\, \mathbb{P}_s(s|h^*(y))$, as well as the following two conditional covariances given parental endowment y:

$$\mathbb{C}_{js}(\kappa_j, s|\, y) \equiv \mathbb{E}_{j,s}\left[\kappa_j\left(s - \bar{s}(y)\right)|y\right], \tag{35}$$

$$\mathbb{C}_{ju}(\theta_j, u|\, y) \equiv \mathbb{E}_{j,u}\left[\theta_j u \,|\, y\right]. \tag{36}$$

The first term in Equation (34) captures the variations in the fixed component of earnings as a function of parental endowment, which captures the earnings of an individual with no schooling ($s = 0$), a unit parental endowment ($y = 1$), and a mean level of talent ($u = 0$). As we saw in Section 4.2, the fixed component of earnings varies negatively with the returns to schooling and talent across occupations. The second term in Equation (34) accounts for the product of the conditional mean return to schooling and conditional mean schooling given parental endowment. This term captures two distinct forces: the patterns of occupational choice through which the children of rich parents may sort into occupations with higher returns to schooling, and the patterns of schooling attainment through which the children of rich parents receive higher educational investment and schooling. Similarly, the third term accounts for the mean return to parental endowment, capturing the potential sorting of the children of rich parents into occupations with higher returns to parental endowment.

The last two terms in Equation (34) account for the patterns of sorting of children with higher schooling and talent toward occupations with higher returns to schooling and talent, respectively, *conditional* on parental endowment. The two covariances defined by Equations (35) and (36) capture how these two patterns of sorting vary across children with different levels of parental endowment. The stronger each of these two sorting patterns, the higher the conditional expected value of the log earnings of the children.

C.4.1 The Decomposition under the Benchmark Model

Figure 15a compares the conditional expected earnings of children $\mathbb{E}_e[\log e|\, y]$ implied by the model with the observed relationship in our PSID sample. The two resemble closely. Accordingly, as reported in the last row of Table 2, the model comes very close to the observed covariance in the data. Figure 15b decomposes the expected log earnings in the model into different components following Equation (34). We find that the first three terms of the equation together explain the lion's share of the expected relationship between log earnings and parental endowment.

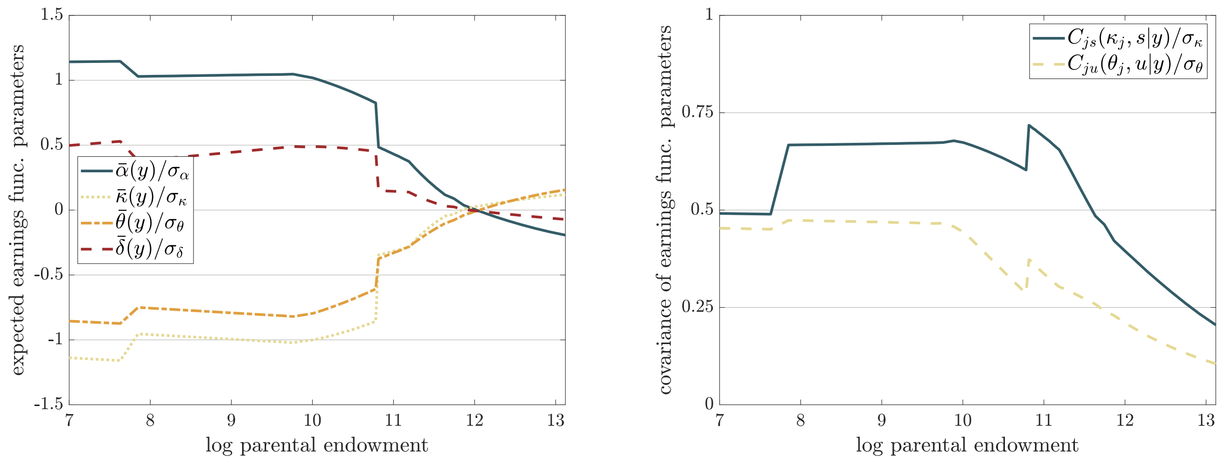
We find that the conditional expectation of fixed earnings $\overline{\alpha}(y)$ falls in parental endowment due to the fact that the children of richer parents sort into occupations with higher returns to schooling and talent and lower fixed earnings. Next, we find that the contribution of schooling $\overline{\kappa}(y)\overline{s}(y)$ increases in parental endowment, due to both the rise in the expected returns to schooling and the expected schooling attainment.[45] However, the estimation results suggest that through the lens of the model the main driver of the *variations* in expected log earnings as a function of parental endowment is the direct effect of parental endowment on earnings through the term $\overline{\delta}(y)\, y$. Despite sizable variations in the patterns of sorting across occupations conditional on parental endowment, Figure 15b shows that these variations make quantitatively negligible contributions to the overall dependence of expected log earnings on parental endowment.

Figure 16b focuses on the two relevant patterns of sorting: the covariance of schooling and returns to schooling, and the covariance of talent and returns to talent. Both these two covariances are initially stable as parental endowment rises, but then eventually fall as parental endowment continues to rise. The reason is that the children of very rich parents become relatively more responsive to their idiosyncratic taste shocks and intrinsic quality of occupations and thus do

[45] Figure 16a in Appendix D shows how the conditional expected value of each component of the earnings function varies with parental endowment. We find that the expected returns to schooling $\overline{\kappa}(y)$ and to talent $\overline{\theta}(y)$ rise in parental endowment, while the returns to parental endowment $\overline{\delta}(y)$ fall in parental endowment.

