DISCUSSION PAPER SERIES

DP16854

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MACROECONOMICS AND GROWTH

MONETARY ECONOMICS AND FLUCTUATIONS

ISSN 0265-8003

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Discussion Paper DP16854
Published 03 January 2022
Submitted 21 December 2021

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www.cepr.org

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JEL Classification: N/A

Keywords: N/A

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Occupational Choice and the Intergenerational Mobility of Welfare*

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October 21, 2021

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

Keywords: Intergenerational mobility; Compensating differentials; Occupational choice.

*We thank Jonathan Becker and Federico Kochen for excellent research assistance on this project, and Hanno Foerster, Isaac Sorkin, Claudia Olivetti, Theodore Papageorgiou, Chris Tonetti and seminar participants at the European Midwest Micro Macro Mini Conference, Columbia Junior Micro Macro Labor Conference, the SED Meeting, the NBER Summer Institute, SITE, UC Berkeley, Washington State University, University of Houston, Princeton University, and the Opportunity and Inclusive Growth Institute for their helpful comments.

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1 Introduction

Modern economies aspire to offer individuals equal opportunities to build productive and fulfilling careers, regardless of the economic background they are born into. The most common measure of the success in realizing this promise is how well parental income predicts the monetary compensation children receive from their work (Black and Devereux, 2011). Nevertheless, 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 automony 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; Hamermesh, 1999; Green, 2006; Kalleberg, 2016). Focusing on career choice, for instance, individuals who choose occupations with higher non-monetary quality are remunerated in part through the higher value they receive from the intrinsic nature of their work throughout their lifetimes (Rosen, 1986).

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

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

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

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

aspects, and combine them into a single index by using principal component analysis. Our measure of intrinsic quality for each occupation is the first principal component of the residualized values, which explains the majority of the variation in responses to all questions. We find that being a machine operator, a farmer, or a housekeeper carries relatively low intrinsic quality, while artists, librarians, or post-secondary teachers enjoy a relatively high intrinsic quality.

We then use micro data from the Panel Study of Income Dynamics (PSID) and the National Longitudinal Survey of Youth 1997 (NLSY) to study the relationship between the labor market outcomes of young adults and their economic background. We summarize the effect of growing up in a rich family on occupational choice in the form of an *occupational choice elasticity* that captures the change in the likelihood that an occupation is chosen as parental income rises. These elasticities show a large, positive, and robust correlation with our measure of intrinsic quality.[3] This correlation holds when controlling for the child's educational attainment, for proxies of potential earnings across all occupations, and for the parent's occupation.

We rationalize this fact with a theory of intergenerational occupational choice, in which preferences are separable in market consumption and the non-monetary quality of work. The monetary compensation that an individual attributes to a given level of intrinsic quality inversely depends on their marginal value of monetary resources. Since children of richer parents receive larger parental monetary transfers, they have higher levels of consumption and thus lower marginal value of monetary resources. Therefore, they demand higher levels of compensation for giving up occupations with a high intrinsic quality. The equilibrium level of compensating differentials thus sorts the children of rich parents into occupations with higher intrinsic qualities.

Our 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. In addition, the productivity of young adults varies across occupations depending on schooling attainment, idiosyncratic and unobserved talent shocks, and parental income. The latter dependence accounts for all potential mechanisms through which richer parents may facilitate higher earnings for their children on the labor market. We close the model by specifying a simple demand for occupational services, which allows us to endogenize occupational wages.

[3] This fact is often anecdotally invoked by the 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).

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 our data. We show that, despite its parsimony, the model matches the patterns of occupational choice and intergenerational mobility in the data.

The model allows us to compute the compensation each individual in the data demands for a certain level of downward change in the intrinsic occupational quality. For instance, the compensation corresponding to the interquartile range of intrinsic qualities is substantial (around 10% of average earnings) and is increasing in parental income. Using the model, we can also compute proxies for the equilibrium compensating differentials corresponding to the variations in intrinsic occupational quality. We find that a standard deviation rise in intrinsic quality is associated with a fall of 10 to 17% in the wage rate across occupations.

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

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

Prior Work Our paper builds on the large literature on intergenerational mobility. Earlier empirical contributions to this literature are summarized by Solon (1999) and Black and Devereux (2011). More recent patterns based on administrative data (Chetty et al., 2014, 2017) are borne in our main data source, the PSID. 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[4] in a framework that can be quantitatively disciplined by rich data on choices of children in a large set of occupations.[5]

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

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

Lastly, the focus on socioeconomic background and occupational choice relates our paper to Bell et al. (2018), who show the chances to become an inventor vary with parents' socioeconomic class, and 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. Our hypothesis that growing up rich makes it more likely that children choose occupations with potentially lower earnings but high intrinsic quality is most similar to Luo and Mongey (2019). They show that higher student debt induces college graduates to accept jobs with higher wages and lower job satisfaction, which has implications for welfare in the context of student debt repayment policies.

[4]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).

[5]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.

2 Data and Facts

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

2.1 Data

We use data from the PSID and the GSS to conduct our empirical work. Appendix A discusses our variable construction and sample restrictions in detail. Here we briefly describe these data sources and the key variables we use.

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

In the cross-section, we define the occupation as the the most frequently held occupation between age 22 and 55 and consider an occupation classification with 54 occupations. Education is defined as the highest level of education attained. Labor earnings in the cross-section are defined as the average earnings in the most frequently held occupation between age 22 and 55, net of age and time effects that vary by occupation. Parental income and wealth in the cross-section are also defined as the average over parental family income and wealth between age 22 and 55, net of age and time effects. Lastly, we define parental endowment, a variable we use in the theoretical model, to be the sum between parental income and parental inherited wealth. We use the PSID to study occupational choice by children as a function of parental income.

