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OCCUPATIONAL CHOICE AND THE INTERGENERATIONAL MOBILITY OF WELFARE

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ABSTRACT

How does parental income shape labor market outcomes? Standard measures of intergenerational mobility typically focus on earnings as the main outcome, but parental income may also influence children's access to more fulfilling careers. Using U.S. survey data, we show that children from higher-income families are significantly more likely to select occupations offering greater non-monetary qualities such as autonomy, intellectual stimulation, and workplace respect. To explain this pattern, we develop and estimate a model where parental resources allow children to prioritize occupational quality over earnings. When we adjust earnings to compensate for the monetary equivalent of these desirable qualities, intergenerational mobility falls by 15–35%, revealing that traditional income-based measures overstate the equality of opportunity. Finally, we document recent labor market shifts toward higher-quality occupations that raise our compensated measure of intergenerational mobility, suggesting structural changes that may have led to more equal distributions of opportunity.

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

1 Introduction

What is the true advantage of being born into a rich family for children's future labor market outcomes? For decades, researchers have focused on how parental income predicts children's future earnings–a classic measure of intergenerational mobility (Black and Devereux, 2011). But the money you earn may not fully capture how your work impacts your career satisfaction, well-being, and overall welfare. Imagine two young adults: one from a affluent background who becomes an academic or an artist, finding deep fulfillment in their work despite modest pay, and another from a less affluent home who, driven by financial necessity, chooses a higher-paying occupation they may find monotonous. This contrast reveals a potentially hidden dimension of inequality: parental income may empower children to choose careers that offer greater non-monetary rewards. Such aspects of one's occupation, which we refer to as its *intrinsic quality*, might be just as important to welfare as one's earnings.[1]

In this paper, we uncover a striking pattern in the U.S. data: children from richer families are significantly more likely to work in occupations with higher intrinsic quality, i.e., those that offer qualities such as greater autonomy, intellectual stimulation, and better physical and social environments. As a result, standard measures of intergenerational mobility overstate how "equal" labor market opportunities truly are. We develop a simple model that explains this pattern through an affordability mechanism. In the model, all else equal, occupations with higher intrinsic quality pay lower wages to compensate for their advantages (Rosen, 1986). The marginal utility cost of these lower wages is smaller for children from wealthy families, as they already receive substantial monetary transfers from their parents. In the resulting equilibrium, these rich children can *afford* to prioritize occupational satisfaction over maximizing income, leading to an invisible form of privilege that traditional mobility measures entirely miss. We estimate the model and use it to construct alternative measures of intergenerational mobility that account for the implicit compensation that workers receive from the quality of their occupations.

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

[1] We adopt this terminology to distinguish 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). We note that 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).

[2] For attempts to organize and classify such indices, see de Bustillo et al. (2011) and Holman (2013). In addition

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 with self-reported job satisfaction when controlling for extrinsic factors such as income and tenure. We project the responses to these questions at 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. This relationship holds conditional on schooling and cohort fixed effects, and robustly appears across different demographic groups in the data as a function of sex, race, schooling group, and cohort of birth.

We highlight two mechanisms to explain this fact. Our main mechanism, the affordability channel, is inherently an income effect and, as already mentioned, 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 qual-

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).

[3] This mechanism is often invoked alongside 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.

ity 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 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 contribution of the idiosyncratic taste shocks for occupations. 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 even lower mobility 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 implications of the trends in the occupational composition of the US labor force over the past three decades (Autor et al., 2006; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Cortes et al., 2017; Jaimovich and Siu, 2020; Cortes et al., 2020). 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).

[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.

Our focus on socioeconomic background and occupational choice relates the paper to Bell et al. (2018), who show the chances to become an inventor vary with parents' socioeconomic class, to 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. (2022), who show that children of more affluent families pursue high-risk and high-return careers. In showing that initial conditions matter for occupational choice and subsequent labor market outcomes, our paper is also related to Luo and Mongey (2019) and Alon et al. (2024), who highlight different margins through which graduating with higher student debt affects the job and occupation choice of graduates and study their the implications in the context of student debt repayment policies.

2 Data and Facts

In this section, we draw on data from the Panel Study of Income Dynamics (PSID), the General Social Survey (GSS), and the National Longitudinal Survey of Youth (NLSY) to provide suggestive evidence that children from richer families are more likely to choose occupations with higher intrinsic quality. We also show that this relationship is robust to several empirical considerations.

2.1 Data

We use data from the PSID and the GSS to establish our main empirical result.[7] Appendix A details our variable construction and sample restrictions. Here, we briefly summarize the data sources and key variables used in the analysis.

PSID. The PSID is a longitudinal survey of a representative sample of approximately 5,000 US households. We employ all survey waves from 1968 to 2015. Our sample reflects the nationally representative core sample and includes 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 most frequently held occupation between age 22 and 55 and consider a classification with 54 occupations, listed in Table 8 in Appendix

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

E. Education is defined as the highest level of education attained. Labor earnings in the cross-section are defined as the average earnings between age 22 and 55 in the most frequently held occupation. Parental income and wealth in the cross-section are also defined as the average of 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 inherited parental wealth.[8]

We use the PSID to study how children's occupational choices vary with parental income. As the only readily available dataset with longitudinal information on occupations and incomes for both parents and children, the PSID is uniquely suited to our analysis. Despite its limited sample size, the PSID is representative of the U.S. population—not only overall, but also with respect to intergenerational mobility. We elaborate on this point in Appendix A.2, where we show that standard measures of intergenerational mobility estimated from the PSID closely match those reported in Chetty et al. (2014b) using administrative data.

GSS. The GSS is a survey that assesses attitudes and behaviors 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 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, as identified in the literature on job quality (e.g., Kohn and Schooler, 1973; Warr, 1990; Hamermesh, 1999; Green, 2006; Kalleberg, 2016). To this end, we select from the GSS a number of survey questions that capture factors highlighted in this literature. In particular, we focus on seven questions 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 *autonomy and control* (variety of tasks, no need to work fast).[9]

We first show that these job characteristics indeed matter for worker well-being. To that end,

[8]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).

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

we examine their association with the self-reported measure of job satisfaction in the survey.[10] We do so by regressing job satisfaction on responses to the questions concerning each characteristic. The regressions control for extrinsic factors, such as log income, an interaction of log income with the characteristic, hours worked, and tenure fixed effects,[11] and are estimated separately for the full sample and for subsamples of respondents with income below and above the median. To make the coefficients comparable across specifications, all variables are standardized.

Figure 1 shows the coefficients for each characteristic and the interaction with income. We make two observations. First, 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 job satisfaction. Second, this pattern does not depend on income, as suggested by 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 similar in the subsamples with income below and above the median.

Having shown that the seven job characteristics reflect worker satisfaction, we next use them to construct a measure of the intrinsic quality of an occupation. We proxy the intrinsic quality of an occupation with the first principal component of the occupation-level variations in these characteristics.[12] To construct this measure, we estimate for each characteristic $d \in \{1, \ldots, 7\}$

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

where $resp_{it}^{d}$ denotes the answer of respondent i in year t to the question about the job characteristic d, $\widetilde{\upsilon}_{j}^{d}$ 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 $\widetilde{\upsilon}_{j}^{d}$. This index loads positively on all job characteristics and explains 51% of the total variance in the seven job characteristics, suggesting that a simple one-dimensional index captures the majority of variation across occupations.[13]

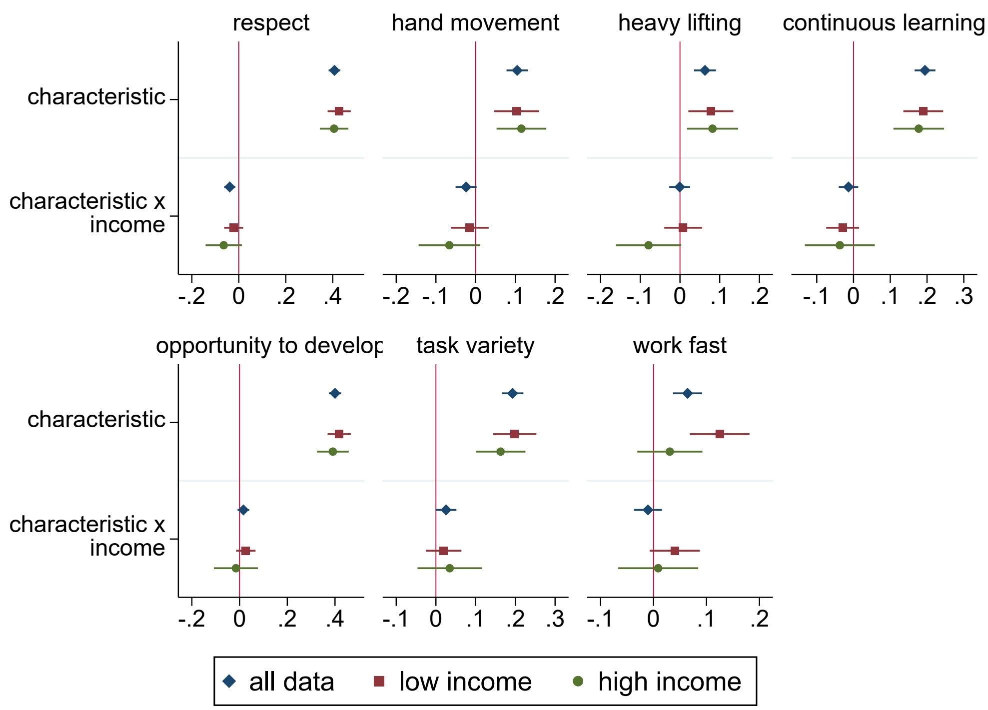
[10]The question is: *"All in all, how satisfied would you say you are with your job?"*

[11]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.

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

[13]See Appendix A.5 for a summary of the results of the principal component analysis.

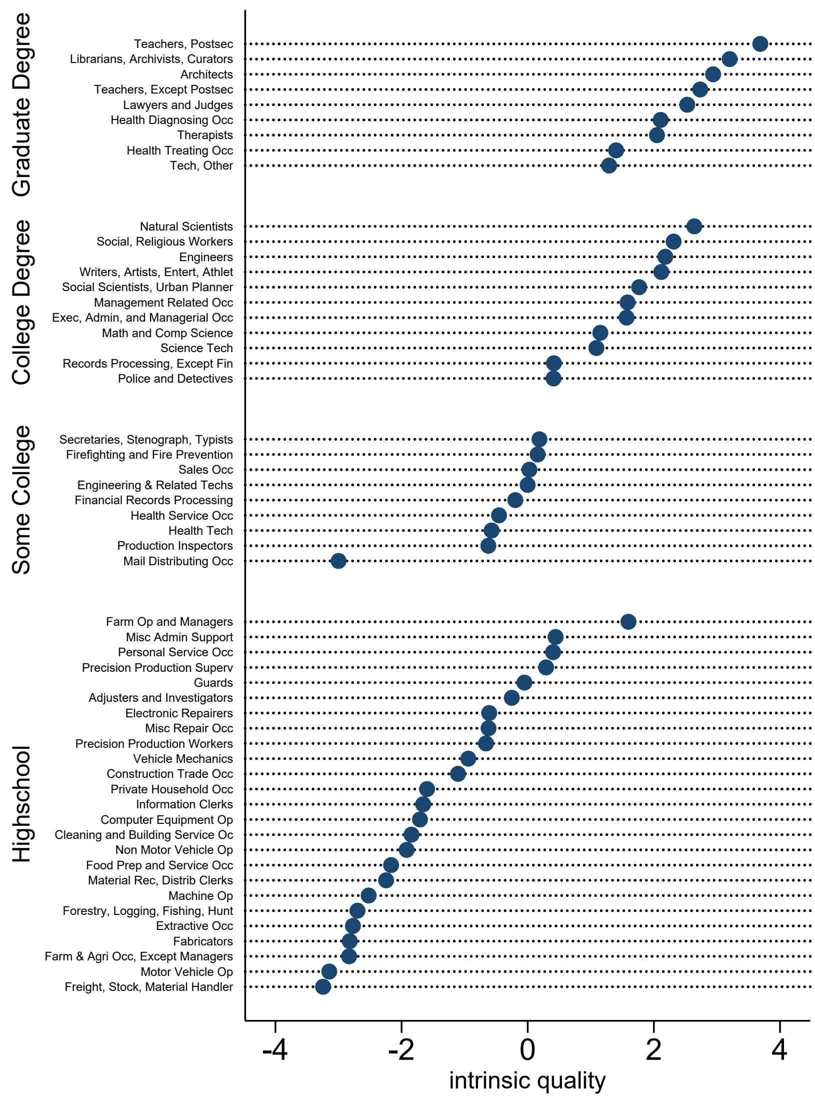
Figure 1: Job Satisfaction and Job Characteristics



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 subsamples with income below median (low income) and above median (high income).

Figure 2 displays the measured intrinsic quality by occupation, sorting occupations by the 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 groups. For instance, among occupations chosen mostly by highschool graduates, those with the lowest intrinsic quality are freight and material handlers and motor vehicle operators, 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, while postsecondary teachers, 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

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 most representative level of education.

measure of job satisfaction in the survey: the correlation is 0.524 (SE=0.118).[14]

[14]In Appendix A.5, we show that the intrinsic quality of occupations correlates with other characteristics of occupations studied in the literature (Autor and Dorn, 2013; Deming, 2017; Kaplan and Schulhofer-Wohl, 2018). Specifically, we find that 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 they also feel more stressed.

2.3 Occupational Choice and Parental Income

We next document that children of richer parents choose careers with higher intrinsic quality and explore potential mechanisms behind this pattern.

2.3.1 Intrinsic Occupation Quality and Parental Income

We begin by showing simple statistics on how parental income relates to the intrinsic quality of the career chosen by children. Figure 3a shows a binscatter plot of the relationship between the intrinsic quality of the child's occupation and parental income (in log scale), 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 intrinsic quality.

Given by the approximately linear relationship observed in Figure 3a, in Figure 3b we summarize the coefficients from regressions of 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 full sample and for subsamples defined by different demographic groups. The coefficient for the full sample is 0.39 (SE=0.03) and is robust across children with different education, sex, race, and cohort groups. These results indicate that the relationship between parental income and children's career choices holds broadly across demographic groups.

2.3.2 Potential Mechanisms

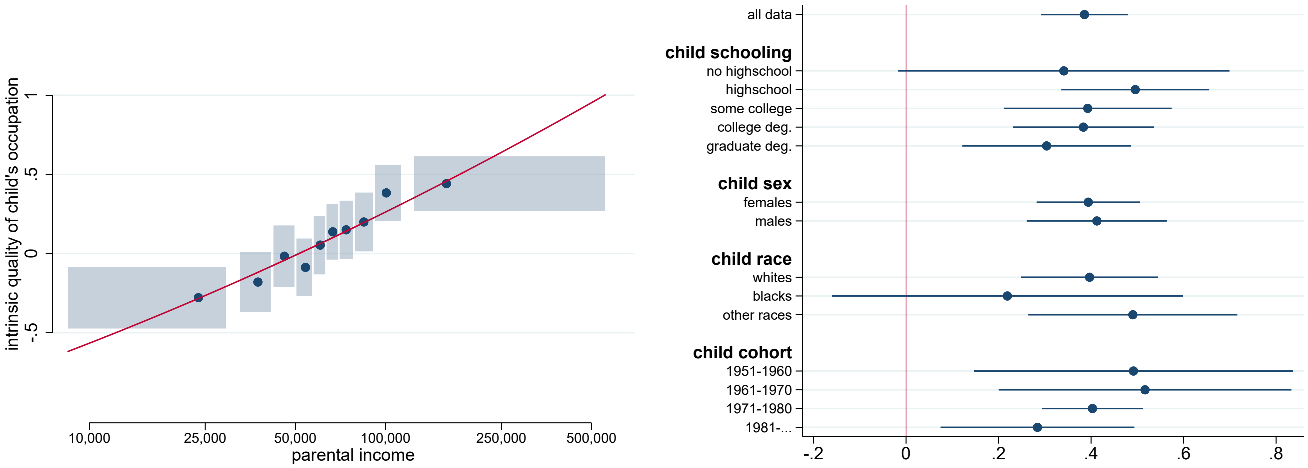
We discuss several potential mechanisms that can give rise to this positive correlation. Our structural model in Section 3 then formalizes some of these mechanisms.