Figure 16: Drivers of Persistence in Earnings

(a) Components of Earnings Function (b) Sorting Across Occupations



Notes: Panel (a) shows how the conditional expectation of different components of the earnings function across occupations vary with parental endowment. Each component is normalized by its corresponding standard deviation across the entire population, e.g., $\sigma_\alpha \equiv \mathbb{V}_j[\alpha_j]$ based on the stationary distribution of occupational choice. Panel (b) shows the normalized conditional covariances of schooling and returns to schooling, and talent and returns to talent.

not respond as strongly to the earnings incentives in their occupational choice.

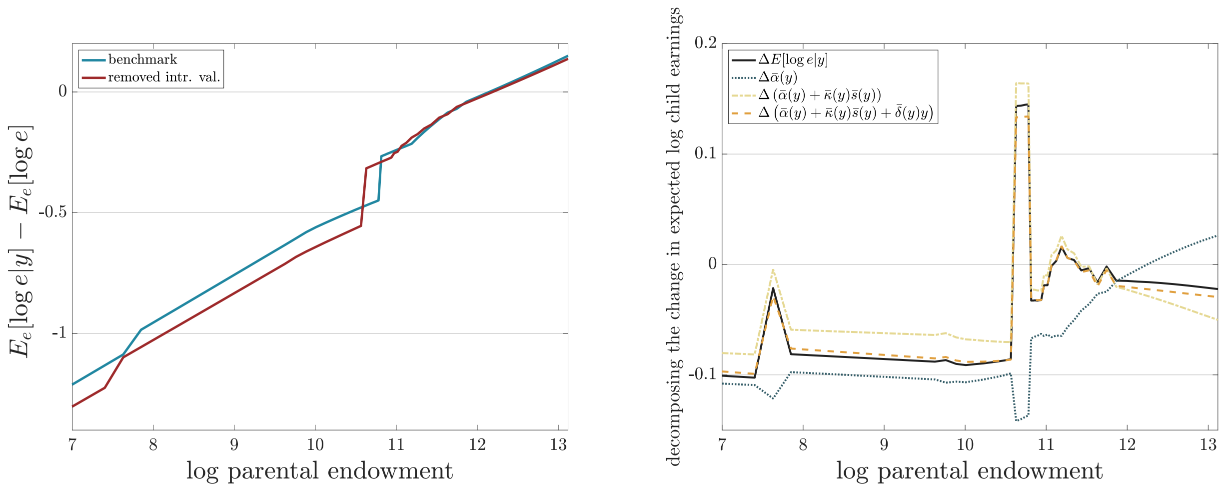
C.4.2 Persistence of Earnings without Intrinsic Qualities

As we saw in Table 3, the persistence in earnings slightly rises relative to the benchmark model when we remove the variations in the intrinsic qualities. Several forces together help shape this change in persistence. First, the most pronounced effect of removing intrinsic qualities for the children of the poorest and richest households is on the general equilibrium response in the fixed component of their earnings. As we saw in Figure 20b, the wage rates fall in low-intrinsic quality occupations, chosen mostly by the children of the poorest parents under the benchmark, and rise in high-intrinsic quality occupations, chosen by the children of the richest. To the extent that the children of poor parents switch to occupations with higher intrinsic qualities, this further lowers the fixed component of their earnings due to the negative correlation between the intrinsic qualities and the fixed components of income α under the benchmark (see Table 1b). The most pronounced effect on the earnings of the children of middle class parents is through their schooling. These children are those most likely to switch to occupations with high intrinsic qualities, which happen to also have higher returns to schooling κ (see Table 1b). Their expected

Figure 17: Expected Log Earning vs. Parental Endowment, Removed Intrinsic Qualities

(a) Benchmark vs. Removed Intr. Val.

(b) Decomposition of the Change



Notes: Panel (a) compares the relationship between conditional expected log earning and log parental endowment between the benchmark model and that with removed variations in intrinsic qualities. Panel (b) decomposes the the change in the conditional expected log earnings of the children given parental endowment to different components based on Equation (34), in going from the benchmark model to the one with removed variations in intrinsic qualities.

earnings rise due to higher schooling investment and attainment.

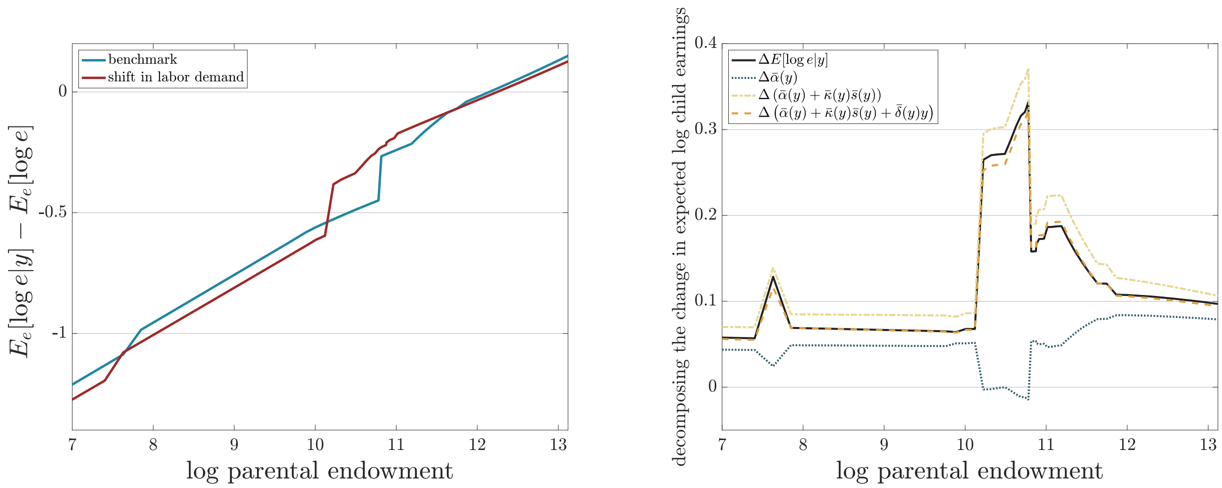
Figure 17a compares the conditional expected log earnings as a function of parental endowment under the benchmark with that under the model with removed variations in intrinsic qualities. Therein, Figure 17b decomposes the changes between the two conditional expectations to the different components based on Equation (34). We can see that the conditional expectation of the fixed component of log earnings $\overline{\alpha}(y)$ explains most of the differences between the children of the poorest and the richest parents, while the term involving the expected returns to schooling $\overline{\kappa}(y)\overline{s}(y)$ explains the change for the children of the middle class.