GSS. The GSS is a survey that assesses attitudes, behaviors, and attributes of a representative sample of US residents. The survey began in 1972, collecting information on a sample between 1,500 and 4,000 respondents. We use the Quality of Working Life module, administered in 2002, 2006, 2010 and 2014. This survey module is asked of respondents who are working and includes questions on hours worked, workload, worker autonomy, layoffs and job security, job satisfaction/stress, and worker well-being. We use a subset of these questions and principal component analysis (PCA) to create a measure of the intrinsic quality of occupations.

2.2 The Intrinsic Quality of Occupations

We first describe our measure of the intrinsic quality of occupations, which aims to capture the bundle of factors linked to worker well-being in the extensive literature on job quality in sociology and psychology (e.g., Kohn and Schooler, 1973; Warr, 1990; Hamermesh, 1999; Green, 2006; Kalleberg, 2016). Our approach is to rely on a representative survey of US workers, the Quality of Worklife module of the GSS, and select questions that cover different dimensions highlighted in this literature. From the list of questions asked in the survey, we select 7 job characteristics, listed in the first column of Table 1. The 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). In practice, we measure the intrinsic quality of an occupation as the first principal component of the variations in the standardized responses to these questions,[6] which as we will see is highly correlated with a general measure of job satisfaction.

Some of the characteristics we focus on are likely to be correlated with extrinsic aspects of the job (e.g., earnings, tenure at the job). For example, tenured workers are arguably more likely to be treated with respect. Therefore, we first purge respondents' assessment of the quality of their worklife from confounding factors. Specifically, for each occupation characteristic ν^x listed in the first column of Table 1,[7] where $x = 1, \ldots, 7$, we estimate

$$\nu^x_{it} = \boldsymbol{\alpha}^x \boldsymbol{X}_{it} + \delta^x_j + \epsilon^x_{it}, \tag{1}$$

where i denotes the respondent and t denotes the wave of the survey module. Here, $\boldsymbol{X}_{it}$ is a vector of controls that includes the logarithm of real income, hours worked, and a dummy variable indicating whether the respondent has been at the current job for less than one year, one year, 2-5 years, 6-10 years, 11-20 years or more than 20 years, and $\boldsymbol{\alpha}^x$ is the corresponding vector of coefficients.[8] The coefficients δ^x_j are occupation specific fixed effects.

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 δ^x_j listed in the first column of Table 1. The second column of Table 1 reports loadings on

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

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

[8] In practice, the effect of these controls is minimal as the correlation coefficient between the intrinsic quality of occupations that we estimate below and its counterpart without these controls is 0.975 (SE=0.031). Also note that the Quality of Worklife Module does not collect information on earnings, so we use the total income of the respondent (earnings + other income) to proxy for work pay.

Table 1: Principal Component Analysis for Occupation Characteristics

Occupation characteristic ν^x	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

each occupation amenity. The occupation quality index loads positively on all characteristics, even though the loadings are not influenced by any prior information about which characteristic is thought to be desirable or undesirable. The first component alone explains 51% of the total variance in the 7 job characteristics. This suggests that a simple one-dimensional index is able to capture the bundle of job qualities likely to matter for worker well-being. The last column of Table 1 reports the variance that remains unexplained in each characteristic and suggests that our measure of the intrinsic quality of an occupation is able to explain the majority of the variation in nearly all dimensions of the quality of worklife that we consider.

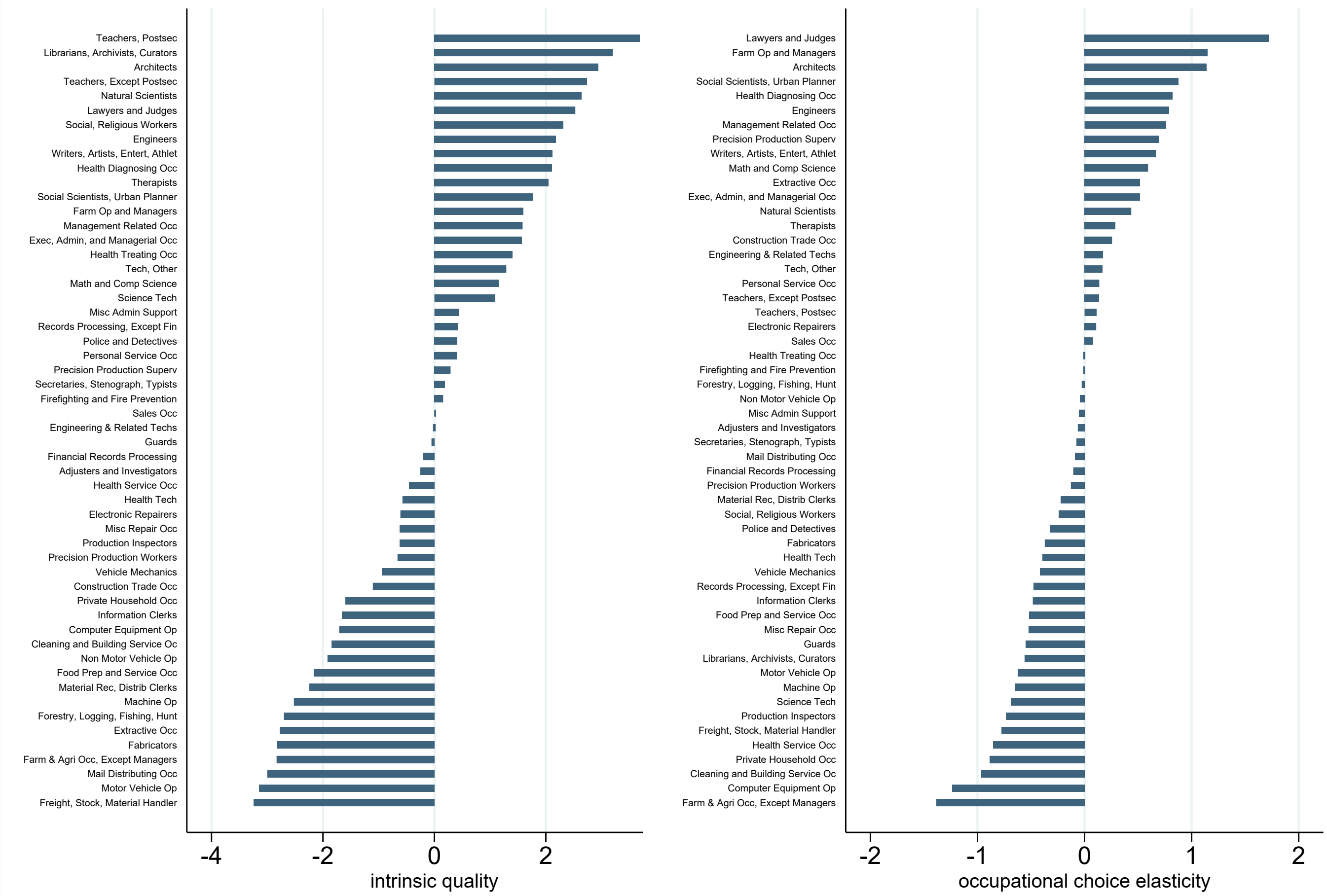
Figure 1a displays the measured intrinsic quality of occupations and reveals substantial heterogeneity. Occupations with low intrinsic quality are material handlers, motor vehicle operators, non-managerial firm occupations, cleaning occupations. Conversely, occupations with high intrinsic quality are post-secondary teachers, librarians, architects, lawyers and judges, writers, artists. While the cardinal information in the estimated intrinsic quality is not readily interpretable, the relative ranking of occupations is meaningful, and is what we exploit in the analysis.