The Affordability Channel Our main mechanism, which we term the *affordability channel*, captures the intuition that the children of rich parents can afford to choose high-intrinsic quality occupations, despite the potentially lower earnings these occupations may offer. If children, on average, value the intrinsic quality of occupations then—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 place less value on this additional monetary compensation and instead sort into occupations with higher intrinsic quality.[15] The affordability channel describes a mechanism through which the inequality of

[15] The logic of the affordability mechanism is fairly similar to the standard income effect on labor supply. Instead of a continuous labor-leisure choice, the affordability effect manifests itself in the discrete choice across

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 the child's years of schooling and birth cohort. Box lengths reflect the number of observations per income bin; box heights reflect confidence intervals. The solid line is a quadratic polynomial fit. Panel (b) plots coefficients on log parental income from linear regressions by demographic group. The dependent variable is the intrinsic quality of the child's occupation, controlling for the child's years of schooling and birth cohort.

opportunity stemming from different economic backgrounds can have consequences on welfare above and beyond those implied by earnings.

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 richer backgrounds might have access to better education, broader professional networks (Kramarz and Skans, 2014), or the opportunity to develop stronger social skills (Deming, 2017; Cortes et al., 2023)—all of which can differentially affect their potential earnings across occupations. If the returns to these attributes are higher precisely in occupations with greater intrinsic quality, we cannot readily interpret the higher likelihood of choosing such occupations as driven by non-monetary attributes.

We use our data to assess the plausibility of the earnings channel. To measure potential earnings across all occupations, we estimate a flexible earnings equation where a child's earnings in each occupation depends on their parent's lifetime income and other covariates (years of

occupations.

schooling, age, gender and race) whose effect is allowed to vary by occupation.[16] We then use this earnings equation to predict the potential earnings that children in our sample would receive in each occupation. If the earnings channel were an important driver of the pattern in Figure 3a, controlling for these potential earnings would substantially reduce the importance of parental income in explaining occupational choice.

To formally 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. Specifically, we estimate logit models in which the probability that a child i chooses occupation $o_i = j$ depends 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 as

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

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

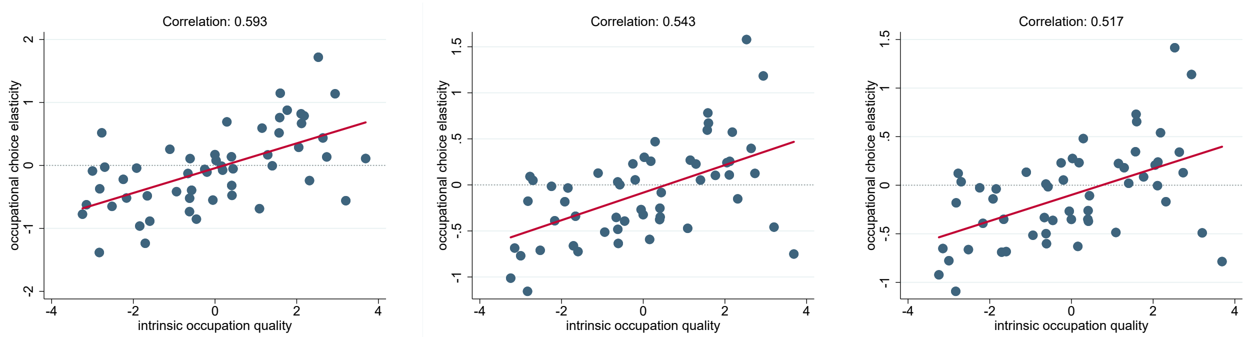
Figures 4a and 4b depict the correlation between the intrinsic quality of occupations and occupational choice elasticities, without and with controls for potential earnings, respectively. We find a large and positive correlation in both cases: 0.59 (SE=0.11) without controls and 0.54 (SE=0.12) with controls. This suggests that even after accounting for the earnings channel, the occupations more likely to be chosen by children from wealthy families also tend to offer greater non-pecuniary rewards. 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 the affordability and earnings channels, there are other mechanisms that could, in principle, drive the relationship between occupational quality and parental income. For instance, the children of rich parents may simply have a stronger preference for high-intrinsic quality occupations. However, Figure 1 shows that this is an unlikely driver of our finding, since the strength of the relationship between various job characteristics and job satistfaction does not depend on income. Moreover, when we measure the intrinsic quality of occupations separately in the GSS subsamples of respondents with income below and above the

[16] See Appendix A.6 for a formal discussion of the specification we estimate. We also experimented with an even more flexible earnings function that includes second-order terms for the continuous covariates and interactions between covariates—again, 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 and the intrinsic quality of occupations. Panel (b) and (c) show the same, but with occupational choice elasticities are estimated controlling for potential earnings in Panel (b), and potential earnings and the occupation of the parent in Panel (c).

median, we find a high correlation between the indices of occupation quality: 0.769 (SE=0.090).

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 preferences for a parent's occupation (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 equal to one if the parent works in that occupation. Figure 4c shows that the correlation between occupational choice elasticities and intrinsic occupational quality remains strong at 0.52 (SE=0.083). The intrinsic quality of occupations still explains 27% of the variation in occupational choice elasticities, compared to 35% in the benchmark. Lastly, as we show in Appendix A.7, intrinsic qualities correlate positively with occupational choice elasticities and continue to explain a sizable share of their variation even after controlling for the degree of earnings risk across occupations.

2.4 Additional Robustness

We report several robustness exercises in Appendix A.8. Figure 10 shows that our findings are robust to *(i)* an alternative intrinsic quality measure based on only five of the job characteristics previously considered, and *(ii)* a finer occupation classification with 80 occupations.

Most importantly, the relationship that we document between parental income and the intrinsic quality of occupations chosen by children is also present in the NLSY data. Figure 11 shows that PSID estimates of occupational choice elasticities correlate positively with those based on the NLSY and Figure 12 shows that our main finding on the association between occupational intrinsic quality and parental income also holds in the NLSY data.

3 Model

We interpret the relationship between parental income and the occupational quality of children through the lens of a dynastic model of occupational choice in which each period features a generation of parents overlaps with one of children. We develop the model in two steps. First, we characterize the occupational choice of a generation of children—this is the core of the model and incorporates the affordability and earnings channels discussed above. Second, we describe the dynamics across generations.

3.1 Occupational Choice Within a Generation

We begin by characterizing the occupational choice of children within a generation. The utility that child i derives from choosing occupation $j \in \{1, \cdots, J\}$ is given by

$$u_{ij} = V\left(y_{ij}^{+}\right) + v_{ij} \tag{2}$$

and is the sum of the value of the cash-on-hand y_{ij}^{+} in occupation j and the non-monetary value v_{ij} of that occupation. Cash-on-hand $y_{ij}^{+} = b_i + e_{ij}$ consists of parental transfers b_i and (lifetime) earnings e_{ij} in occupation j.

We assume the non-monetary value of occupation j is given by

$$v_{ij} = \zeta\, \nu_j + \rho\, \epsilon_{ij}, \tag{3}$$

where ν_j denotes the intrinsic quality of the occupation and ϵ_{ij} is an idiosyncratic taste shock drawn from a zero mean Type-I extreme-value distribution

$$\mathbb{P}_{\epsilon}(\epsilon) = \exp\left(-\exp\left(-\epsilon - \overline{\gamma}\right)\right), \tag{4}$$

where $\overline{\gamma} \equiv \int_{-\infty}^{\infty} u \exp(-u \exp(-u))du$ is the Euler-Mascheroni constant. The parameter ζ determines how much weight children place on intrinsic quality, while ρ governs the dispersion of the taste shocks across occupations. Consistent with the discussion in the previous section, we assume children's preferences over occupations do not directly depend on parental income.

Parental Endowment and Occupational Choice This simple structure generates sharp predictions about how occupational choice varies with parental resources. To illustrate these predictions, let y_i denote the financial resources of child i's parent. For brevity, we refer to y_i as the parental endowment. The distribution of taste shocks implies that the probability that child i chooses occupation j is[17]

$$\mathbb{P}\left(o_i = j\right) \propto \exp\left(\frac{1}{\rho} V\left(b_i + e_{ij}\right) + \frac{\zeta}{\rho}\nu_j\right). \tag{5}$$

To assess the effect of parental endowment on occupational choice, consider two occupations, $j \in \{L, H\}$, where H has higher intrinsic quality than L such that $\Delta\nu \equiv \nu_H - \nu_L > 0$. In order for the child to be indifferent between the two occupations, she demands an additional earning compensation in occupation L to offset the lower intrinsic quality. Equation (5) implies that this *demanded compensation* $d_i \equiv e_{iL} - e_{iH}$ satisfies

$$V\left(b_i + e_{iH} + d_i\right) - V\left(b_i + e_{iH}\right) = \zeta\,\Delta\nu \tag{6}$$

and varies with parental endowment y_i according to

$$\frac{\partial d_i}{\partial y_i} = \left[\frac{V'\left(b_i + e_{iH}\right)}{V'\left(b_i + e_{iH} + d_i\right)} - 1\right]\left(\frac{\partial b_i}{\partial y_i} + \frac{\partial e_{iH}}{\partial y_i}\right). \tag{7}$$

This derivative is positive whenever *(i)* the value function $V(\cdot)$ is concave, and *(ii)* cash-on-hand $y_{iH}^{+} = b_i + e_{iH}$ increases with parental endowment y_i.

Equation (7) illustrates the two potential mechanisms that link parental endowment to occupational quality. The *earnings channel* operates when earnings e_{iH} in high-quality occupations increase with parental endowment. The *affordability channel* operates when parental transfers b_i increase with parental endowment. In both cases, because the marginal value of cash-on-hand is decreasing, children from wealthier families demand more compensation to be equally likely to choose occupations with lower intrinsic quality.[18]

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

[18]The argument relies on the separability between the monetary component and preferences over occupations, but not on the assumption that a child's utility is linear in intrinsic quality. More generally, we can allow for a concave function of intrinsic quality ν_j. We adopt the linear specification for simplicity, as it implies that occupational choice is invariant to uniform shifts in all intrinsic quality values.

3.2 Dynamics Across Generations

We next embed children's occupational choice in an overlapping generations model. The additional components we introduce in this extended framework serve three goals. First, they allow us to endogenize the dependence of parental transfers b_i on parental endowment y_i. Second, they allow occupation-specific wage rates to be determined in general equilibrium, enabling us to study how counterfactual changes in the environment affect occupational choice and mobility. Third, they allow us to account for the potential role of selection based on earnings potential by incorporating unobserved heterogeneity in occupation-specific ability.

Environment Each generation consists of a unit continuum of individuals who live for two periods: childhood and adulthood (parenthood).[19] In adulthood, a parent bears one child and chooses how to allocate her endowment y_i between own consumption c_i and resources provided to the child, either as human capital investment h_i or a direct transfer $b_i \geq 0$.[20] The parent derives utility $\log c_i$ from her own consumption and values the expected future dynastic utility of her child, weighted by an altruism parameters $\beta < 1$, as in Barro (1974).

After the parent chooses human capital investment and direct transfers, three sources of uncertainty about the child's outcomes are realized, and the child then chooses her occupation o_i, as described in Section 3.1. First, the child receives an idiosyncratic human capital shock which determines her observed schooling s_i, drawn from a distribution $\mathbb{P}_s(\cdot|h_i)$ conditional on parental human capital investment. Second, she receives an idiosyncratic talent shock u_i, drawn independently from a distribution $\mathbb{P}_u(\cdot)$. Finally, she draws a J-dimensional vector of taste shocks across occupations, $\boldsymbol{\epsilon} \equiv (\epsilon_j)$, from the distribution $\mathbb{P}_\epsilon(\cdot)$.

The child's earnings e_{ij} in occupation j depend on her occupation-specific ability A_j and the occupation-specific wage rate per efficiency unit w_j. We allow occupation-specific ability to depend on schooling, talent, and parental endowment: $e_{ij} \equiv e_j\left(s_i, u_i, y_i\right) = w_j A_j\left(s_i, u_i, y_i\right)$.[21] The dependence of ability on parental endowment captures the earnings channel discussed above.

[19] Throughout, we focus on stationary equilibria and omit time subscripts to simplify notation.

[20] That $b_i \geq 0$ rules out intergenerational debt markets to finance human capital investment, in line with standard theories of intergenerational mobility (Becker and Tomes, 1986) and recent evidence on how borrowing constraints shape educational attainment (Lochner and Monge-Naranjo, 2012, 2016; Hai and Heckman, 2017).

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

Decision Problems Consider a child with talent u_i, schooling attainment s_i, and taste shocks $\boldsymbol{\epsilon}_i$ who receives parental transfers b_i. As discussed in Section 3.1, her utility in adulthood, after choosing her occupation, is given by

$$V^+ \left(s_i, u_i, \boldsymbol{\epsilon}_i, b_i, y_i\right) \equiv \max_j \; V \left(b_i + e_j \left(s_i, u_i, y_i\right)\right) + \zeta \, \nu_j + \rho \, \epsilon_{ij}. \tag{8}$$

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

$$V\left(y_i\right) \equiv \max_{c,h,b} \log c + \beta \, \mathbb{E}_{s,u} \left[\mathbb{E}_{\boldsymbol{\epsilon}} \left[V^+ \left(s, u, \boldsymbol{\epsilon}, b, y_i\right) | s, u \right] \middle| h \right], \tag{9}$$

$$y_i \geq c + \frac{b}{1+r} + \varphi\left(h\right), \tag{10}$$

where $\varphi(\cdot)$ is a cost function for human capital investment and r is the real interest rate. The parent values the expected utility of the child, defined by Equation (8), and accordingly chooses human capital investment h and transfer b given her 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 as[22]

$$\overline{V}^+ \left(s_i, u_i, y_i\right) \equiv \mathbb{E}_{\boldsymbol{\epsilon}} \left[V^+ | s_i, u_i, y_i \right] = \rho \log \left(\sum_{j=1}^{J} e^{\frac{\zeta \nu_j}{\rho}} \; \exp\left[\tfrac{1}{\rho} V \left(b^* \left(y_i\right) + e_j \left(s_i, u_i, y_i\right)\right) \right] \right), \tag{11}$$

where $b^*\left(\cdot\right)$ is the transfer policy implied by Equation (9).