C.4.3 Decomposition with Shifts in Labor Demand

Figure 18a compares the conditional expected log earnings as a function of parental endowment under the benchmark with that under the model with shifts in labor demand. Figure 17b further decomposes the changes between the two conditional expectations to the different components based on Equation (34). The term involving the expected returns to schooling $\overline{\kappa}(y)\overline{s}(y)$ constitutes the main source of changes in expected log earnings.

Figure 18: Expected Log Earning vs. Parental Endowment, Shift in Labor Demand

(a) Benchmark vs. Shifted Labor Demand (b) Decomposition of the Change



Notes: Panel (a) compares the relationship between conditional expected log earning and log parental endowment between the benchmark model and that with shifts in occupational labor demand. Panel (b) decomposes the the change in the conditional expected log earnings of the children given parental endowment to different components based on Equation (34), in going from the benchmark model to the one with shifts to occupational labor demand.

D Additional Results

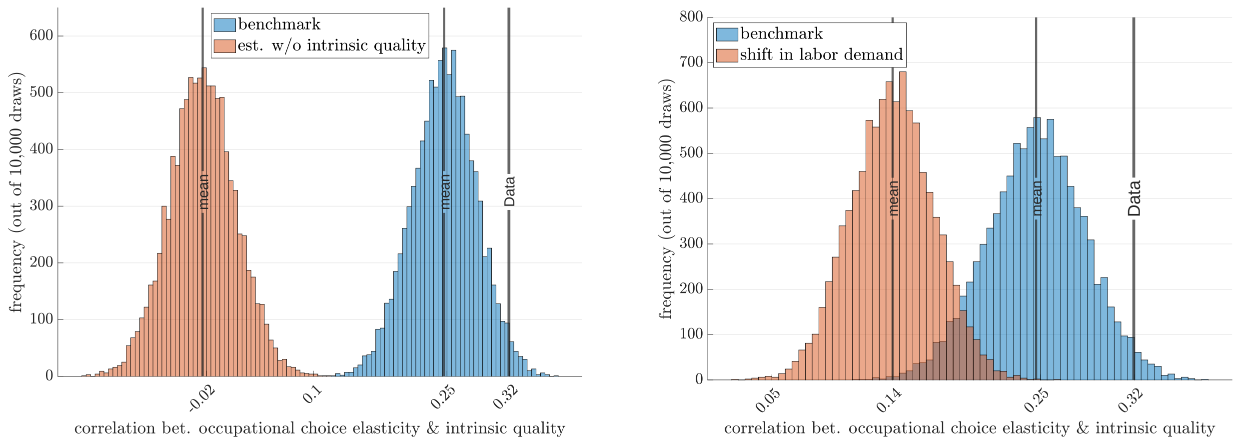
D.1 Intrinsic Occupational Quality and Parental Endowment under Different Variants of the Model

Figure 19a revisits the expected relation between the intrinsic quality of children's occupation and parental endowment in the estimated model using the strategy discussed in Section 4.4. For each re-sampled dataset, we run a linear regression of occupational choice $\mathbb{I}\{o_i = j\}$ for each occupation j on log parental endowment $\log y_i$ and educational attainment s_i. We then compute the correlation between the coefficients on parental endowment and the intrinsic qualities ν_j. Figure 19a shows the distributions of the resulting correlations across the 10,000 re-sampled datasets, corresponding to the benchmark model and the model without variations in intrinsic qualities. The mean value of these correlations falls from 0.25 ($SE = 0.04$) under the benchmark model to -0.02 ($SE = 0.04$) under the model estimated with no intrinsic qualities. Thus, the presence of intrinsic occupation quality allows us to explain the systematic relationship observed in the data between occupational choice elasticities and intrinsic qualities.

Figure 19b shows the distributions of the resulting correlations across the 10,000 re-sampled

Figure 19: Occupational Choice Elasticties and Intrinsic Quality

(a) Estimation w/o Intrinsic Quality (b) Shift in Labor Demand



Notes: Panel (a) shows the histograms of the correlation values between occupational choice elasticities and the intrinsic quality of occupation across 10,000 re-sampled datasets under the benchmark model (blue) and the model estimated with no variations in intrinsic qualities (red). Panel (b) compares similar histograms under the benchmark (blue) and the environment reflecting trends in occupational labor demand (red).