We explore how our measure of the intrinsic quality of occupations correlates with a general measure of job satisfaction by applying the same treatment described above in Equation (1) to the following question asked in the Quality of Worklife module of the GSS: *"All in all, how satisfied would you say you are with your job?"*. Figure 2a shows that our measure of the intrinsic

Figure 1: Intrinsic Quality and Occupational Choice Elasticities

(a) Intrinsic Quality of Occupations

(b) Occupational Choice Elasticities



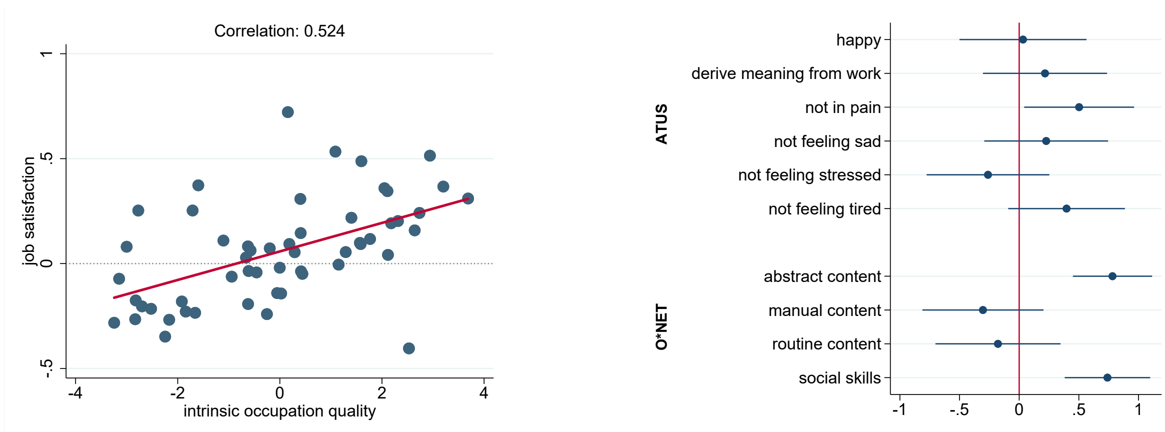
Notes: Bars are indices of intrinsic quality of occupations represented by the first principal component of 7 occupation characteristics in Panel (a) and estimated occupations choice elasticities in Panel (b).

quality of occupations correlates positively with job satisfaction: the correlation coefficient is 0.524 (SE=0.118). However, this general measure of job satisfaction reflects a subjective proxy that is inclusive of both extrinsic (monetary) and intrinsic (non-monetary) aspects of jobs and occupations. For this reason, we proceed in the remainder of the analysis with the PCA-based measure of occupation quality as our preferred one, but note that the empirical fact we document is robust to using the more general index of job satisfaction instead.

Finally, we show 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

Figure 2: Intrinsic Quality of Occupations and Other Occupation Characteristics

(a) Job Satisfaction (b) Other Characteristics of Occupations



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

the American Time Use Survey in 2010, 2012 and 2013. Respondents were asked how meaningful their 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.

Figure 2b summarizes these correlations and shows that in occupations with higher intrinsic quality workers find the work meaningful, are not in pain and do not feel sad or tired when working, but feel stressed. These occupations also have a higher content of abstract tasks, a lower content of manual and routine tasks, and require more social skills.

2.3 What Occupations are Rich Children More Likely to Choose?

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

2.3.1 Occupational Choice and Parental Income

We begin by examining how growing up in a rich family influences the career choice of children. To that end, we estimate a multinomial logit model that allows the probability that a child i chooses occupation $o_i = j$ to depend on the logarithm of parental income and the educational attainment of child i, expressed in years of schooling. Letting $\mathbb{P}(o_i = j)$ denote the unconditional probability that a child i chooses occupation $o_i = j$ and $\bar{y}$ denote lifetime parental income, we then define the elasticity of occupational choice with respect to parental income to be

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

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

Figure 1b displays the estimated occupational choice elasticities for the 54 occupations we consider. The figure reveals substantial heterogeneity in elasticities, ranging from -1.38 for non-managerial farm occupations to 1.72 for lawyers and judges. A positive elasticity reflects that growing up in a rich family makes the child more likely to choose a given occupation. Our estimates indicate that children with rich parents are more likely to become lawyers and judges, architects, social scientists, writers, and artists. Conversely, growing up in a rich family makes children less likely to become farm workers, janitors, housekeepers, or material handlers.