Technology We endogenize the vector of occupation-specific wages $\boldsymbol{w}$ by assuming that competitive firms operate a Cobb-Douglas production function $Y \equiv K^\chi L^{1-\chi}$ which combines capital K and a composite labor input L. The composite labor input is a CES aggregator of different occupations

$$L \equiv \left(\sum_{j=1}^{J} \Psi_j^{\frac{1}{\psi}} \left(Z_j L_j\right)^{\frac{1-\psi}{\psi}} \right)^{\frac{\psi}{1-\psi}}, \tag{12}$$

where ψ is the elasticity of substitution across occupations, Ψ_j is an occupation-specific demand shifter, Z_j is the productivity of occupation j, and L_j is the total efficiency units of labor employed in occupation j. Labor demand for each occupation j satisfies

[22] See Appendix B.1 for the proof.

$$w_j L_j = (1-\chi)\,Y\,\frac{w_j L_j}{\sum_{j'} w_{j'} L_{j'}} = (1-\chi)\,Y\,\Psi_j \left(\frac{w_j}{Z_j W}\right)^{1-\psi}, \tag{13}$$

where W is the price index associated with the CES aggregator in Equation (12). We assume that the interest rate r is exogenous and equal to the rental rate of capital. Normalizing the price of final output to one implies $1 = \left(\frac{r}{\chi}\right)^{\chi}\left(\frac{W}{1-\chi}\right)^{1-\chi}$.

In addition, we assume the presence of an education sector in which competitive institutions transform final goods into human capital investment services using the production function $h \equiv \varphi^{-1}(x)$. This implies the human capital investment cost function $\varphi(\cdot)$ used in Equation (10).

Equilibrium The stationary equilibrium features a distribution of endowments among the adults in each generation $F_y(y)$. The policy functions $b^*(\cdot)$ and $h^*(\cdot)$, which solve the Bellman equation (9), determine children's conditional occupational choices. As described in Equation (5), the probability that a child with schooling s_i, talent u_i, and parental endowment y_i chooses occupation j is

$$\mu_j(s_i,u_i,y_i) \equiv \mathbb{P}(o_i = j) = \frac{e^{\zeta\nu_j/\rho}\exp\left[\frac{1}{\rho}V\left(b^*(y_i) + w_j A_j(s_i,u_i,y_i)\right)\right]}{\sum_{j'=1}^{J} e^{\zeta\nu_{j'}/\rho}\exp\left[\frac{1}{\rho}V\left(b^*(y_i) + w_{j'} A_{j'}(s_i,u_i,y_i)\right)\right]}. \tag{14}$$

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

$$w_j L_j = \int_0^\infty \mathbb{E}_{s,u}\left[e_j(s,u,y)\,\mu_j(s,u,y)\,|\,h^*(y)\right]\,dF_y(y). \tag{15}$$

Equating this with the labor demand in Equation (13) yields $J-1$ equilibrium conditions on the wage vector $\boldsymbol{w}$. A final condition comes from the wage index $W = (1-\chi)\left(\frac{r}{\chi}\right)^{-\frac{\chi}{1-\chi}}$.

Intergenerational Mobility in Equilibrium The model features three channels through which child earnings depend on parental income.[23] First, if the human capital investment policy $h^*(y)$ is increasing in y, children from wealthier families attain higher levels of schooling. Provided that ability function $A_j(s,u,y)$ is increasing in schooling s, this leads to higher earnings. Second, richer parents may provide advantages beyond schooling, such as social, cognitive, or non-cognitive skills, or access to networks and connections that enhance occupational success. These effects are captured by the dependence of $A_j(s,u,y)$ on parental endowment y, which may

[23] We formalize these in Appendix B.2, where we characterize the conditional distribution of child earnings on parental endowment, $F_e(e|y)$.

increase earnings directly for fixed levels of schooling and talent. Third, parental endowment influences occupational choice through the affordability channel, by determining the size of the direct transfers to children and the resulting impact on the choice probabilities in Equation (14). This, in turn, shapes how children with different levels of schooling and talent sort into occupations with varying returns to these attributes. In Appendix B.3, we provide a graphical account of how the affordability channel shapes equilibrium wage differentials across occupations.

4 Model Estimation

We rely on maximum likelihood estimation to estimate the model, leveraging its analytical characterization of the data-generating process. This section outlines our estimation approach and presents the results.

4.1 Maximum-Likelihood Estimation

A period corresponds to a generation, which we assume spans 30 years. We assign values to two parameters based on existing work: we set the exogenous interest rate r to 2.21% per year, following Kaplan and Violante (2014), and the altruism parameter β to 0.5, a value within the range of existing estimates.[24]

Our PSID sample consists of $4,637$ parent-child observations. For each pair i, we observe the childs's earnings e_i, occupation o_i, and schooling s_i, as well as parental endowment y_i. We classify educational attainment into five groups: no high school degree, high school degree, some college, college degree, and graduate degree. Accordingly, we set $s_i \in \{0, \cdots, 4\}$. The occupations are the 54 groups listed in Table 8 in Appendix E.

Functional Form Assumptions We assume a log-linear specification for the ability function A_j, so that the earnings function takes the form

$$\log e_j(s, u, y) \equiv \log [w_j A_j(s, u, y)] = \alpha_j + \kappa_j s + \theta_j u + \delta_j \log y. \tag{16}$$

The constant term α_j absorbs the logarithm of wage rate per efficiency unit of occupational ability and a constant, occupation-specific shifter in the log ability function A_j. Accordingly, α_j is an endogenous variable in counterfactual experiments. The parameters κ_j and θ_j capture

[24]For example, β is 0.2 in Boar (2020), 0.51 in Nishiyama (2002), and 0.69 in Barczyk and Kredler (2017).

the returns to education and talent in occupation j, respectively, while δ_j accounts for the earnings channel and encompasses all mechanisms through which parental endowment influences occupation-specific ability.

We assume that talent is drawn from a standard normal distribution, $\mathbb{P}(u) = \mathcal{N}(0;1)$, and that schooling attainment conditional on human capital investment is drawn from a truncated and discretized Gaussian distribution

$$\mathbb{P}_{s|h}(s|h) \equiv \frac{\exp\left(-\frac{1}{2}\left(\frac{s-h}{\vartheta}\right)^2\right)}{\sum_{s'=0}^{4}\exp\left(-\frac{1}{2}\left(\frac{s'-h}{\vartheta}\right)^2\right)}. \tag{17}$$

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

Maximum Likelihood Estimation Let $\boldsymbol{\varsigma} \equiv (\rho, \zeta, \vartheta, \boldsymbol{\varphi}, \boldsymbol{\alpha}, \boldsymbol{\kappa}, \boldsymbol{\delta}, \boldsymbol{\theta})$ denote the vector of parameters to be estimated, and let $\boldsymbol{d} \equiv (e_i, o_i, s_i, y_i)_{i=1}^{N}$ denote the data. Using Equation (16), we can infer the unobserved talent of each child given the model parameters as

$$u_i = \mathcal{U}(e_i, o_i, s_i, y_i; \boldsymbol{\varsigma}) \equiv \frac{1}{\theta_{o_i}}\left[\log e_i - \left(\alpha_{o_i} + \kappa_{o_i} s_i + \delta_{o_i} \log y_i\right)\right]. \tag{18}$$

This expression allows us to easily compute the joint probability of data $\boldsymbol{d}$, conditional on parental endowment. Appendix C.1 provides the full expression for the log-likelihood function.

In addition to the benchmark model, we also estimate a version of the model without intrinsic qualities, i.e., setting $\nu_j \equiv 0$ for all occupations. The resulting estimates allow us to contrast the predictions of the benchmark model with those of its no-intrinsic-quality counterpart.

4.2 Estimation Results

Table 1a reports the estimated preference parameters ζ and ρ. The weight ζ on intrinsic quality is positive, indicating that individuals value the non-monetary aspects of work. The low value of ρ implies a high average elasticity of occupational choice with respect to earnings, indicating a large role for earnings differences in driving occupational choices. The table also presents the parameters of the cost function for human capital investment and the standard deviation ϑ of the distribution of schooling attainment conditional on investment. The estimated cost parameters imply a convex monetary cost of parental investment in their children's human capital, consis-

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)
	φ_1	92.6 (4.552)
education cost	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 are the estimated model parameters. Standard errors 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.

tent with the observation that children from wealthier families tend to achieve higher levels of educational attainment. However, the sizable estimate of ϑ reflects substantial heterogeneity in this relationship.

Table 1b reports the correlations between the estimated parameters of the earnings function and the intrinsic quality of occupations.[25] We highlight three key findings: *(i)* occupations with higher intrinsic quality have lower fixed components of earnings and 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, indicating a tradeoff between the fixed components and the return of occupations, and *(iii)* occupations with higher returns to education also show higher returns to talent.

While our maximum likelihood estimation fits the model to full the joint distribution of the observed data, without targeting specific moments, we show in Appendix C.2 that the model successfully reproduces key patterns central to our theory. In particular, consistent with the affordability channel in Equation (7), the transfer policy function $b^*(y)$ is increasing in parental

[25]See Table 10 in Appendix E.2 for the full set of parameter estimates.

endowment y, in line with the existing evidence. Moreover, the magnitude of intergenerational transfers implied by this policy is quantitatively consistent with available estimates. The appendix further shows that the model replicates several moments related to patterns of educational attainment and occupational choice as a function of parental endowment.

In the remainder of this section, we focus on the model's ability to account for the two most important moments of interest: *(i)* the relationship between parental endowment and the intrinsic occupational quality of children discussed in the motivating facts in Section 2.3, and *(ii)* the observed persistence of earnings across generations.

4.3 Parental Endowment and Occupational Choice

We begin by examining the model's predictions for the relationship between children's occupational choice and parental endowment. To that end, we use the structure of the estimated model to compute the expected intrinsic quality for each child in the data as[26]

$$\overline{\nu}_i^+ \equiv \mathbb{E}_{\boldsymbol{\epsilon}}\left[\nu_{o_i}|s_i, u_i, y_i\right] = \sum_j \mathbb{P}\left(o_i = j\right)\, \nu_j, \tag{19}$$

where the unobserved talent u_i is inferred from Equation (18), and the occupational choice probabilities $\mathbb{P}\left(o_i = j\right)$ are given by Equation (14).

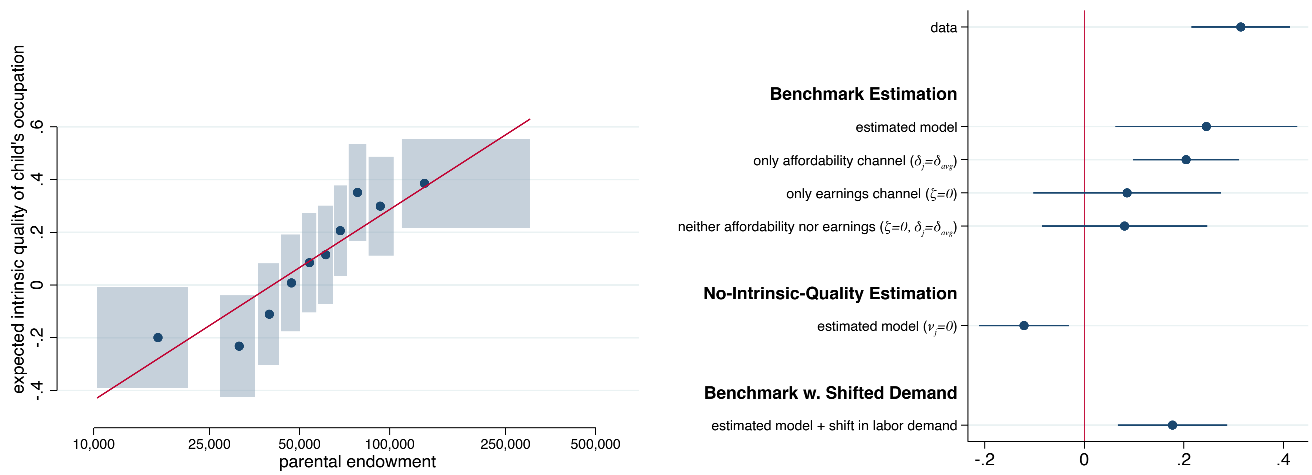
Figure 5a illustrates the relationship between parental endowment and the model-predicted intrinsic quality, controlling for education group fixed effects. We find a positive relationship that closely resembles the pattern observed in actual occupational choices, shown in Figure 3a. As reported in the second row of Figure 5b, a regression of the expected intrinsic occupational quality $\overline{\nu}_i^+$ on log parental endowment y_i (controlling for education group fixed effects) yields a coefficient of 0.25 ($SE = 0.07$), close to the corresponding estimate of 0.31 ($SE = 0.04$) based on observed occupational choices in the data.

The Role of the Affordability and Earnings Channels We next assess how the affordability and earnings channels contribute to this relationship. To isolate the affordability channel, we eliminate cross-occupation variation in the parameters δ_j from Equation (16) by setting them all to the average value accross occupations ($\delta_j \equiv \delta_{avg}$ for all j). This removes the earnings channel. We then recompute expected occupational qualities from Equation (19), adjusting earnings e_{ij} accordingly for each child. Figure 5b shows that removing the earnings channel in this way

[26]We can show that $\overline{\nu}_i^+ \equiv \partial \log \overline{V}_i^+ / \partial \zeta$ where the child's expected utility $\overline{V}_i^+$ is given by Equation (11).

Figure 5: 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 education group fixed effects. Box lengths reflect bin sizes, and box heights indicate confidence intervals. The solid line is a linear fit. Panel (b) plots coefficients on log parental endowment from linear regressions of $\bar{v}_i^+$ on log parental endowment, controlling for education group fixed effects.

only mildly attenuates the relationship between occupational quality and parental endowment, yielding a coefficient of 0.20 ($SE = 0.04$) on log parental endowment.

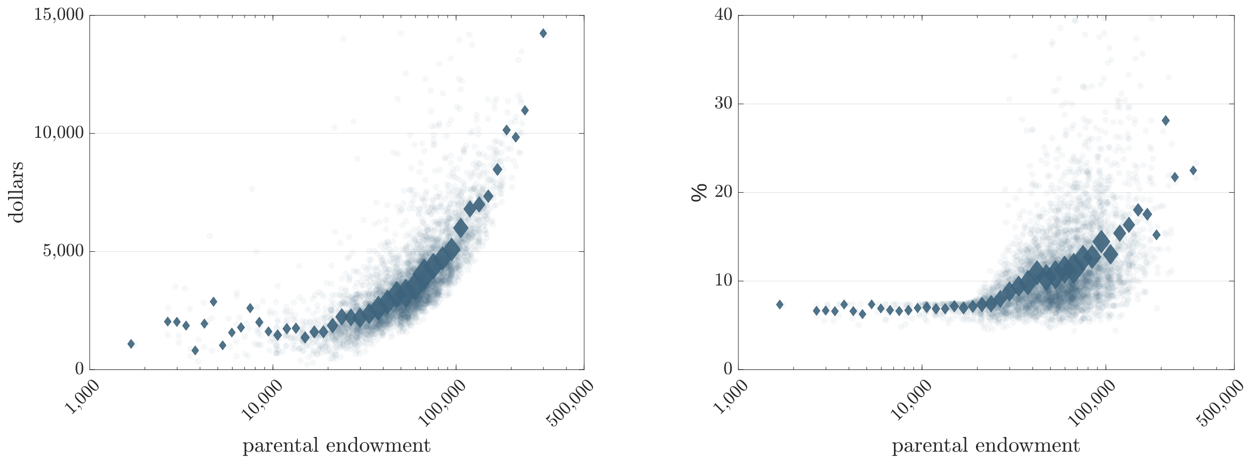
To isolate the earnings channel, we instead remove preferences for intrinsic quality by setting $\zeta = 0$. Figure 5b shows that removing the affordability channel substantially weakens the relation between expected occupational quality and parental endowment, reducing the coefficient on log parental endowment to 0.09 ($SE = 0.07$). This estimate is only slightly larger than that from a version of the model with both channels removed ($\zeta = 0$ and $\delta_j \equiv \delta_{avg}$ for all j), which yields a coefficient of 0.08 ($SE = 0.06$). Neither estimate is statistically significant. Figure 5b further shows that the model estimated without preferences for occupational quality actually implies a negative relationship between occupational quality and parental endowment.