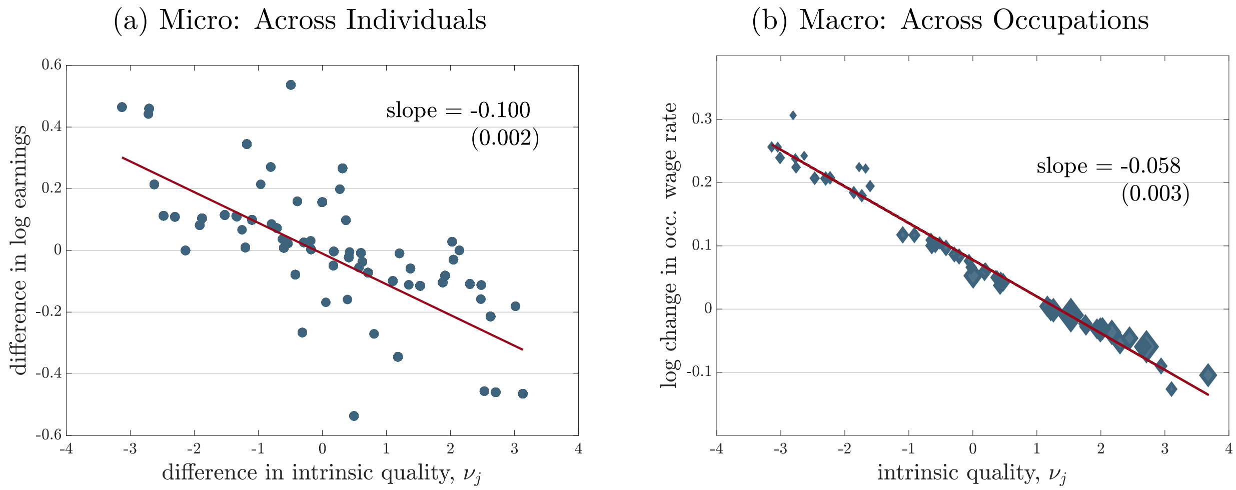
datasets from the benchmark model and the model with shifts in occupational labor demand. The mean value of these correlations falls from 0.253 ($SE = 0.036$) under the benchmark model to 0.140 ($SE = 0.031$) under the model that features the shifts in occupational labor demand.

D.2 Uncovering Compensating Differentials under Benchmark Model

We take two distinct strategies to provide proxies for the equilibrium compensating differentials through the lens of the estimated model. First, we construct a micro-level proxy for compensating differentials that corresponds to the tradeoff faced by the average individual in the data. The idea is that each individual, given their talent and schooling, chooses their occupation from a distinct set that lies on the frontier of the space of earnings and quality for them. For each individual in the data, we consider the top two most likely occupations predicted by the model, and compare the difference in log earnings between the two occupations against the difference between their intrinsic quality. Figure 20a shows the scatter plot of these differences. The linear fit implies that in the tradeoff between top two choices faced by each individual, a standard deviation gain in intrinsic quality is, on average, associated with a fall of over 17% in earnings.

In our second approach, we take a macro view and answer the following question. Suppose we

Figure 20: Compensating Differentials

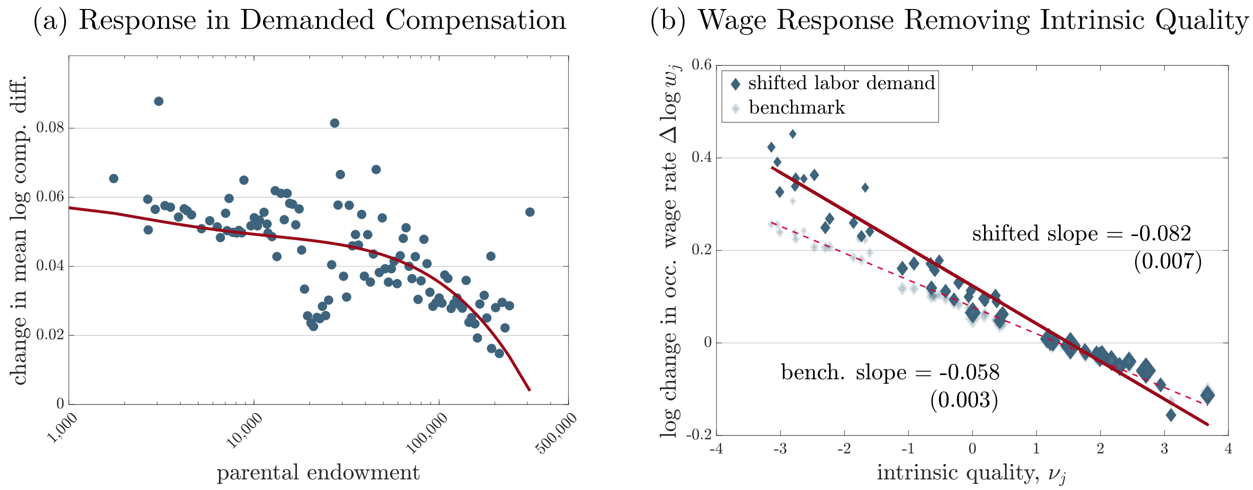


Notes: Panel (a) plots the differences in log earnings between the top two most likely occupations for each individual as predicted by the model and the corresponding differences in intrinsic qualities. Panel (b) plots the change $\alpha_j - \alpha_j^n$ against intrinsic qualities, where α^n is the earnings shifter corresponding to the counterfactual experiment of eliminating differences in intrinsic qualities while maintaining the benchmark occupational wage bills. The area of each diamond is proportional to the wage bill for that occupation. The lines show linear fits.

were to remove variations in the intrinsic quality of occupations. How much do we have to increase the wage rate for occupations with higher benchmark intrinsic quality to recover the original supply of labor for these occupations? Let τ denote such a variation in the environment faced by individuals, compared to the benchmark set of parameters. To solve for the general equilibrium response to this variation, we jointly solve for the new vector of fixed components of the earnings function $\boldsymbol{\alpha}^\tau$, the corresponding value function V^τ, and stationary distribution of endowments F_y^τ that satisfy conditions in Equation (13) for the same original levels of occupational wage bill. In this case, the variation in the environment consists of removing all differences across occupations in their intrinsic valuations, that is, setting $\nu_j \equiv 0$, which we will denote as $\tau \equiv n$.