2.3.2 Occupational Choice Elasticities and The Intrinsic Quality of Occupations

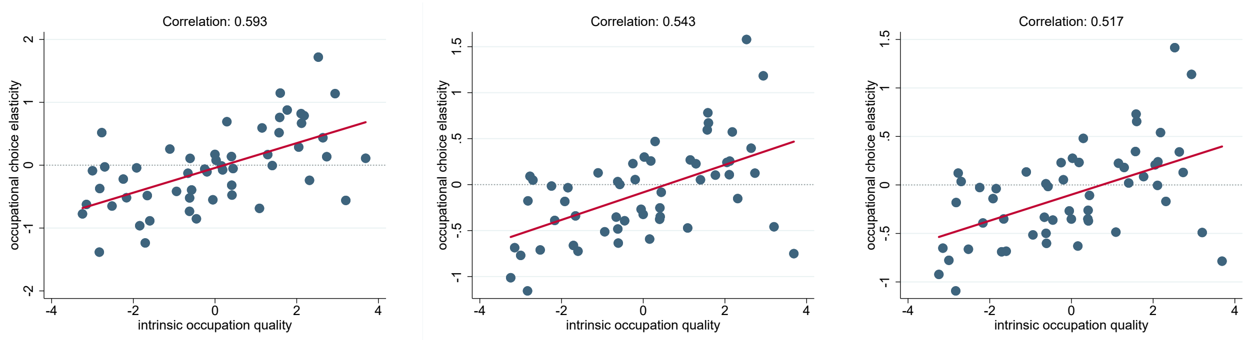
We now turn to the joint analysis of occupational choice elasticities and the intrinsic quality of occupations. Figure 3a depicts the correlation between occupational choice elasticities and the intrinsic quality of occupations. We find a large and positive correlation between these two variables, equal to 0.593 (SE=0.111). This suggests that, on average, those occupations more likely to be chosen by children born into rich families also yield higher non-pecuniary qualities and highlights a channel through which the inequality of opportunity stemming from different economic backgrounds can have consequences on welfare above and beyond those implied by earnings. This channel is quantitatively substantial as variation in intrinsic occupation quality explains 35% of the variation in occupational choice elasticities.

2.4 Robustness

We next show that the relationship between occupational choice, parental income and the intrinsic quality of occupations is robust to a wide range of of considerations.

Figure 3: Occupational Choice Elasticities and the Intrinsic Quality of Occupations

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



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

2.4.1 What Occupations Are Poor or Rich Children Better At?

A concern with the occupational choice elasticities estimated above is that parental income might influence the occupational choice of children through its effect on potential earnings across different occupations. For example, children from a richer background might have access to a better quality education, a more extensive professional network (Kramarz and Skans, 2014), or have the chance to develop better social skills (Deming, 2017), all of which can differentially affect their potential earnings across occupations. If the children of richer parents are more productive exactly in occupations with higher intrinsic quality, we cannot readily interpret higher likelihood of choosing those occupations as being driven by the non-monetary attributes.

To explore this, we first estimate a flexible earnings equation that allows the earnings of the child to depend on occupation, their parent's lifetime income, as well as covariates (years of schooling, age, gender and race) whose effect on earnings is allowed to vary by occupation.[9] Second, we use this earnings equation to predict potential earnings that children in our sample would earn in each occupation. Third, we re-estimate the occupational choice elasticities controlling for (counterfactual) potential earnings for each individual across all occupations.[10]

[9]See Appendix A.4 for a formal discussion of the specification we estimate. We also experimented with an even more flexible earnings function that allows for second order terms of the continuous covariates, as well as interactions between covariates, all allowed to vary by occupation, and found similar results.

[10]Formally, we estimate an alternative specific conditional logit model (McFadden, 1973), where we allow the probability of working in occupation j to also depend on occupation specific characteristics, which in our case are

Figure 3b shows that the relationship between occupational choice elasticities and the intrinsic quality of occupations is robust to netting out the effect of parental income on potential earnings in the estimation of occupational choice elasticities. In particular, the correlation coefficient is 0.54, very similar to the 0.59 in the benchmark. More importantly, the intrinsic quality of occupations continues to explain a sizable share of the variation in occupational choice elasticities: 30%, compared to 35% in the benchmark.

2.4.2 Intergenerational Transmission of Preferences for Occupations

In light of the well documented intergenerational persistence of occupational choice (Long and Ferrie 2013; Lo Bello and Morchio 2019), it is conceivable that the sorting of children into occupations reflects, in part, the transmission of taste for the occupation of one's parents (Doepke and Zilibotti, 2008, 2017). To account for this, we re-estimate occupational choice elasticities controlling not only for potential earnings across all occupations, as above, but also for a dummy variable that is equal to one if the parent works in that given occupation. Figure 3c shows that the correlation between occupational choice elasticities and the intrinsic quality of occupations equal to 0.52 (SE=0.083), and the intrinsic quality of occupations still explains 27% of the variation in occupational choice elasticities, compared to 35% in the benchmark.

2.4.3 NLSY

Our results are robust to estimating occupational choice elasticities with NLSY data. Appendix A discusses the details of sample selection. Figure 19 in Appendix D shows that PSID estimates of occupational choice elasticities correlate positively with those based on the NLSY. With respect to the correlation with the intrinsic quality of occupations, Figure 20 in Appendix D shows that our finding that the occupations that are more likely to be chosen if growing up rich are those with a higher intrinsic quality also holds in the NLSY data.