We thus conclude that the affordability channel accounts for most of the relationship between occupational quality and parental endowment predicted by the estimated model.

Demanded Compensation We further illustrate the workings of the affordability channel by building on the concept of demanded compensation introduced in Section 3.1 and computing for each child i in the PSID the compensation d_i required to make the child indifferent between their current occupation and one with intrinsic quality that is $\Delta\nu$ lower. Specifically, d_i solves

Figure 6: 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 one with 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 percentage of the life-time earnings of the child 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.

$$V\left(b^*\left(y_i\right)+e_i+d_i\right)-V\left(b^*\left(y_i\right)+e_i\right)=\zeta\Delta\nu, \tag{20}$$

where $\Delta\nu$ is set equal to the difference between the 75^{th} and 25^{th} percentiles of the intrinsic quality distribution. Figure 6 shows that, consistent with the theory in Section 3.1, the required compensation increases with parental endowment. On average, it represents about 10% of the (lifetime) earnings of the child in the most densely populated region of the parental endowment distribution, and rises to as much as 25% of earnings for children from wealthy families.[27]

4.4 Intergenerational Mobility of Earnings

We next examine the degree of intergenerational mobility implied by the model. In addition to the 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 s_i and the inferred talent u_i of each child in the data to compute expected occupational quality. To

[27]In Appendix D.2, we quantify equilibrium compensating differentials as a function of occupational intrinsic quality. We show that the model predicts sizable differentials both at the micro level—in terms of earnings across occupations most likely to be considered by each individual—and at the macro level—in terms of equilibrium wage rates across all occupations.

Table 2: Intergenerational Mobility of Earnings

	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: Model moments are averages over 10,000 simulated samples. Standard deviations across samples are in parentheses. In each sample, we re-draw schooling attainment, occupational choice, and earnings for each child.

further incorporate the model-predicted heterogeneity in schooling and talent in our analysis, we take the following strategy. For each 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 $\mathbb{P}(u)$. We then re-draw educational attainment s_i, occupational choice o_i, and earnings e_i for each child based on the conditional distribution implied by the model. We generate 10,000 instances of such re-sampled datasets and study indices of intergenerational mobility averaged across these datasets.[28]

Table 2 compares several measures of intergenerational mobility in the model and in the data. The first is the intergenerational elasticity of earnings, defined as the slope coefficient from a regression of log child earnings on log parental endowment (Black and Devereux, 2011). The second is the rank-rank slope, obtained by regressing the child's rank in the earnings distribution $r_{e,i} \in [0,1]$ on the parent's rank in the endowment distribution $r_{y,i} \in [0,1]$. The third is the share of children who exceed their parents' decile in the respective distributions. The fourth is the covariance between log child earnings and log parental endowment. As the table shows, the model, despite its parsimony, reproduces between 72% and 100% of the intergenerational persistence observed in the data. In Appendix C.3, we further explore the mechanisms driving earnings persistence in the model.

[28] In Appendix D.1, we confirm that this alternative approach leads to similar conclusions about the model's predictions for the relationship between intrinsic quality and parental endowment as in Section 4.3.

5 The Intergenerational Mobility of Welfare

In this section, we examine the model's implications for the intergenerational mobility of welfare, using welfare proxies that capture not only monetary compensation for work in the form of earnings, but also non-monetary, welfare-relevant rewards such as the intrinsic quality of occupations and the idiosyncratic taste for occupations.

5.1 Compensated Earnings and Welfare

We first describe how we construct these welfare proxies. The most comprehensive measure of welfare in the model is V^+, defined in Equation (8), which accounts for both the monetary and non-monetary components of welfare. To compare the mobility of welfare with standard measures based solely on monetary outcomes (e.g. earnings), we convert V^+ into a money-metric equivalent using the concept of *compensating variation*, i.e., the amount of money required to make an individual indifferent across occupations that differ in non-monetary attributes. A challenge in this conversion is that while we observe the intrinsic quality of occupations, the idiosyncratic occupation-specific taste shocks—also part of the non-monetary component of welfare—are unobserved.

We address this challenge with two alternative strategies. The first relies on computing the expected welfare, defined as $\overline{V}_i^+ \equiv \mathbb{E}_{\boldsymbol{\epsilon}}\left[V^+|e_i, o_i, s_i, y_i\right]$. In doing so, we exploit the fact that, conditional on parental endowment y_i, talent u_i, schooling s_i, and occupation o_i, the cumulative distribution function of V^+ is given by[29]

$$F_v\left(v^+|s_i, u_i, y_i\right) \equiv \mathbb{P}\left(V^+ < v^+|s_i, u_i, y_i, o_i\right) = \exp\left[-\exp\left(-\frac{v^+ - \overline{V}^+(s_i, u_i, y_i)}{\rho} - \overline{\gamma}\right)\right], \quad (21)$$

and therefore does not vary in realized occupation o_i. This implies that, conditional on (s_i, u_i, y_i), the remaining variation in welfare that stems from idiosyncratic taste shocks is identically distributed across individuals. In other words, knowing schooling, talent, and parental endowment for a child in the data, we can characterize their welfare subject to an additional shock that has the same distribution regardless of the occupation they choose. Since schooling s_i and parental endowment y_i are readily observed and, as discussed above, talent u_i can be inferred from Equation (18), we can compute the expected welfare $\overline{V}_i^+$ for each child i in the data by evaluating Equation (11) at (s_i, u_i, y_i).

[29] See Lemma 3 in Appendix B.1.

In the second strategy, we simply abstract from the idiosyncratic taste shock and compute

$$\widetilde{V}_i^{+} \equiv V\left(b^*(y_i) + e_i\right) + \zeta\, \nu_{o_i}, \tag{22}$$

which combines the value of monetary compensation with the intrinsic quality of the chosen occupation.[30] We note that $\overline{V}_i^{+} - \widetilde{V}_i^{+} \equiv \rho \mathbb{E}_{\boldsymbol{\epsilon}}\left[\epsilon_{o_i} | e_i, o_i, s_i, y_i\right]$, so the difference between two measures allows us to separately quantify the contribution of intrinsic quality versus taste shocks to welfare.

We express these welfare measures in monetary terms using the concept of compensating variation. We conduct a thought experiment in which each child i is hypothetically reassigned from their occupation o_i to a benchmark occupation—specifically, the one with the lowest intrinsic quality $\underline{\nu}$—and compute the additional earnings required to make them indifferent between the two occupations. For the expected welfare measure $\overline{V}_i^{+}$, the required compensation $\overline{d}_i$ satisfies

$$V\left(b^*\left(y_i\right) + e_i + \overline{d}_i\right) + \zeta \underline{\nu} = \overline{V}_i^{+}, \tag{23}$$

assuming no additional taste shock in the benchmark occupation. Similarly, for the welfare measure $\widetilde{V}_i^{+}$, the required compensation $\widetilde{d}_i$ is defined by

$$V\left(b^*\left(y_i\right) + e_i + \widetilde{d}_i\right) - V\left(b^*\left(y_i\right) + e_i\right) = \zeta\left(\nu_{o_i} - \underline{\nu}\right). \tag{24}$$

In both cases, the compensation reflects the income equivalent of the loss in intrinsic occupational quality. We then define *compensated earnings* $\overline{ce}_i$ and $\widetilde{ce}_i$ as

$$\overline{ce}_i \equiv e_i + \overline{d}_i \qquad \text{and} \qquad \widetilde{ce}_i \equiv e_i + \widetilde{d}_i, \tag{25}$$

which serve as money-metric proxies for welfare that incorporate both the monetary and non-monetary value of work.

5.2 Mobility of Compensated Earnings

The approach outlined above allows us to compute the compensated earnings for each child in the data, given their observed (uncompensated) earnings, schooling attainment, occupational choice, and parental endowment. We then assign ranks $r_{\overline{ce},i}$ and $r_{\widetilde{ce},i} \in [0, 1]$ within the respective distributions of compensated earnings, and estimate rank-rank slopes between parental endowment

[30] The two measures are highly correlated: regressing $\widetilde{V}_i^{+}$ on $\overline{V}_i^{+}$ yields a coefficient of 0.9995 ($SE = 0.001$).

and both realized and compensated earnings as our measures of intergenerational mobility.

The first row of Table 3 summarizes these rank-rank slopes and shows that accounting for the non-monetary value of work reduces intergenerational mobility relative to what is implied by earnings alone. More specifically, the rank-rank slope between parental endowment and compensated earnings $\widetilde{ce}$ ($\overline{ce}$) is 16% (35%) larger than the slope based on realized earnings.[31] The fact that $\overline{ce}$, which incorporates both intrinsic quality and idiosyncratic taste, implies less mobility than $\widetilde{ce}$, which captures only intrinsic quality, has an important implication: children from wealthier families not only sort into higher-quality occupations, but *also benefit from being able to choose occupations that better reflect their idiosyncratic taste.* Overall, our results suggest that failing to account for differences in worklife quality across occupations leads to an overstatement of the degree of intergenerational mobility in opportunity and welfare.

The next three rows in Table 3 report statistics of intergenerational mobility when we do not treat schooling, talent, occupational choice and earnings as fixed in the data, but instead re-draw them from the model-implied distribution conditional on parental endowment, as described in Section 4.4.[32] We do this for the estimated benchmark model, as well as for two alternative specifications: *(i)* the model estimated without intrinsic qualities, and *(ii)* the benchmark model with intrinsic qualities removed post-estimation. As the second row of the table shows—and consistent with the results based on observed data—the benchmark model predicts the highest mobility in terms of uncompensated earnings and the lowest in terms of the compensated measure that accounts for both intrinsic qualities and taste shocks. In both models without variation in intrinsic quality, mobility in uncompensated earnings is slightly lower than in the data. More importantly, in the benchmark model, mobility declines when we account for intrinsic quality via the compensated measure $\widetilde{ce}$. By construction, the models without intrinsic qualities yield identical predictions for uncompensated earnings and $\widetilde{ce}$, and thus imply no difference between the two. Finally, in all models, mobility is lowest when using the fully compensated measure $\overline{ce}$, which also incorporates idiosyncratic taste shocks.

[31] If, instead, we set the common benchmark occupation to the 25^{th} percentile of the intrinsic quality distribution, we obtain $r_{\widetilde{ce}} = 0.39$ and $r_{\overline{ce}} = 0.47$, implying that the intergenerational mobility of compensated earnings is 8% and 31% lower, respectively, than that of realized earnings.

[32] These measures serve as benchmarks for evaluating mobility in counterfactual environments, as in Section 6, accounting for the model's endogenous responses in schooling and occupational choice.

Table 3: Mobility of Uncompensated and Compensated Earnings

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

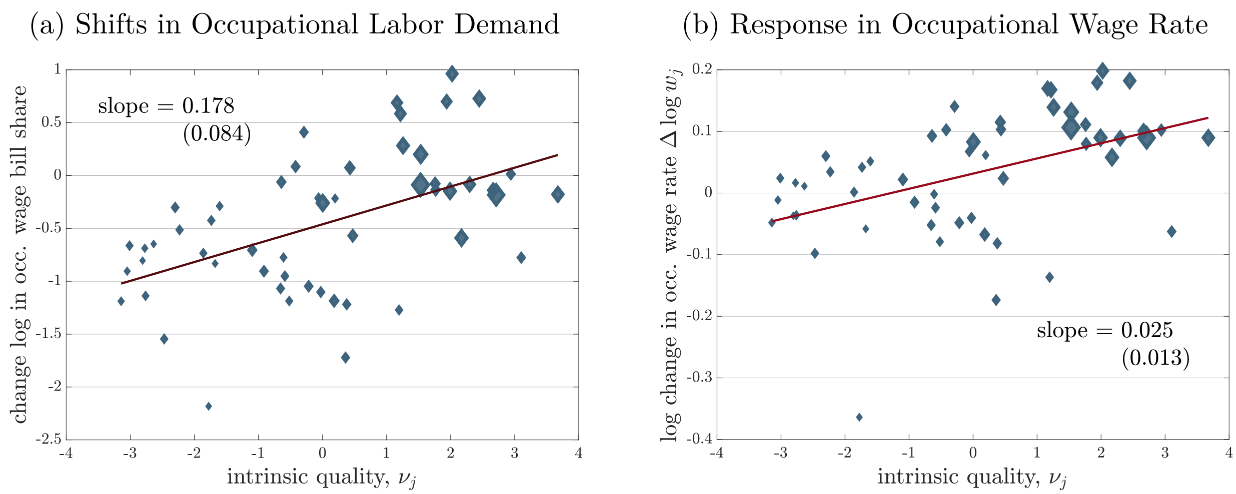
6 Trends in Occupational Labor Demand

Motivated by a large literature that documented substantial changes in occupational composition of the US labor force over the past three decades (Autor et al., 2006; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Cortes et al., 2017; Jaimovich and Siu, 2020; Cortes et al., 2020), in this section, we use our model to study the effects of these changes on workers' welfare, focusing on intergenerational mobility, inequality, and earnings growth.

6.1 Changing Labor Demand and Intrinsic Quality

We first document that the composition of the labor force has shifted towards occupations with higher intrinsic quality. Following the above mentioned 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 wage bill share over the past three decades. In our calculations, we restrict attention to workers aged 16 to 64 and compute, for each occupation, the average

Figure 7: Shifts in Occupational Labor Demand



Notes: Panel (a) plots the change in the log occupational wage bill shares from the 1980–1985 average to the 2010–2015 average against occupational intrinsic qualities ν_j. Panel (b) plots the prediction of the model for the change in the log occupational wage rates $\alpha_j^d - \alpha_j$ against intrinsic qualities ν_j.

wage bill share between 1980–1985 and 2010–2015.[33] Figure 7a shows a substantial rise in the share of occupations with high intrinsic quality: the slope of the linear fit suggests that a one standard deviation increase in intrinsic quality is associated with a roughly 40% increase in wage bill share.

6.2 Effect on Equilibrium Wages

Before examining the implications of these trends for worker welfare, we first analyze their impact on equilibrium wages. Understanding how the wage structure responds in general equilibrium is crucial, as it shapes patterns of occupational sorting and ultimately determines welfare outcomes. To this end, we consider a change in occupational wage bill shares that mirrors the shift observed in the data from the 1980s to the 2010s, along with a 17.2% increase in the total wage bill, $\sum_j w_j L_j$, as reported by the Bureau of Labor Statistics (BLS) over the same period. We assume this change stems from a shift in the fixed components of the earnings function.[34] We then use the labor market clearing condition in Equation (15) to recover a new vector of fixed components, $\boldsymbol{\alpha}^d$, which determine the new occupational wage rates w_j.