In the environment with removed variations in intrinsic quality, the idiosyncratic taste shocks for occupations still provide a source of heterogeneity for the non-monetary dimension of working across different occupations. However, these idiosyncratic shocks average to zero across the population and only lead to a finite elasticity of occupational labor supply. The only difference between the new environment and our benchmark is the absence of intrinsic qualities. Thus, we may think of the resulting changes in the log occupational wage rates (given by $\boldsymbol{\alpha} - \boldsymbol{\alpha}^n$) as a proxy for the *general equilibrium* compensating differentials that satisfy the constraints imposed by the original levels of occupational wage bill under the benchmark model.

Figure 21: Compensating Differentials with Shifts in Occupational Labor Demand



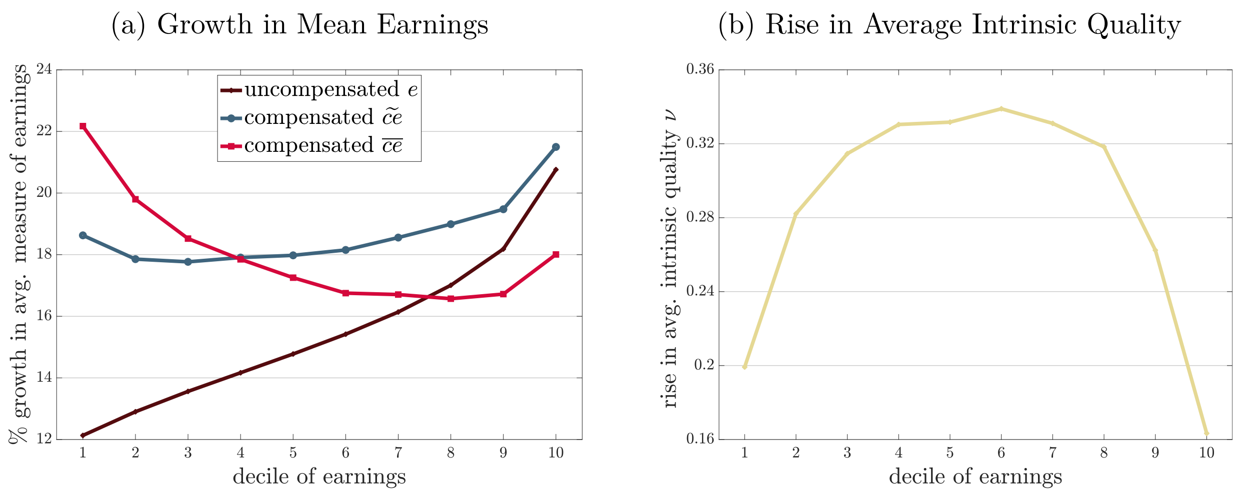
Notes: Panel (a) shows the binscatter plot of the change in the mean logarithm of the compensation required to make the child indifferent between two occupations at the 25th and 75th of instrinsic values, from Equation (18), in the model with shifted labor demand relative to the benchmark, across 10,000 resampled datasets from each model. Panel (b) plots the change in the log occupational wage rates $\alpha_j^d - \alpha_j^{nd}$ against occupational intrinsic qualities ν_j, where nd represents the counterfactual experiment of eliminating differences in intrinsic occupation values under the model with shifted labor demand, and d represents the model with shifted demand.

Figure 20b shows that the response of occupational wages is indeed strongly correlated with intrinsic quality: compared to the model with no intrinsic qualities, the benchmark economy reduces the (per efficiency unit) wage rate in occupations that compensate workers through higher intrinsic qualities under the benchmark model. We find that a linear fit captures most of the variations in the occupational wages, providing us an alternative characterization of the trade-off between intrinsic quality and earnings: one standard deviation rise in the intrinsic quality is accompanied by an average fall of around 11.4% in the (per efficiency unit) wage rate.

D.3 Demanded Compensation and Compensating Differentials with Shifts in Labor Demand

To study the effects on long-run labor supply in the shifts in labor demand, Figure 21a shows the response in the compensation required to make children indifferent between two occupations at the 25th and 75th percentile of the intrinsic quality distribution, as a function of parental endowment. The figure shows the change in the mean logarithm of the demanded compensation in the model with shifted labor demand relative to the benchmark, across 10,000 re-sampled datasets from each model. The shifts in labor demand lead to a rise of approximately 4% in the

Figure 22: Change in Welfare Across Deciles of Earnings



Notes: Panel (a) shows the growth in mean uncompensated and compensated earnings across occupations in response to the growth in occupational labor demand over the period across different deciles of earnings. Panel (b) plots the change in mean intrinsic quality of the occupation for people in each decile of earnings when moving from the benchmark to the model with shifted labor demand.

demanded compensation. The rise is simply due to the overall rise in the earnings of the children, who now focus relatively more on the intrinsic quality of occupations. The rise is stronger among the children of poorer parents, for whom the relative impact of the rise in earnings e_i is stronger since their receive a lower transfer $b^*(y_i)$.