2.4.4 The Intrinsic Quality of Occupations, Occupation Classification, and Risk

Throughout our analysis we maintain the assumption that children of poor and rich parents evaluate the non-pecuniary aspects of occupations similarly. While the GSS data does not have information on parental income, we are able to verify that this is likely to be the case by applying our procedure for measuring the intrinsic quality of occupations to the sample of respondents

potential earnings across all occupations.

with annual income below and above the median, separately. We find a large correlation between the indices of occupation quality estimated on the two samples, equal to 0.769 (SE=0.090).

Lastly, Figure 21 in Appendix D shows that our findings are robust to *(i)* an alternative measure of the intrinsic quality of occupations that considers only 5 of the job characteristics listed in Table 1, and *(ii)* a finer occupation classification with 80 occupations. Table 7 shows that intrinsic qualities correlate positively with occupational choice elasticities and continue to explain a sizable share of their variation when controlling for how risky occupations are.[11]

3 Model

In this section, we construct a dynastic model of occupational choice and intergenerational mobility to rationalize the patterns uncovered in the data and study their implications.

3.1 Environment

3.1.1 Dynastic Occupational Labor Supply

The economy is populated by overlapping generations of agents who are altruistic toward their children. Each generation is comprised of a unit continuum of agents and lives for two periods: childhood and adulthood (parenthood).[12] An agent starts adulthood in one occupation $j \in \{1, \cdots, J\}$ with total endowment of $y = b + e$, comprised of her own (lifetime) earnings e as well as a direct transfer b received from her parent. She bears one child, and then chooses how to allocate her total endowment y between own market consumption c and the resources to offer her child, in the form either of a human capital investment h or a direct transfer $b \geq 0$.[13]

After the decisions on human capital investment and direct transfer are made, three components of uncertainty about the child's outcomes are resolved and the child chooses her own

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

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

[13] The latter assumption rules out the possibility of intergenerational debt markets, and is in line with the assumption of credit constraints typically made in the standard theories of intergenerational mobility (Becker and Tomes, 1986). Early empirical work (see, e.g., Heckman and Mosso, 2014; Lee and Seshadri, 2019) questioned this assumption, but more recent work has reinforced the notion that credit constraints play an important role in shaping the patterns of educational attainment (Lochner and Monge-Naranjo, 2012, 2016; Hai and Heckman, 2017). We note that the key facts and mechanisms that are the focus of our interest in this paper involve the children's choice of occupation *conditional on the attained level of education*.

adulthood occupation j. First, the child receives an idiosyncratic talent shock u, drawn independently of other outcomes from a distribution $\mathbb{P}_u(\cdot)$. Second, the child receives an idiosyncratic human capital shock that leads to her observed schooling s based on a distribution $\mathbb{P}_s(\cdot|h)$ conditional on parental investment h. Third, the child draws a J-dimensional vector $\boldsymbol{\epsilon} \equiv (\epsilon_j)$ of taste shocks across different occupations, drawn as *i.i.d.* samples from a distribution $\mathbb{P}_\epsilon(\cdot)$.

The earnings of the child who works in occupation j in her adulthood depend on her occupation-specific ability A_j and the occupation-specific wage rate per efficiency units of ability w_j. We allow the occupation-specific abilities to be functions of schooling, talent, and the endowment of the parent as $e_j(s,u,y) = w_j A_j(s,u,y)$.[14] The dependency of occupation-specific ability on parental endowment y accounts for potential channels for the direct intergenerational persistence of income, including the persistence of ability.

A vector $\boldsymbol{\nu} \equiv (\nu_j)_{j=1}^{J}$ denotes the mean intrinsic quality of occupations. The child chooses her own adulthood occupation j, having observed her talent u, schooling attainment s, taste shocks $\boldsymbol{\epsilon}$, as well as the transfers b from the parent, to maximize her future adulthood utility[15]

$$V^{+}(s,u,\boldsymbol{\epsilon},b,y) \equiv \max_j \; V\left(b + e_j(s,u,y)\right) + \zeta\,\nu_j + \rho\,\epsilon_j, \tag{2}$$

where $V(\cdot)$ denotes the pecuniary component of utility as an adult parent. The last two terms in Equation (2) account for the non-pecuniary value derived from working in occupation j. The parameter ζ characterizes the weight of intrinsic qualities and the parameter ρ controls the dispersion of the zero-mean, occupation-specific taste shocks $\boldsymbol{\epsilon}$. We assume that the distribution $\mathbb{P}_\epsilon$ of taste shocks is a normal Type-I extreme-value distribution with zero-mean, that is,

$$\mathbb{P}_\epsilon(\epsilon) = \exp(-\exp(-\epsilon - \overline{\gamma}))), \tag{3}$$

where $\overline{\gamma} \equiv \int_{-\infty}^{\infty} u \, \exp(-u \, \exp(-u))du$ is the Euler-Mascheroni constant. Accordingly, we can analytically compute the expected value in Equation (4), as we will see below.

The welfare of the adult parent depends on the intrinsic quality ν_j of her own occupation, as well as on her market consumption and expected future dynastic utility (with a corresponding

[14] We can offer an alternative rendition of our model by characterizing the conditional distribution of a multi-dimensional ability vector $\boldsymbol{a}_t \in \mathbb{R}^J$ that characterizes the ability of the child across J different occupations, given the endowment of the parent and the schooling attainment of the child. See footnote 26 below.