Figure 7b illustrates how occupational wages respond to shifts in labor demand by plotting

[33] 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.

[34] Such a shift could equivalently reflect changes in occupational technologies Z_{jt} or demand shifters Ψ_{jt}.

the change in occupational wage rates relative to the benchmark, $\alpha_j^d - \alpha_j$, against the intrinsic quality of occupations, ν_j. The model predicts that the increased demand for high-intrinsic-quality occupations leads to higher wages in those occupations: the linear fit implies that a one standard deviation increase in intrinsic quality is associated with a wage increase of approximately 4.7%. Additionally, the average wage rate rises by about 2.5%, reflecting the component of labor demand shift that captures the growth in average earnings.

The endogenous response of wages in the model reflects general equilibrium adjustments in both labor demand and supply. Here, changes in labor supply are partly driven by changes in demanded compensation. Appendix B.3 provides a simple graphical illustration of the intuition behind the response of demanded compensation to shocks in occupational labor demand. Furthermore, in Appendix D.3, we use the estimated model to illustrate the quantitative size of the rise demanded compensation in response to the labor demand shock, as higher mean earnings make high-quality occupations more affordable, especially for children from poorer families, whose monetary resources depend more heavily on their own earnings.

6.3 Effect on Occupational Choice and Intergenerational Mobility

We next examine the effect of shifts in occupational labor demand on the relationship between parental endowment and children's occupational choices, as well as on intergenerational mobility. We follow the same strategy as in Section 4.3: we compute the expected occupational quality for each individual using Equation (19) and regress it on on log parental endowment, controlling for education group fixed effects. We find an estimated coefficient of 0.18 ($SE = 0.04$), suggesting a weaker relationship between children's occupational quality and parental endowment as a result of the shifts in labor demand (see the last row of Figure 5b).[35] Interestingly, this finding appears consistent with the gradual decline in the corresponding regression coefficient for later birth cohorts in the data, as shown in Figure 3b.

Turning to intergenerational mobility, the last row of Table 3 shows the rank-rank slope of a child's earnings on parental endowment in the new environment. We find that the intergenerational mobility of realized earnings rises relative to the benchmark model. The main driver of this increase is the rise in the expected returns to schooling, as children of poorer parents shift into high-intrinsic-quality occupations that also offer higher returns to schooling κ.[36]

[35] In Appendix D.1 we show that this result is robust to re-sampling schooling and talent based on the conditional probabilities implied by the model.

[36] See Appendix C.3.2 for a more detailed discussion and Table 1b for the correlation between returns to schooling and intrinsic quality.

The mobility of welfare, as proxied by compensated earnings $\widetilde{ce}_i$ and $\overline{ce}_i$, also increases. To understand why, let us consider the case of $\widetilde{ce}_i$. Two distinct forces shape the contribution of the compensation $\widetilde{d}_i$, defined in Equation (24), to intergenerational mobility in terms of $\widetilde{ce}_i$: *(i)* the dependence of occupational intrinsic quality ν_{o_i} on parental endowment y_i, and *(ii)* the dependence of cash-on-hand $b^*(y_i) + e_i$ on parental endowment. Both components exhibit a weakening of the intergenerational link: the former as shown in the last row of Figure 5b, and the latter as shown in Table 3. Together, these forces lead to an increase in the mobility of welfare: children of poorer parents move into occupations with higher intrinsic quality, and the value they place on this quality increases as they become relatively richer. The overall effect is a decline in the correlation between compensation $\widetilde{d}_i$ and parental endowment y_i, which drives the patterns in Table 3. This logic extends to the case of $\overline{ce}_i$.

6.4 Growth in Compensated Earnings

As shown above, the trends in labor demand have led to both an increase in earnings and a reallocation of workers towards occupations with high intrinsic quality. Since workers value this rise in occupational quality in ways that are not captured by earnings alone, the observed increase in earnings likely understates the full welfare gains associated with these changes. We therefore use our model to compute the growth rate in compensated earnings, which incorporate the welfare contributions of both intrinsic occupational quality and idiosyncratic taste.

To that end, we define a measure of average compensated earnings for each of the two measures introduced in Section 5.1 as

$$\mathbb{E}\left[ce\right] \equiv \sum_j \int_0^\infty \mathbb{E}_{s,u}\left[\left(e_j\left(s,u,y\right) + d_j\left(s,u,y\right)\right)\mu_j\left(s,u,y\right) \mid h^*(y)\right] dF_y\left(y\right), \tag{26}$$

where $d_j\left(s,u,y\right)$ either satisfies either Equation (24) or Equation (23). As before, in the first case, individuals are compensated only for the intrinsic quality of their occupation; in the second, the compensation additionally reflects the expected value of their idiosyncratic taste shock. We compute the growth in average compensated earnings when moving from the benchmark to the equilibrium with shifted labor demand, and compare it to the growth in average earnings, $\mathbb{E}\left[e\right] \equiv \sum_j w_j L_j$.

The growth in the average earnings from shifting labor demand is 17.1%. The corresponding growth in compensated earnings, $\mathbb{E}\left[\widetilde{ce}\right]$ and $\mathbb{E}\left[\overline{ce}\right]$, is 19.2% and 17.7%, respectively. Therefore, accounting for the role of taste for occupations *raises* our estimates of growth by 0.6 to 2.1 percentage points over a baseline of around 17 percentage points, or by approximately 4 to 12 percent of the measured growth. The intuition for this upward correction is straightforward: the labor market has shifted labor toward occupations that workers enjoy more. As a result, a larger share of worker compensation now comes from the intrinsic quality of work, meaning that ignoring these non-monetary components leads to an underestimation of welfare gains if one relies solely on observed earnings.

In Appendix D.4, we show that the small size of the gap between the growth of uncompensated and compensated earnings masks masks substantial heterogeneity across the earnings distribution. In particular, we find that compensated earnings grow significantly more than uncompensated earnings in the lower quantiles of the earnings distribution. Whereas growth in uncompensated earnings is skewed toward high-earning groups, growth in compensated earnings is more evenly distributed across the income spectrum. We thus conclude that accounting for the welfare contributions of intrinsic occupational quality and the resulting shifts in occupational composition has an *equalizing effect* on measured 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 higher intrinsic quality. We define intrinsic quality as a welfare-relevant attribute of occupations that goes beyond earnings, proxied by the first principal component of a bundle of job amenities valued by workers and implicitly priced through compensating differentials. We find a robust positive correlation between parental income and intrinsic occupational quality—consistent across datasets, occupation classifications, and alternative measures of quality. This correlation may reflect either the fact that rich children can afford to pursue high-quality occupations (the affordability channel), or that they earn more in those occupations (the earnings channel).

To interpret these facts and explore their implications, we develop and estimate a quantitative model of intergenerational mobility and occupational choice. The model predicts that the affordability channel accounts for most of the observed relationship. Under standard assumptions on preferences, the marginal value of income is lower for children of rich parents, who receive larger transfers. As a result, they require greater compensation to accept low-quality occupations.

We use the model to assign a monetary value to intrinsic occupational quality and revisit standard measures of intergenerational mobility. Incorporating this non-monetary component reveals substantially lower mobility across generations, suggesting that conventional measures based solely on earnings overstate the extent of opportunity.

Finally, we examine how recent shifts in occupational labor demand have affect earnings, welfare, and intergenerational mobility. We find that earnings growth is accompanied by even greater growth in welfare, as a larger share of compensation reflects intrinsic occupational quality. Welfare gains are more evenly distributed than earnings gains. Moreover, intergenerational mobility increases for both earnings and welfare.

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Appendix For Online Publication

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 the 54 occupations 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 groups 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 and other variables. First, earnings and all other nominal variables are expressed in 1996 US dollars. Second, earnings of the parent refer to the sum between the earnings of the father and 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. Income is the sum of taxable income, transfers and social security income of all members of the family. 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 since income includes labor earnings. 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.

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 $k = 1, \ldots, 5$. 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

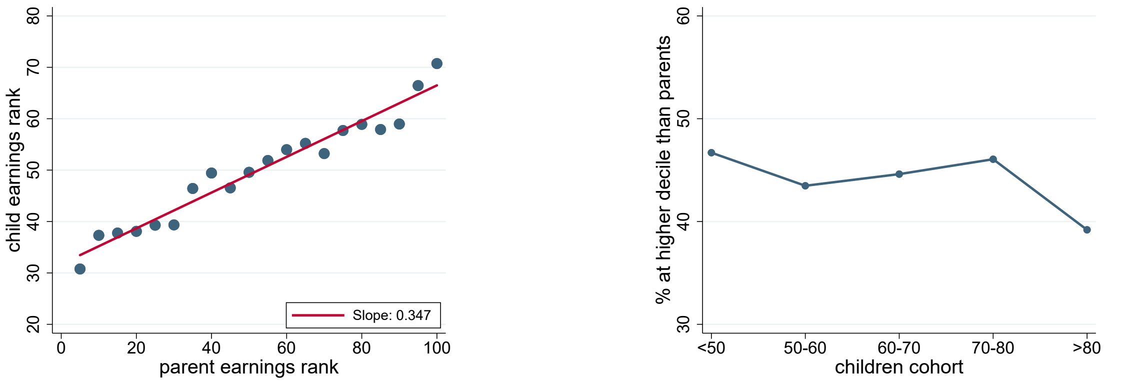
We revisit the patterns of intergenerational mobility using the PSID data and compare our results with those reported by Chetty et al. (2014a) using de-identified federal income tax records to establish that the PSID is suitable for the study of intergenerational mobility. We consider two measures of intergenerational mobility. The first is the *rank-rank slope*: the slope of a regression of the child's rank in the earnings distribution on the rank 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. 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. The second is 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 declining over time, consistent with Chetty et al. (2014a) and Chetty et al. (2017). Figure 8a and Figure 8b below offer a depiction of these statistics.

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

Figure 8: 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 parent earnings bins for 20 bins. Panel (b) plots the fraction of children who are in a higher decile of the lifetime earnings distribution than their parents, by birth cohort.

and 4,000 respondents. We use seven questions from the Quality of Working Life module, administered in 2002, 2006, 2010 and 2014. These 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 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. We obtain earnings in the cross-section by averaging earnings in the most frequently held occupation.

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 and 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

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

remains unexplained in each characteristic.

A.5.2 Intrinsic Quality and Other Occupational Characteristics

Figure 9b 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.

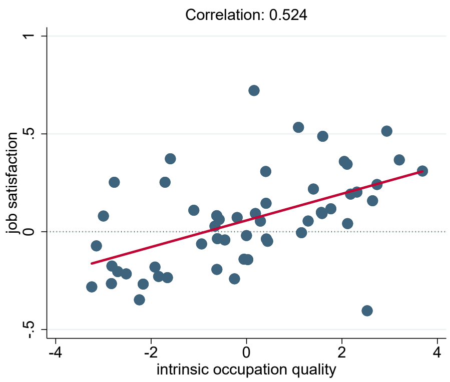
A.6 Estimating Potential Earnings

We estimate the following specification

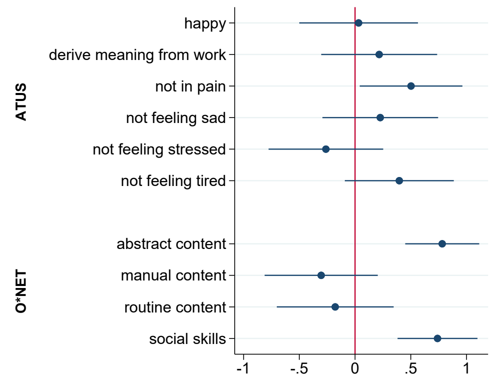
$$\ln e_{ij} = \alpha_{1j} \ln \bar{y}_i + \tilde{\boldsymbol{X}}'_i \boldsymbol{\alpha}_j + \delta_j + \epsilon_{ij},$$

Figure 9: Intrinsic Quality of Occupations and Other Occupation Characteristics

(a) Job Satisfaction



(b) Other Characteristics of Occupations



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

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 the role of earnings risk. Column (1) reports results from regressing occupational choice elasticities on the intrinsic qualities of occupations. Columns (2) and (3) add a control for the coefficient of variation of log earnings, measured as the ratio between standard deviation and average log earnings by occupation. In column (2) the latter 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) it is is calculated controlling for age (16-25, 26-35, 36-45, 46-55, 56-64), sex, race (white, Black, other) and year.

A.8 Additional Robustness Exercises

Figure 10 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

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

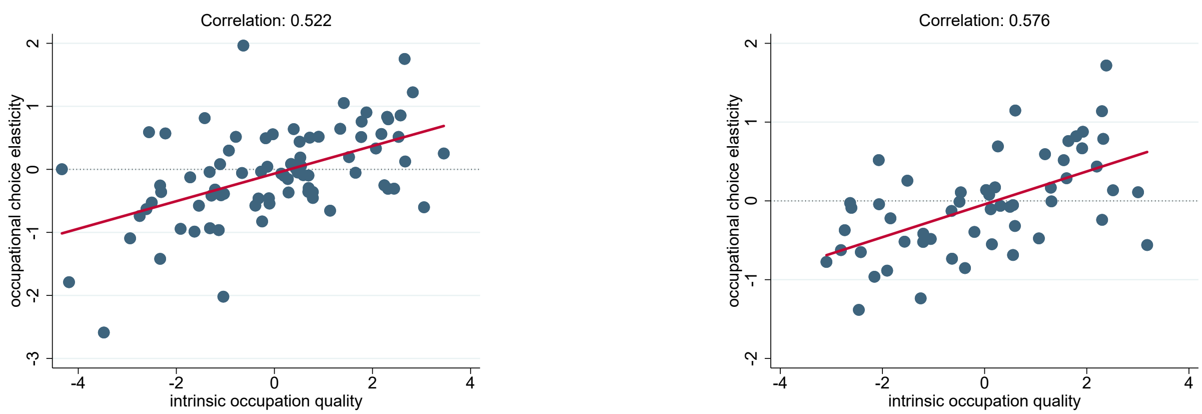
	(1)	(2)	(3)
Intrinsic quality, ν	0.197	0.183	0.188
	(0.037)	(0.038)	(0.039)
Coeff. of variation log earnings		-3.101	-2.570
		(2.383)	(3.396)
Constant	-0.043	0.183	0.319
	(0.069)	(0.307)	(0.286)
Controls	–	No	Yes
R^2	0.352	0.372	0.359

Notes: The table shows the results from regressing occupational choice elasticities on intrisic quality (column 1) and on the coef. of variation of log earnings by occupation (columns 2 and 3).