Figure 21b shows that in our quantitative exercise compensating differentials indeed rise due to the increases in demanded compensation. The figure shows the response of occupational wages if we remove the variations in intrinsic qualities under the model with shifted labor demand, which we interpret as equilibrium compensating differentials. We find this relationship to become stronger.[46]

D.4 Inequality, Growth in Welfare, and Occupational Quality

Figure 22a shows how the growth in uncompensated and compensated earnings varies across earnings deciles. Uncompensated earnings growth is larger for higher deciles. While the shifts in labor demand *raise the mobility* in uncompensated earnings, as discussed in Section 6.1, they also *increase the inequality* in uncompensated earnings. We also find that the contribution of

[46]The linear fit implies that one standard deviation rise in the intrinsic quality is now accompanied by a fall of around 14.2% in the wage rate (from a baseline of 10.3%), corresponding to a rise of over 38% in terms of this proxy for compensating differentials

non-monetary components of work is larger for the median (compared to the average) worker: the growth in earnings in the two measures of compensated earnings $\widetilde{ce}$ and $\overline{ce}$ are 14.8%, 18.0%, and 17.3%, respectively, implying an additional contribution of around 2.5-3.2 percentage points.

The two measures of compensated earnings display distinct patterns. Accounting only for the intrinsic quality of occupations ($\widetilde{ce}$), most additional gains are disproportionately accrued to workers in the lower deciles of earnings. This result is driven by a combination of two factors: *(i)* the change in the intrinsic quality of the occupations chosen by individuals in each decile, and *(ii)* the change in the value attributed to these changes in intrinsic qualities. Figure 22b examines the first factor, showing that the expected intrinsic quality of the occupations chosen by the workers in the middle deciles of earnings sees the highest gains. Comparing Figure 22a and Figure 22b, we infer that workers in the lowest deciles of earnings witness only modest increases in the mean intrinsic quality of their occupations, but attribute substantially larger monetary values to these gains. This measure of compensated earnings suggests that the welfare improvements stemming from the shifts in occupational labor demand have been more equally distributed across workers than is suggested by the uncompensated earnings measures.

Focusing on the compensated measure $\overline{ce}$ tilts the balance even further in favor of workers in the lowest earnings deciles. The growth in $\overline{ce}$ for workers in the highest deciles is even lower than the growth of uncompensated earnings. These workers earn the highest earnings working in occupations with the highest intrinsic qualities. As a result, they become less likely to be swayed by their idiosyncratic tastes toward occupations with lower earnings and intrinsic qualities. In contrast, the overall growth in the earnings among workers in the lowest earnings deciles allows them to additionally become more responsive to their idiosyncratic taste, compared to all other workers. Thus, they gain more in terms of this bundle of compensated earnings.

E Additional Tables

E.1 Occupation Classification

Table 8 lists the 54 occupations we use in our benchmark analysis.

Table 8: Occupation Groups, Baseline

Occ	Description	% children in occ	% parents in occ
1	Executive, Administrative, and Managerial Occupations	10.934	20.250

2	Management Related Occupations	3.494	2.372
3	Architects	0.194	0.237
4	Engineers	1.531	3.494
5	Mathematical and Computer Scientists	1.596	0.970
6	Natural Scientists	0.712	0.733
7	Health Diagnosing Occupations	0.819	1.359
8	Health Assessment and Treating Occupations	2.415	0.410
9	Therapists	0.755	0.194
10	Teachers, Postsecondary	0.863	0.884
11	Teachers, Except Postsecondary	5.823	2.308
12	Librarians, Archivists, and Curators	0.173	–
13	Social Scientists and Urban Planners	0.431	0.022
14	Social, Recreation, and Religious Workers	1.617	0.863
15	Lawyers and Judges	1.035	0.970
16	Writers, Artists, Entertainers, and Athletes	2.286	1.014
17	Health Technologists and Technicians	1.682	0.388
18	Engineering and Related Technologists and Technicians	0.690	1.035
19	Science Technicians	0.216	0.194
20	Technicians, Except Health, Engineering, and Science	1.316	1.121
21	Sales Occupations	9.144	5.844
22	Miscellaneous Administrative Support Occupations	3.235	0.323
23	Computer and Communication Equipment Operators	0.280	0.194
25	Secretaries, Stenographers, and Typists	3.429	0.194
25	Information Clerks	0.669	0.086
26	Records Processing Occupations, Except Financial	0.453	0.518
27	Financial Records Processing Occupations	1.596	0.151
28	Mail Distribution Occupations	0.496	0.712
29	Material Recording, Scheduling, and Distributing Clerks	1.531	1.423
30	Adjusters and Investigators	1.596	0.323
31	Private Household Occupations	0.819	0.151
32	Guards	0.561	0.453
33	Firefighting and Fire Prevention Occupations	0.129	0.582
34	Police and Detectives	1.251	1.596

35	Food Preparation and Service Occupations	5.435	0.474
36	Health Service Occupations	3.062	0.194
37	Cleaning and Building Service Occupations	1.617	2.027
38	Personal Service Occupations	3.451	0.474
39	Farm Operators and Managers	0.604	3.278
40	Farm and Agricultural Occupations, Except Managerial	0.474	1.078
41	Forestry, Logging, Fishing and Hunting Occupations	0.259	0.561
42	Vechicle Mechanics	2.653	4.960
43	Electronic Repairers	0.863	1.466
44	Miscellaneous Repair Occupations	0.496	1.014
45	Construction Trade Occupations	4.011	6.491
46	Extractive Occupations	0.151	0.302
47	Precision Production Supervisors	0.712	2.372
48	Precision Production Workers	1.423	3.429
49	Machine Operators	3.105	7.160
50	Fabricators	1.380	1.639
51	Production Inspectors	0.410	0.518
52	Motor Vehicle Operators	3.105	6.448
53	Non Motor Vehicle Operators	1.790	2.674
54	Freight, Stock and Material Handlers	1.229	2.070

Table 9 reports the 80 occupation groups in the finer occupation classification we use in the robustness exercises.