[15] We can motivate Equation (2) by assuming that each occupation j has a vector of qualities $\boldsymbol{x}_j$, which are valued by each child as $\boldsymbol{\xi}'\boldsymbol{x}_j$ where the vector of coefficients $\boldsymbol{\xi}$ is heterogeneous across children. We then consider a setting where the coefficients $\boldsymbol{\xi}$ are distributed such that $\zeta\nu_j \equiv \mathbb{E}\left[\boldsymbol{\xi}'\boldsymbol{x}_j\right]$. The idiosycratic taste shocks are then given by $\rho\epsilon_j \equiv \boldsymbol{\xi}'\boldsymbol{x}_j - \mathbb{E}\left[\boldsymbol{\xi}'\boldsymbol{x}_j\right]$.

weight $\beta < 1$). More specifically, the pecuniary component of the utility of a parent with total endowment y in occupation j is given by

$$V(y) \equiv \max_{c,h,b} \log c + \beta\, \mathbb{E}_{s,u}\left[\mathbb{E}_{\boldsymbol{\epsilon}}\left[V^{+}(s,u,\boldsymbol{\epsilon},b,y)\,|s,u\right]\,\middle|h\right], \tag{4}$$

$$y \geq c + \frac{b}{1+r} + \varphi(h), \tag{5}$$

where $\varphi(\cdot)$ is a function that characterizes the cost for different levels of human capital investment h, and r is the real rate of interest from one period to the next. The parent values the expected utility of the child $\mathbb{E}[V^{+}]$, defined by Equation (2), and accordingly decides on human capital investment h and direct transfer b depending on the available endowment y. Given our distributional assumption on the taste shocks $\boldsymbol{\epsilon}$, we can write the expected utility of a child with schooling s, talent u, and parental endowment y in Equation (4) as [16]

$$\overline{V}^{+}(s,u,y) \equiv \mathbb{E}_{\boldsymbol{\epsilon}}\left[V^{+}|s,u,y\right] = \rho \log\left(\sum_{j=1}^{J} e^{\frac{\zeta\nu_j}{\rho}} \exp\left[\tfrac{1}{\rho}V\left(b^{*}(y)+e_j(s,u,y)\right)\right]\right). \tag{6}$$

Parents and children in a given period take the future paths of occupation-specific wages, interest rate, and schooling costs as given, and make decisions regarding consumption, transfers, schooling investments and occupational choice.[17]

3.1.2 Production and Occupational Labor Demand

We endogenize the vector of occupation-specific wages $\boldsymbol{w}$ by assuming that competitive firms produce a final good using a Cobb-Douglas technology $X \equiv K^{\chi}L^{1-\chi}$ that combines capital K and a composite L of different types of labor. The composite L is a CES aggregator of different occupations, given by[18]

$$L \equiv \left(\sum_{j=1}^{J} \Psi_j^{\frac{1}{\psi}} \left(Z_j L_j\right)^{\frac{1-\psi}{\psi}}\right)^{\frac{\psi}{1-\psi}}, \tag{7}$$

where the parameter ψ is the elasticity of substitution in occupational labor demand, Ψ_j is an occupational demand shifter, and where Z_j and L_j denote the productivity and the total

[16] See Lemma 1 in Appendix B.

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

[18] All the results of the paper, as well as the quantitative exercises presented, further extend to any specification of labor demand with a general aggregator of the form $L = \mathcal{L}(Z_1L_1, \cdots, Z_JL_J)$.

efficiency units employed in occupation j.

We normalize the price of final goods to unity, implying $1 = \left(\frac{R}{\chi}\right)^{\chi}\left(\frac{W}{1-\chi}\right)^{1-\chi}$, where W is the price index corresponding to the CES aggregator in Equation (7). The labor demand for occupation-j in is then given by

$$w_j L_j = (1-\chi)\, X \, \frac{w_j L_j}{\sum_{j'} w_{j'} L_{j'}} = (1-\chi)\, X \, \Psi_j \left(\frac{w_j}{Z_j W}\right)^{1-\psi}. \tag{8}$$

We further assume an education sector, in which competitive institutions transform final goods to human capital investment services according to the production function $h \equiv \varphi^{-1}(x)$. This implies the cost function for human capital investment $\varphi(\cdot)$ in Equation (5).

3.2 Equilibrium

In this section, we examine the stationary equilibrium of the model, along which wage rates $\boldsymbol{w} \equiv (w_j)$, interest rate r, and schooling costs $\varphi(\cdot)$ are constant.

3.2.1 Core Mechanism: Demanded Compensation and Compensating Differentials

The policy functions $b^*(\cdot)$ and $h^*(\cdot)$ that solve the Bellman equation (4) allow us to find the conditional occupational choices of the children. Relying on the properties of the extreme value distribution, we can show that the probability that a child with schooling s, talent u, and of a parent with endowment y chooses occupation j is given by[19]

$$\mu_j(s,u,y) = \frac{e^{\zeta \nu_j/\rho} \exp\left[\frac{1}{\rho} V\left(b^*(y) + w_j A_j(s,u,y)\right)\right]}{\sum_{j'=1}^{J} e^{\zeta \nu_{j'}/\rho} \exp\left[\frac{1}{\rho} V\left(b^*(y) + w_{j'} A_{j'}(s,u,y)\right)\right]}. \tag{9}$$

Correspondingly, the probability that a child with schooling s and parental endowment y chooses occupation j is given by $\mathbb{E}_u[\mu_j(s,u,y)]$.

Parental Income and Occupational Choice To unpack the predictions of the model regarding the relationship between parental endowment and occupation choice, let us consider the occupational choice probabilities from Equation (9) for a child with parental endowment y, schooling attainment s, and talent u. Dropping the arguments (s,u,y) to simplify the expression, the log likelihood ratio of choosing two different occupations, a high-intrinsic quality occupation

[19]See Lemma 2 in Appendix B.