Figure 10: Occupational Choice Elasticities and The Intrinsic Quality of Occupations, Robustness

(a) Alternative Occupation Classification

(b) PCA 5 Job Characteristics



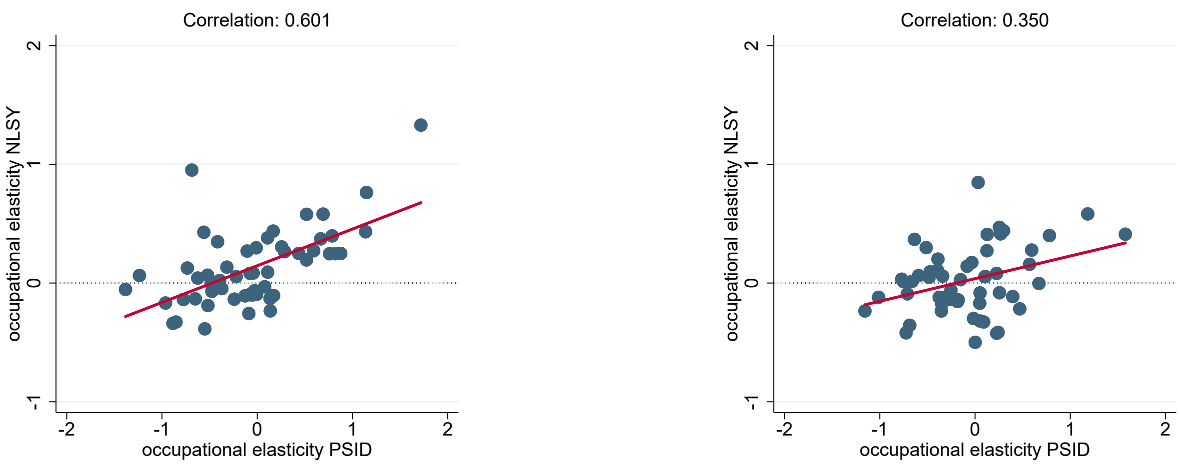
Notes: The left panel is based on a classification with 80 occupations. In the right panel intrinsic quality is estimated based on 5 job characteristics. The standard error of the correlation is 0.097 (left) and 0.113 (right).

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 11 displays the correlation between elasticities estimated with the PSID and NLSY data. Figure 12 displays the relationship between occupational choice elasticities estimated with

Figure 11: 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 is 0.111 (left) and 0.131 (right).

the NLSY data and the intrinsic quality of occupations.

B Model Appendix

B.1 Proofs and Derivations

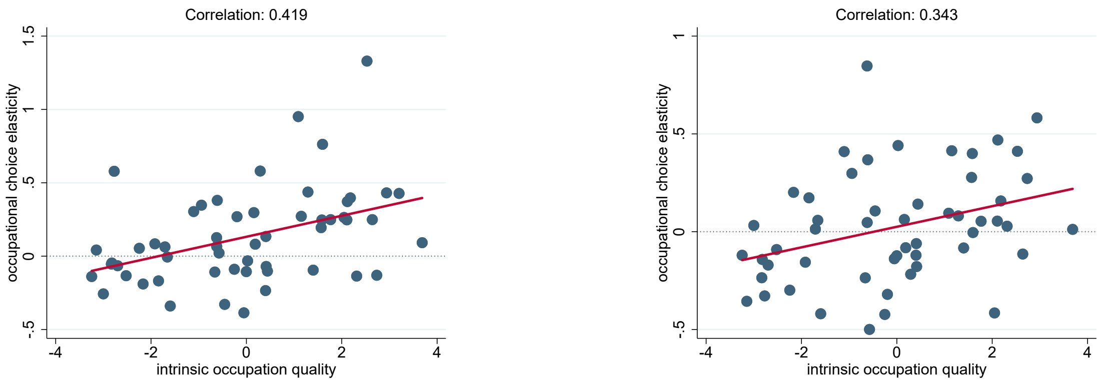
Lemma 1. *The probabilities of occupational choice under a stationary distribution are given by Equation (5) (and also Equation (14)).*

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

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

Figure 12: 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 and the intrinsic quality of occupations. Panel (b) shows the same, but with elasticities estimated controlling for potential earnings. The standard error of the correlation coefficient is 0.126 (left) and 0.132 (right).

$$= \int_{-\infty}^{\infty} \exp\left(-\epsilon_j - \overline{\gamma}\right) \exp\left(-e^{-\epsilon_j - \overline{\gamma}} \left(1 + \sum_{j' \neq j} e^{-\frac{1}{\rho}\left(\vartheta_{ij} - \vartheta_{ij'}\right)}\right)\right) d\epsilon_j,$$

$$= \frac{1}{1 + \sum_{j' \neq j} e^{-\frac{1}{\rho}\left(\vartheta_{ij} - \vartheta_{ij'}\right)}} \int_0^{\infty} \exp\left(-x\right) dx = \frac{e^{\frac{1}{\rho}\vartheta_{ij}}}{\sum_{j'} e^{\frac{1}{\rho}\vartheta_{ij'}}},$$

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 (9) is given by Equation (11).*

Proof. We use the same notation as in the proof of Lemma 1. 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 expected adult utility is below v is given by

$$F_v(v) \equiv \mathbb{P}\left[V^+\left(s_i, u_i, \boldsymbol{\epsilon}_i, b_i, y_i\right) < v\right] = \mathbb{P}\left[\max_j \ \vartheta_{ij} + \rho\, \epsilon_{ij} < v\right],$$

$$= \prod_{j=1}^{J} \mathbb{P}\left(\epsilon_{ij} \leq \tfrac{1}{\rho}\left(v - \vartheta_{ij}\right)\right) = \prod_{j=1}^{J} F\left(\tfrac{1}{\rho}\left(v - \vartheta_{ij}\right)\right),$$

$$= \prod_{j=1}^{J} \exp\left(-\exp\left(-\tfrac{1}{\rho}\left(v - \vartheta_{ij}\right) - \overline{\gamma}\right)\right) = \exp\left(-\exp\left[-\tfrac{1}{\rho}v + \log\left(\sum_{j=1}^{J} e^{\frac{1}{\rho}\vartheta_{ij}}\right) - \overline{\gamma}\right]\right).$$

This allows us to calculate

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

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

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

□

Lemma 3. *For a stationary equilibrium, define V^{+} as in Equation (8). We then have $\mathbb{P}\left(V^{+}<v|y,s,u,j\right)=\mathbb{P}\left(V^{+}<v|y,s,u\right)$, where $\mathbb{P}\left(V^{+}<v|y,s,u,j\right)$ is defined as*

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

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:

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

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

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

$$\mathbb{P}\left(\boldsymbol{d};\boldsymbol{\varsigma}\right) = \prod_{i=1}^{N} \left\{ \frac{\exp\left[\frac{\zeta}{\rho}\nu_{o_i} + \frac{1}{\rho}V\left(b^*\left(y_i\right) + e_{o_i}\left(s_i, \mathcal{U}\left(e_i, s_i, o_i, y_i; \boldsymbol{\varsigma}\right), y_i\right)\right)\right]}{\sum_j \exp\left[\frac{\zeta}{\rho}\nu_j + \frac{1}{\rho}V\left(b^*\left(y_i\right) + e_j\left(s, \mathcal{U}\left(e_i, s_i, o_i, y_i; \boldsymbol{\varsigma}\right), y\right)\right)\right]} \right.$$
$$\left. \times \frac{1}{\sqrt{2\pi\,\theta_{o_i}^2}} \exp\left(-\frac{1}{2}\mathcal{U}\left(e_i, s_i, o_i, y_i; \boldsymbol{\varsigma}\right)^2\right) \times \frac{\exp\left(-\frac{1}{2}\left(\frac{s_i - h^*(y_i)}{\vartheta}\right)^2\right)}{\sum_{s'=0}^{4} \exp\left(-\frac{1}{2}\left(\frac{s' - h^*(y_i)}{\vartheta}\right)^2\right)} \right\}, \tag{27}$$

where $\mathcal{U}\left(e_i, s_i, o_i, y_i; \boldsymbol{\varsigma}\right)$ *is defined by Equation (18).*

Proof. The observations are independent, so $\mathbb{P}\left(\boldsymbol{d};\boldsymbol{\varsigma}\right) = \prod_i \mathbb{P}\left(e_i, o_i, s_i | y_i\right)$. We also have

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

where in the fourth equality we used the change of variables $x \equiv u_i/\theta_{o_i}$. $\square$

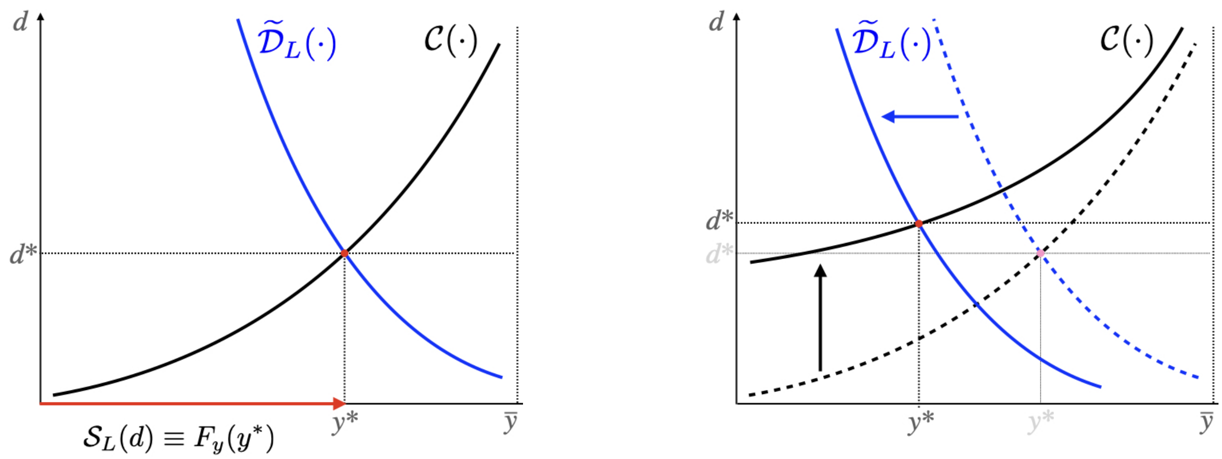
B.2 Stationary Distributions

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 $u \equiv \widetilde{E}_j^{-1}(e_j(s, u, y); s, y)$. We can write the cdf for the earnings of the children of parents with endowment y as

$$F_e\left(e | y\right) = \mathbb{E}_s\left[F_e(e | s, y) \,\middle|\, h^*(y)\right], \tag{28}$$

Figure 13: Demanded Compensation and Compensating Differentials

(a) Benchmark (b) Shifted Labor Demand



Notes: Panel (a) depicts the determination of equilibrium compensating differentials in a special case with two occupations. The curve $\mathcal{C}$ is demanded compensation as a function of parental endowment and the curve $\widetilde{\mathcal{D}}$ is a monotonic transformation of relative occupational labor demand. The equilibrium compensating differential is d^*. Panel (b) represents the change in equilibrium compensating differentials from a shift in labor demand.

where we have defined the cdf $F_e(e|s, y)$ as

$$F_e(e|s, y) \equiv \sum_{j=1}^{J} \int^{\widetilde{E}_j^{-1}(e;s,y)} \mu_j\left(s, u, y\right) \, d\mathbb{P}_u(u), \tag{29}$$

where μ_j satisfies Equation (14). Equation (29) accounts for two effects of parental endowment on child earnings. First, higher parental endowment may raise the earnings within the occupation, as reflected in the upper bound on the integral. Second, parental endowment shapes the patterns of occupational choice, as reflected through the dependence of the μ_j on y. Finally, Equation (28) 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

$$F_y\left(y^+\right) = \int_0^\infty F_e(y^+ - b^*(y)|y) \, dF_y(y). \tag{30}$$

The dispersion in total endowment is shaped by the dependence of child earnings on parental total income $F_e(\cdot|y)$, as well as the transfer policy $b^*(y)$.

B.3 The Affordability Channel in Equilibrium

To illustrate how parental endowment shapes occupational choice through our main mechanism, the affordability channel, we consider a simplified setting with two occupations, $j \in \{L, H\}$, and assume that differences in parental endowment are the only source of heterogeneity across children—that is, $A_j(s, u, y) \equiv A_j$ and $\rho = 0$. Since earnings are independent of parental endowment, the earnings channel does not operate.

Figure 13a depicts how the demanded compensation, defined in Equation (6), and labor demand jointly determine *equilibrium compensating differentials* between the two occupations and the resulting occupational sorting.[37] Let $\mathcal{D}_L(\cdot)$ denote the labor demand for occupation L and $d = \mathcal{C}(y)$ denote the demanded compensation d that makes a child with parental endowment y indifferent between the two occupations, as defined by Equation (6). If in equilibrium the compensating differentials between the two occupations is d, children with parental endowment $y < \mathcal{C}^{-1}(d)$ choose occupation L, leading to the sorting of children from poorer families into occupations with lower intrinsic quality. Accordingly, the supply of labor to occupation L is given by $\mathcal{S}_L(d) \equiv F_y(\mathcal{C}^{-1}(d))$, where $F(\cdot)$ is the cumulative distribution function of parental endowment y. We can define a monotonic transformation $\widetilde{\mathcal{D}}_L(\cdot) \equiv F_y^{-1}(\mathcal{D}_L(\cdot))$ of the labor demand for occupation L, depicted in the figure. The equilibrium compensating differential d^* is then determined by the intersection of the demanded compensation curve $\mathcal{C}$ and the transformed labor demand curve $\widetilde{\mathcal{D}}_L$. In equilibrium, children with parental endowment $y < \mathcal{C}^{-1}(d^*)$ sort into low intrinsic quality occupations. This logic extends to the richer environment in the paper.

Response to Changes in Occupational Labor Demand Figure 13b illustrates how rising compensating differentials emerge from such a shift. As demand for low-intrinsic quality occupations declines, the transformed demand curve $\widetilde{\mathcal{D}}_L$ shifts to the left. Absent any supply response, this would reduce equilibrium compensating differentials and modestly expand the supply of labor to high-intrinsic quality occupations, particularly from children of poorer parents. However, the model implies an additional response through occupational labor supply. As shown in Equation (7), the shape of the demanded compensation curve $\mathcal{C}(\cdot)$ depends on the marginal value of the sum of parental transfers and earnings. Since the shift in $\widetilde{\mathcal{D}}_L$ affects earnings across occupations, $\mathcal{C}(\cdot)$ shifts as well. Therefore, to understand the effect on compensating differentials, occupational sorting and wages, we must account for the full general equilibrium effect.

[37] For recent evidence on the size of job-specific compensating differentials, see Mas and Pallais (2017), Hall and Mueller (2018), Sorkin (2018), and Taber and Vejlin (2020). Here, we instead emphasize occupation-specific compensating differentials, complementing the work of Kaplan and Schulhofer-Wohl (2018).