Table 9: Occupation Groups, Robustness

Occ	Description
1	Executive, Administrative, and Managerial Occupations
2	Management Related Occupations
3	Architects
4	Engineers
5	Mathematical and Computer Scientists
6	Natural Scientists
7	Health Diagnosing Occupations

8	Health Assessment and Treating Occupations
9	Therapists
10	Teachers, Postsecondary
11	Teachers, Except Postsecondary
12	Librarians, Archivists, and Curators
13	Social Scientists and Urban Planners
14	Social, Recreation, and Religious Workers
15	Lawyers and Judges
16	Writers, Artists, Entertainers, and Athletes
17	Health Technologists and Technicians
18	Engineering and Related Technologists and Technicians
19	Science Technicians
20	Technicians, Except Health, Engineering, and Science
21	Supervisors and Proprietors, Sales Occupations
22	Sales Representatives, Finance and Business Services
23	Sales Representatives, Commodities Except Retail
24	Sales Workers, Retail, Personal Services and Sales Related Occupations
25	Supervisors, Administrative Support Occupations
26	Computer Equipment Operators
27	Secretaries, Stenographers, and Typists
28	Information Clerks
29	Records Processing Occupations, Except Financial
30	Financial Records Processing Occupations
31	Duplicating, Mail, and Other Office Machine Operators
32	Communications Equipment Operators
33	Mail and Message Distributing Occupations
34	Material Recording, Scheduling, and Distributing Clerks
35	Adjusters and Investigators
36	Miscellaneous Administrative Support Occupations
37	Private Household Occupations
38	Supervisors, Protective Service Occupations
39	Firefighting and Fire Prevention Occupations
40	Police and Detectives

41	Guards
42	Food Preparation and Service Occupations
43	Health Service Occupations
44	Cleaning and Building Service Occupations, Except Household
45	Personal Appearance Occupations
46	Recreation and Hospitality Occupations
47	Child Care Workers
48	Misc. Personal Care and Service Occupations
49	Farm Operators and Managers
50	Farm and Agricultural Occupations, Except Managerial
51	Forestry and Logging Occupations
52	Fishers, Hunters, and Trappers
53	Supervisors, mechanics and repairers
54	Vehicle and Mobile Equipment Mechanics and Repairers
55	Electrical and Electronic Equipment Repairers
56	Miscellaneous Mechanics and Repairers
57	Supervisors, Construction Occupations
58	Construction Trades, Except Supervisors
59	Extractive Occupations
60	Supervisors, Production Occupations
61	Precision Metal Working Occupations
62	Precision Woodworking Occupations
63	Precision Textile, Apparel, and Furnishings Machine Workers
64	Precision Workers, Assorted Materials
65	Precision Food Production Occupations
66	Plant and System Operators
67	Metalworking and Plastic Working Machine Operators
68	Metal and Plastic Processing Machine Operators
69	Woodworking Machine Operators
70	Printing Machine Operators
71	Textile, Apparel, and Furnishings Machine Operators
72	Machine Operators, Assorted Materials
73	Fabricators, Assemblers, and Hand Working Occupations

74	Production Inspectors, Testers, Samplers, and Weighers
75	Motor Vehicle Operators
76	Rail Transportation Occupations
77	Water Transportation Occupations
78	Material Moving Equipment Operators
79	Helpers, Construction and Extractive Occupations
80	Freight, Stock, and Material Handlers

E.2 Estimated Earnings Function

Table 10 reports the estimated parameters of the earnings function for each occupation.

Table 10: Estimated Earnings Function

Occ	Description	α	κ	θ	δ
1	Executive, Administrative, and Managerial Occupations	7.876	0.203	0.188	0.540
		(0.081)	(0.021)	(0.007)	(0.077)
2	Management Related Occupations	7.704	0.233	0.190	0.549
		(0.078)	(0.023)	(0.007)	(0.080)
3	Architects	7.478	0.241	0.188	0.579
		(0.052)	(0.066)	(0.016)	(0.098)
4	Engineers	7.515	0.251	0.194	0.578
		(0.054)	(0.026)	(0.009)	(0.085)
5	Mathematical and Computer Scientists	7.735	0.194	0.193	0.568
		(0.083)	(0.031)	(0.008)	(0.092)
6	Natural Scientists	7.458	0.272	0.188	0.586
		(0.080)	(0.045)	(0.012)	(0.089)
7	Health Diagnosing Occupations	7.408	0.303	0.183	0.608
		(0.091)	(0.076)	(0.022)	(0.102)
8	Health Assessment and Treating Occupations	7.728	0.244	0.184	0.548
		(0.059)	(0.023)	(0.007)	(0.084)
9	Therapists	7.468	0.281	0.188	0.560
		(0.057)	(0.032)	(0.011)	(0.097)
10	Teachers, Postsecondary	7.352	0.309	0.185	0.561