H and a low-intrinsic quality occupation L, satisfies

$$\rho \log \frac{\mu_H}{\mu_L} = \zeta\nu_H - \zeta\nu_L + V\left(b^*\left(y\right) + e_H\right) - V\left(b^*\left(y\right) + e_L\right). \tag{10}$$

Let $\Delta\nu \equiv \nu_H - \nu_L > 0$ denote the difference in intrinsic quality between the two occupations. In order for the child to be equally likely to choose the two occupations, the child demands some earnings compensation for the lower level of intrinsic quality she would enjoy in occupation L. Equation (10) suggests that this *demanded compensation* $d \equiv e_L - e_H$ satisfies

$$V\left(b^*\left(y\right) + e_H + d\right) - V\left(b^*\left(y\right) + e_H\right) = \zeta\,\Delta\nu. \tag{11}$$

Furthermore, Equation (11) implies that the derivative of the demanded compensation with respect to parental endowment is given by

$$\frac{\partial d}{\partial y} = \left[\frac{V'\left(b^*\left(y\right) + e_H\right)}{V'\left(b^*\left(y\right) + e_H + d\right)} - 1\right]\left(b^*\right)'(y), \tag{12}$$

which is positive valued whenever the value function is concave and the transfer policy function is monotonically increasing. That is, the compensation required to make a child equally as likely to choose the occupation with a lower intrinsic quality rises in the endowment of the parent.

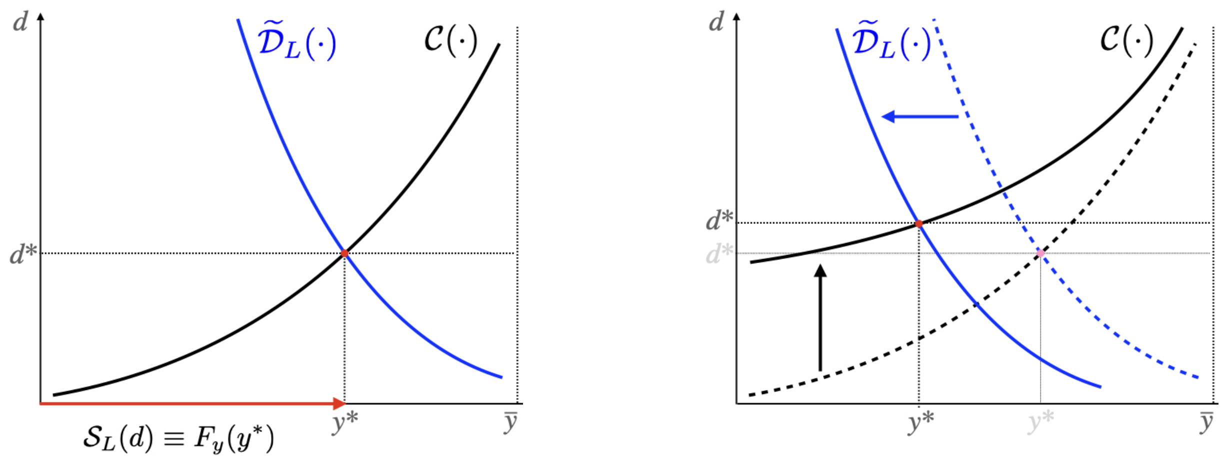
The intuition behind the result above is simple. Equation (2) shows the tradeoff faced by the child between the earnings and the intrinsic quality she enjoys in her occupation. The marginal value of an extra dollar of earnings is given by the derivative of the value function $V(\cdot)$, evaluated at the sum of the transfer b and occupational earnings e_j. Since under standard assumptions this value function is concave, higher levels of parental transfers made by rich parents lower the marginal value of extra income. In other words, the value of an extra dollar of earnings is lower for a richer child. Thus, they demand a higher level of earnings in occupation L to compensate them for the loss $\Delta\nu$ in intrinsic quality compared to occupation H.[20]

Compensating Differentials and Occupational Sorting Figure 4a provides a visual representation of how the demanded compensation defined in Equation (11) and the occupational labor demand together determine equilibrium compensating differentials. To focus on the core

[20]The argument relies on the assumption of separability between the monetary component and the taste for occupations, but not on the assumption that the child utility is a linear function of intrinsic quality, we can allow for a concave function of intrinsic quality ν_j. We choose the linear specification for simplicity, as it implies that occupational choice is invariant to uniform shifts in all intrinsic qualities.

Figure 4: Demanded Compensation and Compensating Differentials

(a) Benchmark (b) Shifted Labor Demand



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

mechanism, the figure considers a simplified setting with only two occupations $\{L, H\}$ where differences in parental endowment are the only relevant source of heterogeneity among workers, i.e., $A_j(s, u, y) \equiv A_j$ and $\rho = 0$. The curve $d = \mathcal{C}(y)$ shows the demanded compensation $d \equiv e_L - e_H = w_L A_L - w_H A_H$ to become indifferent between the two occupations as a function of parental endowment y. Assume wage rates (w_L, w_H) and a corresponding compensating differentials $d > 0$.[21] Agents with parental endowment $y < \mathcal{C}^{-1}(d)$ choose occupation L, implying the sorting of the children of poorer parents into occupation with the lower intrinsic quality.

Letting $F_y(\cdot)$ denote the cumulative distribution of parental endowment in equilibrium, the labor supply of occupation L is simply given by $\mathcal{S}_L(d) \equiv F_y(\mathcal{C}^{-1}(d))$. Accordingly, if we define a monotonic transformation $\widetilde{\mathcal{D}}_L(\cdot) \equiv F_y^{-1}(\mathcal{D}_L(\cdot))$ of the labor demand $\mathcal{D}_L(\cdot)$ for occupation L, the equilibrium compensating differentials d^* is the intersection of the demanded compensation curve $\mathcal{C}$ and the transformed labor demand curve $\widetilde{\mathcal{D}}_L$.