C Estimation Appendix

C.1 Log-Likelihood Function

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

$$\begin{aligned}\mathcal{L}(\boldsymbol{d};\boldsymbol{\varsigma}) \equiv \sum_{i=1}^{N} \log \mathbb{P}(e_i, o_i, s_i | y_i) = \frac{\zeta}{\rho}\left(\sum_{i=1}^{N} \nu_{o_i}\right) + \frac{1}{\rho}\sum_{i=1}^{N} V\left(b^*(y_i) + e_j\left(s_i, y_i, \mathcal{U}\left(e_i, o_i, s_i, y_i; \boldsymbol{\varsigma}\right)\right)\right), \\ - \sum_i \log\left(\sum_j \exp\left[\frac{\zeta}{\rho}\nu_j + \frac{1}{\rho}V\left(b^*(y_i) + e_j\left(s_i, y_i, \mathcal{U}\left(e_i, o_i, s_i, y_i; \boldsymbol{\varsigma}\right)\right)\right)\right]\right) \\ - \frac{1}{2}\sum_i \mathcal{U}\left(e_i, o_i; \boldsymbol{\varsigma}\right)^2 - \tfrac{1}{2}\sum_i \log \theta_{o_i} \qquad (31) \\ - \frac{1}{2}\sum_i \left(\frac{s_i - h^*(y_i)}{\vartheta}\right)^2 - \sum_i \log \sum_{s'=0}^{4} \exp\left(-\frac{1}{2}\left(\frac{s' - h^*(y_i)}{\vartheta}\right)^2\right). \qquad (32)\end{aligned}$$

The first and second lines of Equation (31) characterize the conditional distribution of occupational choice, given schooling, earnings, and parental endowment. The third and fourth lines characterize the conditional distribution of talent and schooling, given parental endowment.

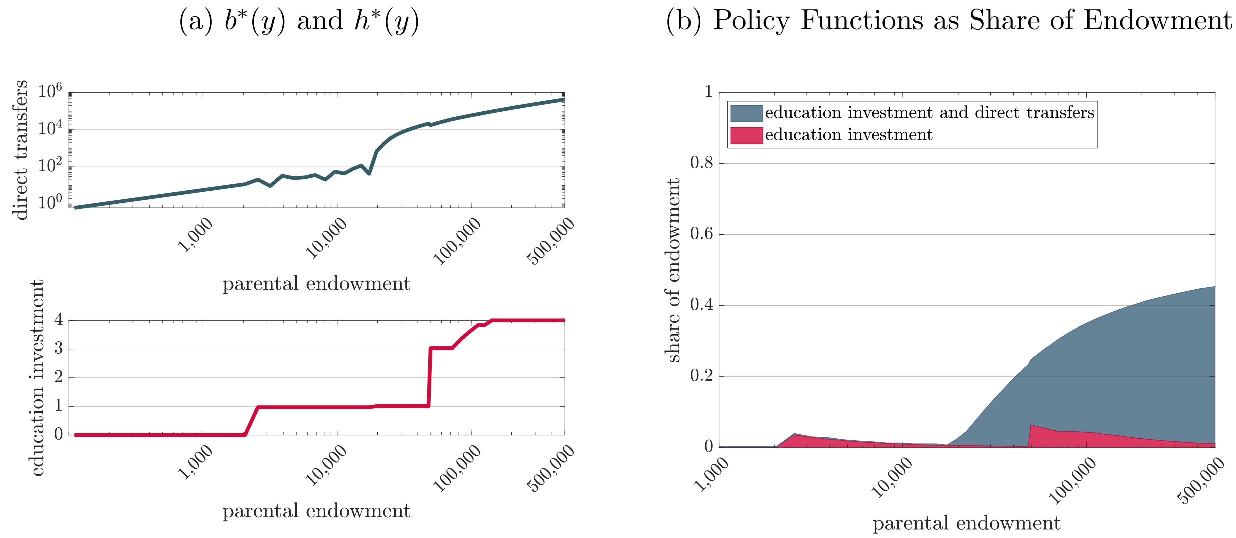
C.2 Additional Estimation Results

C.2.1 Policy Functions

Figure 14 displays the policy functions for education investment $h^*(y)$ and direct transfers $b^*(y)$. As Panel (a) 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 (7). As we argue below, it is also in line with patterns regarding intergenerational transfers in survey data:

Figure 14: Investment in Education and Direct Transfers



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.

1. *National Longitudinal Survey of Youth 1997 (NLSY97)*

   We use the inter-vivos transfers dataset constructed by Abbott et al. (2019) from the "Income" and "College Experience" sections of the NLSY97. The authors provide two measures: one for direct transfers to children and another that also includes the imputed value of rent.

   Two limitations complicate comparison with the model-implied transfer function. First, the data include only inter-vivos transfers, while the model's $b^*(y_i)$ includes both inter-vivos transfers and inheritances. Second, the NLSY97 sample is younger than in the model, covering individuals aged 16–22. Given these differences, we focus on qualitative patterns, particularly the monotonicity of transfers with parental resources.

   We divide the NLSY97 sample into parental net worth quartiles and compute the average transfer in each. Transfers rise with parental wealth. Average direct transfers (1996 USD) by quartile are: $773, $965, $1,034, $1,504. Including rent equivalents, the averages are: $3,920, $4,050, $4,373, $5,021.

2. *Health and Retirement Study (HRS) and Asset and Health Dynamics Study (AHEAD)*

   McGarry (1999) uses data from the HRS and AHEAD to study how the likelihood of making inter-vivos transfers or leaving bequests varies with parent and child characteristics. The

HRS surveys individuals born 1931–1941, and AHEAD covers those born in 1923 or earlier, whereas the average parent in our PSID sample was born in 1943. The surveys began in 1992 and 1993, when respondents were 51–61 (HRS) and 70+ (AHEAD), making these samples older than the model counterpart.

Respondents were asked about transfers of $500 or more made to children in the past year and their bequest intentions. In Table 3, McGarry (1999) shows that wealthier and higher-income parents are more likely to give transfers, consistent with our model. Moving from the lowest to the highest income quartile raises the probability of an inter-vivos transfer by 20–26 percentage points, depending on the dataset. Bequest likelihood also rises with parental income and wealth, though exact magnitudes are not reported.

C.2.2 Other Moments of Interest

Parental Endowment and Intergenerational Transfers We compare the model's prediction for transfers as a function of parental endowment to the data. Our estimated model implies that aggregate transfers represent 49.1% of aggregate parental endowment. To compute the empirical counterpart, we use two data moments. First, Gale and Scholz (1994) estimate in Table 4 that intergenerational transfers (inter-vivos transfers, bequests and college expenses) represent 63.8% of aggregate wealth. Excluding college expenses lowers this to 51.8%, which we denote as $\frac{B}{W}$. Second, Kuhn and Rios-Rull (2020) report an average earnings-to-wealth ratio of 13.9% from 1989 to 2019, denoted $\frac{E}{W}$, which also holds in 2001—the reference year for our model. We compute the transfer-to-endowment ratio in the data as $\frac{B}{Y} = \frac{B/W}{(E+W)/W} = \frac{B/W}{E/W+1}$, which is 0.560 with college expenses and 0.455 without, both close to the model's 0.491.

Parental Endowment, Schooling Attainment and Occupational Choice Table 6 compares the model's predictions about schooling attainment as a function of parental endowment with the data. As in the data, children of rich parents have a higher educational attainment and are more likely to obtain a college or graduate degree. Table 7 assesses the model's ability to predict the dependence of occupational choice on parental endowment and schooling attainment. The table reports correlations between occupational choice probabilities conditional on parental endowment and schooling predicted by the model and their PSID counterpart. These correlations are positive and large, suggesting that the model captures which occupations are more likely to be chosen by children, given education and parental endowment.

C.3 The Decomposition of Persistence in Earnings

Our model offers a simple characterization of the determinants of the 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

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

To further characterize this, we first define the conditional joint probability of occupational choice, talent, and schooling given parental endowment as $\mathbb{P}\left(j, s, u|y\right) \equiv \mu_j(s, u, y)\, \mathbb{P}_u(u)\, \mathbb{P}_{s|h}(s|h^*(y))$, where $\mu_j(s, u, y)$ are given by Equation (14). Using this joint distribution, and with slight abuse of notation, we can define a number of marginal conditional distributions: the conditional distribution of occupational choice given y, $\mathbb{P}(j|y) \equiv \int \sum_s \mathbb{P}\left(j, s, u|y\right) du$, and the conditional distribution of schooling given y, $\mathbb{P}(s|y) \equiv \int \sum_j \mathbb{P}\left(j, s, u|y\right) du = \mathbb{P}_{s|h}(s|h^*(y))$. Based on these, Equation (16) implies that

$$\mathbb{E}_e[\log e|\, y] = \overline{\alpha}(y) + \overline{\kappa}(y)\, \overline{s}(y) + \overline{\delta}(y)\ \log y + \mathbb{C}_{js}\left(\kappa_j, s|\, y\right) + \mathbb{C}_{ju}\left(\theta_j, u|\, y\right), \tag{33}$$

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 $\overline{\kappa}(y)$. Similarly, we have defined the expected level of schooling conditional on parental income as $\overline{s}(y) \equiv \mathbb{E}_s\left[s|y\right] = \sum_s s\, \mathbb{P}_s(s|h^*(y))$, as well as the following two conditional covariances given parental endowment y: $\mathbb{C}_{js}\left(\kappa_j, s|\, y\right) \equiv \mathbb{E}_{j,s}\left[\kappa_j\left(s - \overline{s}(y)\right)|y\right]$ and $\mathbb{C}_{ju}\left(\theta_j, u|\, y\right) \equiv \mathbb{E}_{j,u}\left[\theta_j u\,|\, y\right]$.

The first term in Equation (33) captures variation in the fixed component of earnings as

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: Entries are probabilities of obtaining a given schooling attainment (rows) conditional on parental endowment. Poor (rich) parents are those with endwoment below (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: Entries are correlation coefficients between occupational choice probabilities conditional on parental endowment and schooling predicted by the model and their PSID counterpart. Poor (rich) parents are those with endwoment below (above) the median.

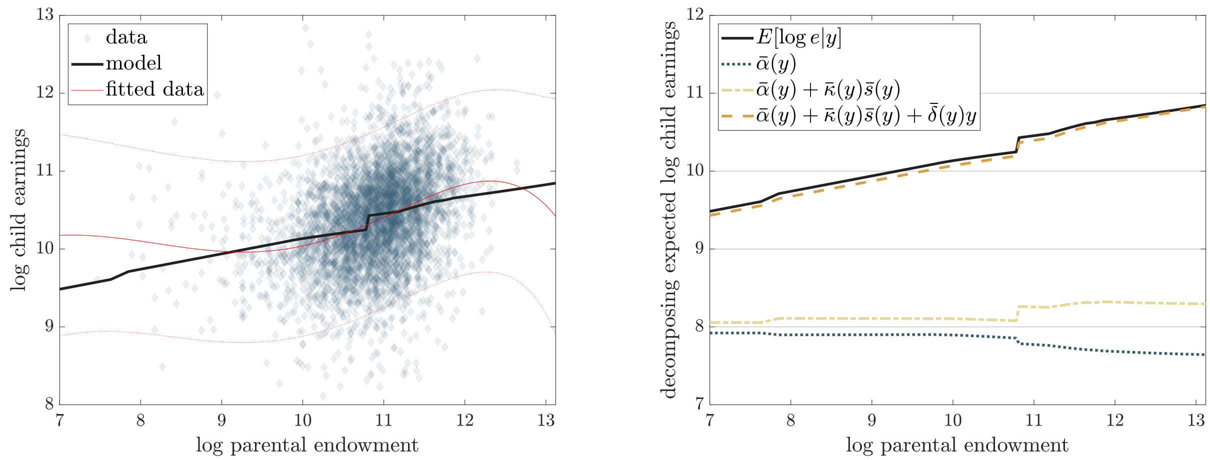
a function of parental endowment, reflecting the earnings of an individual with no schooling ($s = 0$), unit parental endowment ($y = 1$), and average talent ($u = 0$). The second term reflects the product of the conditional mean return to schooling and mean schooling given parental endowment. It incorporates two forces: occupational sorting, where children of rich parents select into occupations with higher returns to schooling; and schooling investment, where they receive more educational investment and schooling. The third term captures sorting into occupations with higher returns to parental endowment. The final two terms account for how children with higher schooling or talent sort into occupations with higher returns to those attributes, conditional on parental endowment. The two covariance terms measure how these sorting patterns vary with parental endowment: the stronger the sorting, the higher the expected log earnings.

C.3.1 The Decomposition under the Benchmark Model

Figure 15a plots the conditional expected earnings of children $\mathbb{E}_e[\log e | y]$ in the model and the data. The two resemble closely. Figure 15b decomposes the expected log earnings in the model following Equation (33). We find that the first three terms explain the lion's share of the relationship between log earnings and 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 are initially stable as parental endowment rises, but eventually fall. 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 not respond as strongly to the earnings incentives in their occupational choice.

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 (33).

C.3.2 Decomposition with Shifts in Labor Demand

Figure 17a 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 (33). The term involving the expected returns to schooling $\overline{\kappa}(y)\overline{s}(y)$ constitutes the main source of changes in expected log earnings.

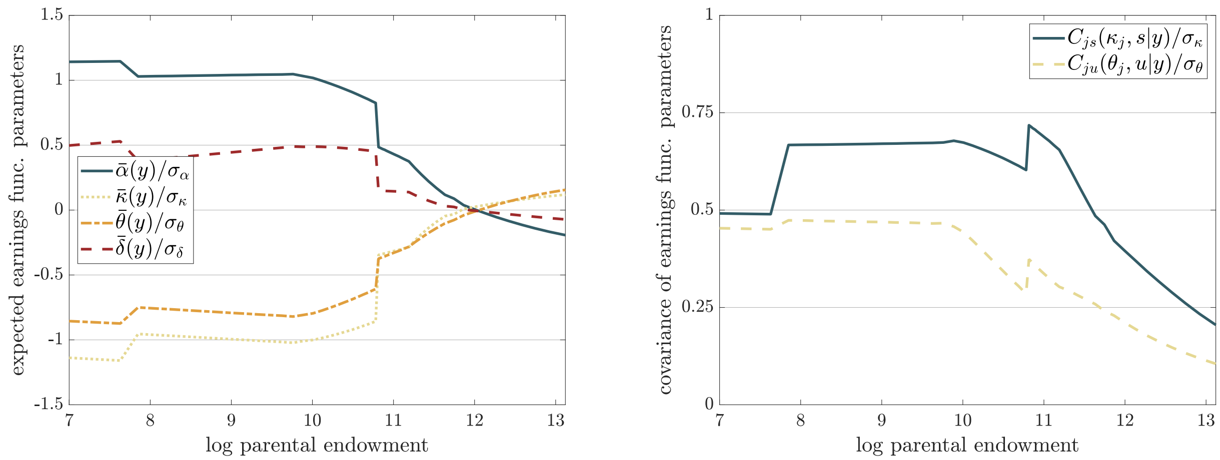
D Additional Results

D.1 Occupational Choice under Different Variants of the Model

We revisit 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 18a shows the distributions of the resulting correlations across the 10,000 re-sampled

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.

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.