		(0.076)	(0.059)	(0.014)	(0.093)
11	Teachers, Except Postsecondary	7.428	0.292	0.198	0.497
		(0.079)	(0.017)	(0.010)	(0.046)
12	Librarians, Archivists, and Curators	7.358	0.267	0.189	0.488
		(0.052)	(0.059)	(0.011)	(0.121)
13	Social Scientists and Urban Planners	7.451	0.276	0.186	0.597
		(0.065)	(0.046)	(0.015)	(0.095)
14	Social, Recreation, and Religious Workers	7.428	0.266	0.199	0.473
		(0.059)	(0.022)	(0.009)	(0.074)
15	Lawyers and Judges	7.470	0.283	0.184	0.599
		(0.081)	(0.047)	(0.014)	(0.091)
16	Writers, Artists, Entertainers, and Athletes	7.534	0.233	0.202	0.528
		(0.088)	(0.014)	(0.008)	(0.071)
17	Health Technologists and Technicians	7.806	0.178	0.198	0.486
		(0.060)	(0.028)	(0.009)	(0.100)
18	Engineering and Related Technologists and Technicians	7.811	0.156	0.192	0.566
		(0.076)	(0.042)	(0.015)	(0.094)
19	Science Technicians	7.710	0.157	0.193	0.554
		(0.066)	(0.049)	(0.012)	(0.111)
20	Technicians, Except Health, Engineering, and Science	7.676	0.243	0.183	0.589
		(0.060)	(0.049)	(0.014)	(0.097)
21	Sales Occupations	7.953	0.175	0.192	0.507
		(0.086)	(0.020)	(0.007)	(0.076)
22	Miscellaneous Administrative Support Occupations	7.886	0.156	0.195	0.468
		(0.087)	(0.016)	(0.009)	(0.068)
23	Computer and Communication Equipment Operators	7.863	0.066	0.202	0.489
		(0.096)	(0.076)	(0.019)	(0.099)
24	Secretaries, Stenographers, and Typists	7.909	0.151	0.195	0.457
		(0.068)	(0.015)	(0.006)	(0.069)
25	Information Clerks	7.789	0.147	0.201	0.458
		(0.091)	(0.036)	(0.010)	(0.088)
26	Records Processing Occupations, Except Financial	7.741	0.179	0.193	0.538
		(0.070)	(0.044)	(0.012)	(0.104)

27	Financial Records Processing Occupations	7.857	0.157	0.196	0.482
		(0.057)	(0.024)	(0.010)	(0.089)
28	Mail Distribution Occupations	7.890	0.092	0.202	0.537
		(0.092)	(0.063)	(0.019)	(0.098)
29	Material Recording, Scheduling, and Distributing Clerks	7.920	0.133	0.199	0.463
		(0.062)	(0.023)	(0.012)	(0.090)
30	Adjusters and Investigators	7.883	0.143	0.196	0.495
		(0.066)	(0.023)	(0.007)	(0.091)
31	Private Household Occupations	7.888	0.047	0.203	0.414
		(0.074)	(0.021)	(0.008)	(0.072)
32	Guards	7.816	0.144	0.195	0.535
		(0.088)	(0.041)	(0.015)	(0.098)
33	Firefighting and Fire Prevention Occupations	7.550	0.143	0.205	0.599
		(0.076)	(0.044)	(0.013)	(0.085)
34	Police and Detectives	7.785	0.189	0.191	0.559
		(0.084)	(0.029)	(0.010)	(0.091)
35	Food Preparation and Service Occupations	7.957	0.126	0.200	0.423
		(0.067)	(0.015)	(0.009)	(0.066)
36	Health Service Occupations	7.833	0.146	0.202	0.431
		(0.063)	(0.017)	(0.008)	(0.073)
37	Cleaning and Building Service Occupations	7.932	0.117	0.199	0.477
		(0.072)	(0.027)	(0.012)	(0.087)
38	Personal Service Occupations	7.877	0.147	0.195	0.483
		(0.085)	(0.014)	(0.008)	(0.062)
39	Farm Operators and Managers	7.561	0.205	0.200	0.537
		(0.073)	(0.028)	(0.011)	(0.075)
40	Farm and Agricultural Occupations, Except Managerial	7.868	0.048	0.207	0.464
		(0.082)	(0.029)	(0.015)	(0.084)
41	Forestry, Logging, Fishing and Hunting Occupations	7.539	0.134	0.220	0.573
		(0.051)	(0.019)	(0.010)	(0.058)
42	Vechicle Mechanics	7.931	0.120	0.200	0.486
		(0.075)	(0.019)	(0.010)	(0.092)
43	Electronic Repairers	7.861	0.129	0.196	0.547

		(0.070)	(0.031)	(0.009)	(0.087)
44	Miscellaneous Repair Occupations	7.796	0.113	0.197	0.584
		(0.099)	(0.034)	(0.013)	(0.092)
45	Construction Trade Occupations	7.953	0.114	0.201	0.498
		(0.137)	(0.020)	(0.015)	(0.089)
46	Extractive Occupations	7.520	0.098	0.220	0.594
		(0.074)	(0.022)	(0.011)	(0.062)
47	Precision Production Supervisors	7.771	0.137	0.199	0.555
		(0.074)	(0.016)	(0.007)	(0.081)
48	Precision Production Workers	7.879	0.123	0.199	0.501
		(0.079)	(0.025)	(0.010)	(0.090)
49	Machine Operators	8.041	0.092	0.198	0.463
		(0.078)	(0.023)	(0.011)	(0.089)
50	Fabricators	7.952	0.100	0.201	0.509
		(0.086)	(0.021)	(0.012)	(0.091)
51	Production Inspectors	7.797	0.139	0.196	0.551
		(0.073)	(0.047)	(0.013)	(0.092)
52	Motor Vehicle Operators	8.056	0.085	0.198	0.457
		(0.066)	(0.024)	(0.011)	(0.093)
53	Non Motor Vehicle Operators	7.959	0.097	0.200	0.475
		(0.104)	(0.023)	(0.011)	(0.086)
54	Freight, Stock and Material Handlers	7.953	0.070	0.204	0.500
		(0.108)	(0.033)	(0.015)	(0.074)

Notes: Table entries show the estimated parameters of the earnings function. Standard errors for each parameter, computed based on re-estimating the model for 25 bootstrapped samples, are in the parentheses.