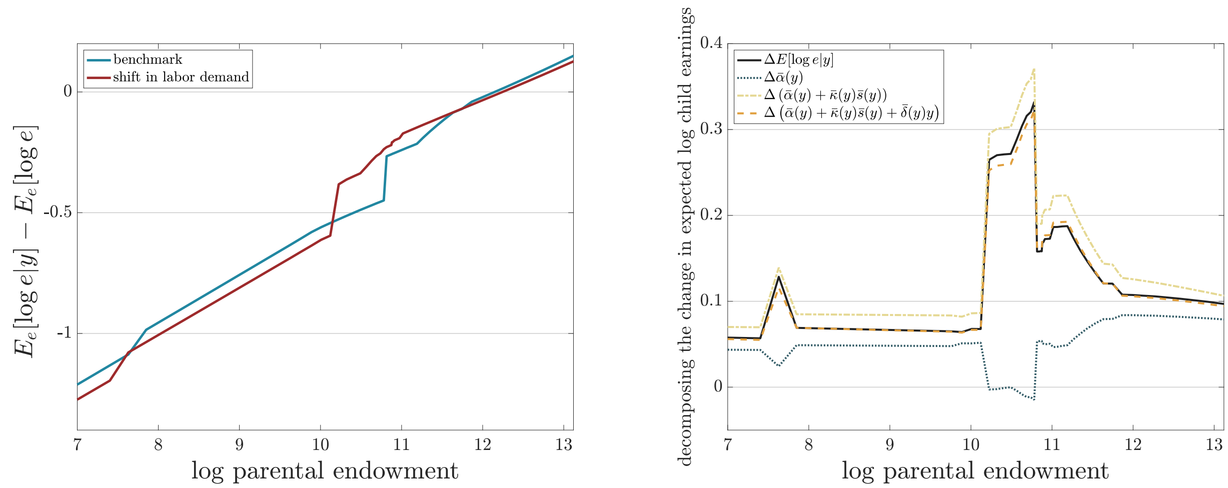
Figure 18b shows the distributions of the resulting correlations across the 10,000 re-sampled datasets from the benchmark model and the model with shifts in occupational labor demand. The mean value of these correlations falls from 0.253 ($SE = 0.036$) under the benchmark model to 0.140 ($SE = 0.031$) under the model that features the shifts in occupational labor demand.

D.2 Compensating Differentials in the Benchmark Model

We take two approaches to proxy equilibrium compensating differentials. The first is a micro-level strategy based on the tradeoffs faced by individuals. Each individual, given their talent and schooling, chooses among occupations that lie on their earnings-quality frontier. For each, we identify the top two most likely occupations predicted by the model and compare differences in log earnings and intrinsic quality. Figure 19a plots these differences; a linear fit implies that a

Figure 17: Expected Log Earning vs. Parental Endowment, Shift in Labor Demand

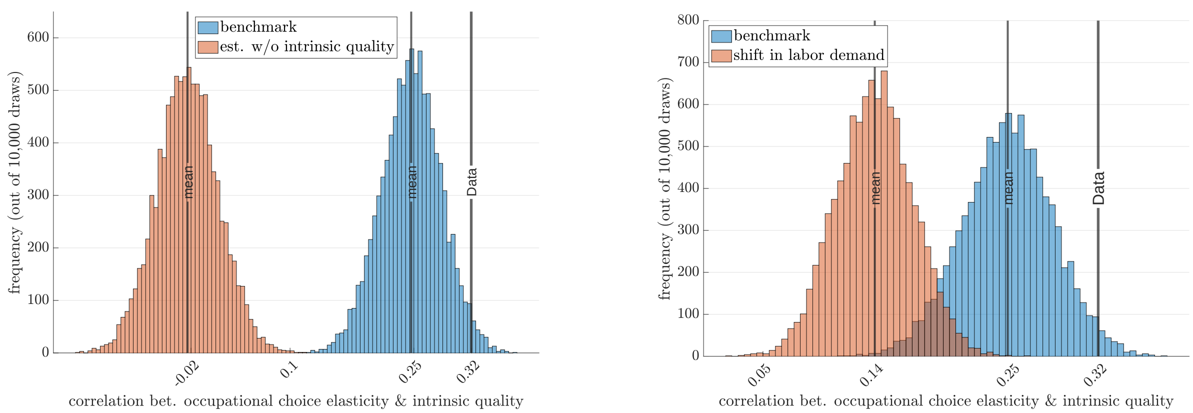
(a) Benchmark vs. Shifted Labor Demand (b) Decomposition of the Change



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 (33), in going from the benchmark model to the one with shifts to occupational labor demand.

Figure 18: Occupational Choice Elasticties and Intrinsic Quality

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



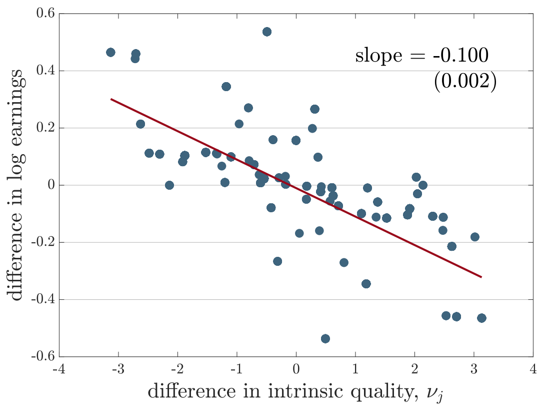
Notes: Panel (a) shows the histograms of the correlation values between occupational choice elasticities and the intrinsic quality of occupation across 10,000 re-sampled datasets under the benchmark model (blue) and the model estimated with no variations in intrinsic qualities (red). Panel (b) compares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

one standard deviation increase in intrinsic quality leads to an average earnings loss of over 17%.

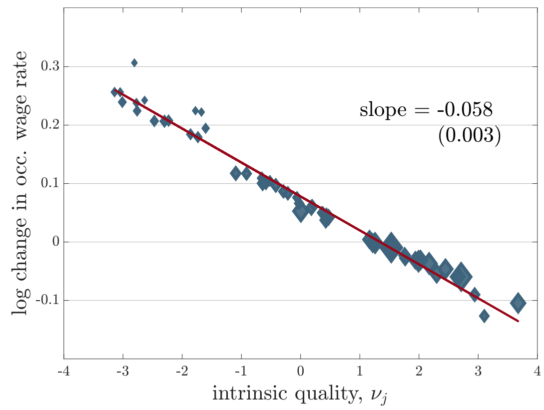
The second is a macro-level approach. We ask: how much must wages rise in high-quality

Figure 19: Compensating Differentials

(a) Micro: Across Individuals



(b) Macro: Across Occupations



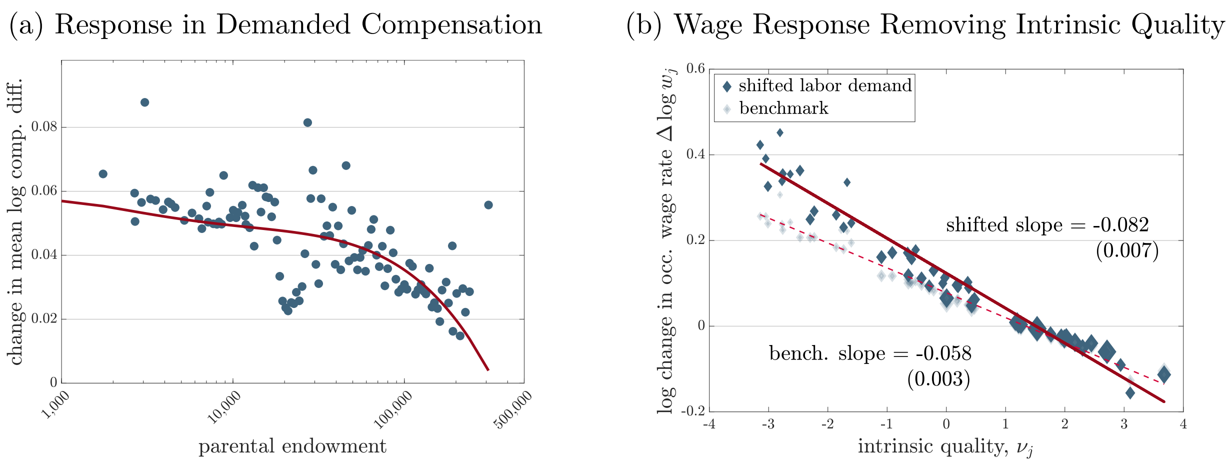
Notes: Panel (a) plots the differences in log earnings between the top two most likely occupations for each individual as predicted by the model and the corresponding differences in intrinsic qualities. Panel (b) plots the change $\alpha_j - \alpha_j^n$ against intrinsic qualities, where α^n is the earnings 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.

occupations to restore their labor supply if differences in intrinsic quality are eliminated? Let τ this counterfactual environment. We solve for the new vector of fixed earnings components $\boldsymbol{\alpha}^\tau$, corresponding value function V^τ, and stationary distribution of endowments F_y^τ that satisfy conditions in Equation (15) 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 without variations in intrinsic quality, the idiosyncratic taste shocks still provide a source of heterogeneity for the non-monetary dimension of work but these shocks average to zero 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 benchmark occupational wage bills.

Figure 19b shows that wage adjustments are strongly correlated with intrinsic quality: the benchmark model lowers wages in occupations that offer higher non-monetary compensation. A linear fit implies that a one standard deviation increase in intrinsic quality is associated with an 11.4% reduction in the per-efficiency-unit wage rate.

Figure 20: Compensating Differentials with Shifts in Occupational Labor Demand



Notes: Panel (a) shows the change in the mean log of the compensation required for the child to be indifferent between occupations at the 25th and 75th percentile of instrinsic values in the model with shifted labor demand relative to the benchmark. Panel (b) plots the change in the log occupational wage rates $\alpha_j^d - \alpha_j^{nd}$ against intrinsic qualities ν_j, where nd is the counterfactual with no differences in intrinsic qualities in the model with shifted labor demand, and d is the model with shifted demand.

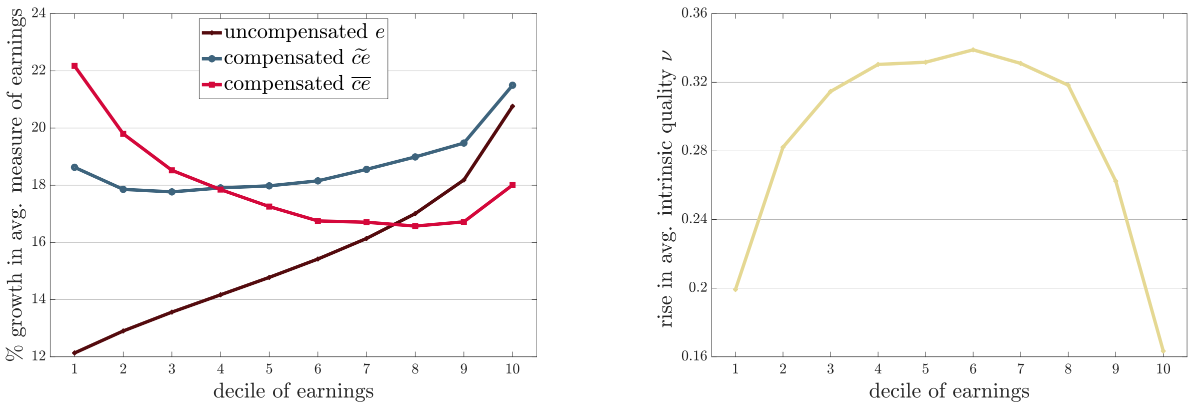
D.3 Compensating Differentials with Shifts in Labor Demand

To study the effects on long-run labor supply in the shifts in labor demand, Figure 20a 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 log 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 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.

Figure 20b shows that compensating differentials 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. This relationship becomes stronger.

Figure 21: Change in Welfare Across Deciles of Earnings

(a) Growth in Mean Earnings (b) Rise in Average Intrinsic Quality



Notes: Panel (a) shows the distribution of the growth in mean uncompensated and compensated earnings in response to shifts in occupational labor demand. Panel (b) plots the change in mean intrinsic quality for each earnings decile in response to the shift.

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

Figure 21a shows how the growth in uncompensated and compensated earnings varies across earnings deciles. Uncompensated earnings growth is larger for higher deciles. The two measures of compensated earnings display distinct patterns. When accounting only for intrinsic occupational quality ($\widetilde{ce}$), most gains accrue to workers in the lower deciles. This is driven by: *(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 21b examines the first factor and shows that workers in the middle deciles experience the largest average quality gains. We therefore 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 suggests that welfare gains from shifts in labor demand are more evenly distributed than uncompensated earnings would imply.

Focusing on the compensated measure $\overline{ce}$ strengthens this conclusion. The growth in $\overline{ce}$ for workers in the highest deciles is even lower than the growth of uncompensated earnings. This is because these workers earn the highest earnings working in occupations with the highest intrinsic qualities, so are 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 become more responsive to their idiosyncratic taste.

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 classification with 80 occupation groups.

Table 9: Occupation Groups, Robustness

Occ	Description	Occ	Description
1	Executive, Admin, and Managerial Occ	41	Guards
2	Management Related Occ	42	Food Preparation and Service Occ
3	Architects	43	Health Service Occ
4	Engineers	44	Building Service Occ, Except Household
5	Mathematical and Computer Scientists	45	Personal Appearance Occ
6	Natural Scientists	46	Recreation & Hospitality Occ
7	Health Diagnosing Occupations	47	Child Care Workers
8	Health Assessment and Treating Occupations	48	Misc. Personal Care and Service Occupations
9	Therapists	49	Farm Operators and Managers
10	Teachers, Postsecondary	50	Farm & Agricultural Occ, Except Managerial
11	Teachers, Except Postsecondary	51	Forestry and Logging Occupations
12	Librarians, Archivists, and Curators	52	Fishers, Hunters, and Trappers
13	Social Scientists and Urban Planners	53	Supervisors, Mechanics and Repairers
14	Social, Recreation, and Religious Workers	54	Vehicle Mechanics and Repairers
15	Lawyers and Judges	55	Electrical and Electronic Equipment Repairers
16	Writers, Artists, Entertainers, and Athletes	56	Miscellaneous Mechanics and Repairers
17	Health Technologists and Technicians	57	Supervisors, Construction Occupations
18	Engineering & Related Technicians	58	Construction Trades, Except Supervisors
19	Science Technicians	59	Extractive Occupations
20	Technicians, Except Health, Eng & Science	60	Supervisors, Production Occupations
21	Supervisors and Proprietors, Sales Occupations	61	Precision Metal Working Occupations
22	Sales Rep, Finance and Business Services	62	Precision Woodworking Occupations
23	Sales Rep, Commodities Except Retail	63	Textile & Furnishings Machine Workers
24	Sales Workers, Retail, Personal Services	64	Precision Workers, Assorted Materials

Occ	Description	Occ	Description
25	Supervisors, Admin Support Occ	65	Precision Food Production Occupations
26	Computer Equipment Operators	66	Plant and System Operators
27	Secretaries, Stenographers, and Typists	67	Metalworking & Plastic Machine Operators
28	Information Clerks	68	Metal & Plastic Processing Machine Operators
29	Records Processing Occ, Except Financial	69	Woodworking Machine Operators
30	Financial Records Processing Occupations	70	Printing Machine Operators
31	Duplicating, Mail & Office Machine Operators	71	Textile, Apparel, Furnishings Machine Op
32	Communications Equipment Operators	72	Machine Operators, Assorted Materials
33	Mail and Message Distributing Occupations	73	Fabricators, Assemblers & Hand Working Occ
34	Material Recording & Scheduling Clerks	74	Production Inspectors, Testers & Weighers
35	Adjusters and Investigators	75	Motor Vehicle Operators
36	Misc Administrative Support Occupations	76	Rail Transportation Occupations
37	Private Household Occupations	77	Water Transportation Occupations
38	Supervisors, Protective Service Occupations	78	Material Moving Equipment Operators
39	Firefighting and Fire Prevention Occupations	79	Helpers, Construction & Extractive Occ
40	Police and Detectives	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: Standard errors based on 25 bootstrapped samples are in the parentheses.