The logic of sorting based on parental endowment presented in Section 3.2.1 continues to

[21] Here, the key assumption is that the labor market does not differentiate workers based on their parental endowment.

operate under the richer setting that includes heterogeneity in idiosyncratic occupational taste ($\rho > 0$), occupational ability (dependence of A_j on s, u, and y), and multiple occupations. Next, we discuss the determination of equilibrium wage rates $\boldsymbol{w} \equiv (w_j)$ in this more general case.

3.2.2 General Equilibrium and Intergenerational Mobility

The stationary equilibrium of the model features a stationary distribution of endowments for the adults in each generation $F_y(y)$, and a corresponding conditional distribution of child earnings $F_e(e|y)$ given parental endowment y. As we will discuss below, the first distribution determines the occupational labor supply function, while the latter accounts for the drivers of intergenerational persistence of earnings and income under the model.[22]

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

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

Equating the supply function above with the labor demand Equation (8) yields $J-1$ constraints on the vector of wage rates $\boldsymbol{w}$. We assume that the interest rate r is exogenous to the model, pinning down the steady state rental price of capital as $R = r + \xi$, where ξ is the depreciation rate of capital. From the fact that final good is the numeraire, we find that the wage index is given by $W = (1-\chi) \left((r+\xi)/\chi \right)^\chi$, which yields an additional constraint on the vector of wage rates $\boldsymbol{w}$. Having determined the wage rate, we can find the aggregate labor supply L by summing Equation (13) across all occupations.[23]

Under this equilibrium, the model features three potential channels for the dependence of child earnings on parental income, captured by the distribution $F_e(e|y)$. First, an increasing human capital investment policy function $h^*(y)$ implies that the children of richer parents are expected to acquire higher levels of schooling and higher earnings if the ability function $A_j(s,u,y)$ is increasing in schooling attainment s. Second, the children of rich parents may be endowed by other social, cognitive, or non-cognitive skills that are not captured by schooling, or by networks and connections that help them succeed in given occupations. Such channels are captured by a potentially increasing dependence of the ability function $A_j(s,u,y)$ on parental endowment y, leading to positive associations between parental endowment and children earnings. The

[22] Appendix B.1 characterizes these distributions and discusses the different channels for the persistence of earnings, income, and welfare in the model.

[23] It is straightforward to determine the other aggregate variables in the model. For instance, the aggregate capital to (efficiency units of) labor ratio as $K/L = (\chi/R)^{1/(1-\chi)}$. Note that we do not clear asset markets since the real interest rate across generations is exogenous here.

third and final channel stems from the patterns of occupational choice, as captured by the dependence of the occupational choice probabilities in Equation (9) on parental endowment y. This dependence may affect the sorting of children with different levels of schooling attainment and talent across occupations with varying returns to these characteristics, contributing to the dependence of earnings on parental endowment for otherwise similar children.

4 Model Estimation

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

4.1 Maximum-Likelihood Estimation

A period in the model corresponds to a generation, which we assume spans 30 years. Prior to the estimation, we calibrate two parameters based on existing work: the exogenous interest rate r and the altruism parameter β. We set r equal to 2.21% per year, as in Kaplan and Violante (2014), and β equal to 0.5, a value that is within the range of estimates in the literature.[24]

Our PSID sample is composed of $4,637$ parent-child observations. For each pair i, we observe the earnings e_i, occupation o_i and schooling s_i of the child, and parental endowment y_i.[25] Schooling in the data takes one of the five values: no high-school degree, high-school degree, some college, college degree, graduate degree. Correspondingly, we will set these values to take values $s_i \in \{0, \cdots, 4\}$. The occupations in the data are the 54 groups listed in Table 8 in Appendix A.

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

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

The constant term α_j absorbs the logarithm of wage rate per efficiency unit of occupational ability , as well as a constant occupation-specific shifter for the logarithm of occupation-specific ability function A_j. Thus, this term is an endogenous variable. Exogenous parameters κ_j and

[24]For example, the altruism parameter is 0.04 in Kaplan (2012), 0.2 in Boar (2020), 0.51 in Nishiyama (2002) and 0.69 in Barczyk and Kredler (2017).

[25]See Section 2.1, as well as Appendix A for a discussion of the construction of each variable.

θ_j capture the returns to education and talent in occupation-specific ability, respectively. Finally, the exogenous parameter δ_j accounts for all potential mechanisms through which parental endowment may impact occupation-specific ability.[26]

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

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

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

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

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

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

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

[26] Our model is isomorphic to the following Roy model. Each child i receives a vector of occupational abilities $(a_{ij})_{j=1}^J$ such that log earnings are given by $\log e_j\left(s_i, a_{ij}\right) = \alpha_j + \kappa_j s_i + a_{ij}$. We assume that the vector of abilities has a multivariate Gaussian distribution with the following conditional expected value and covariances

$$\begin{aligned}\mathbb{E}\left[a_{ij}|y_i\right] &= \delta_j y_i, \qquad \forall j \in \{1, \cdots, J\}, \\ \mathbb{C}\left[a_{ij}, a_{ij'}|y_i\right] &= \theta_j\theta_{j'}, \qquad \forall j, j' \in \{1, \cdots, J\}.\end{aligned}$$

Table 2: Estimation Results

(a) Preference and Education Parameters

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

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

(b) Estimated Earnings Function

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

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

4.2 Estimation Results

Table 2a reports the estimated preference parameters ζ and ρ. The weight ζ on the intrinsic quality is positive, suggesting that agents value the non-material aspect of occupations. A small value of ρ implies a large average elasticity of occupational choice to earnings, suggesting that the model accounts for the sensitivity of agents to the variations in earnings across occupation. The table also presents the parameters of the human capital investment cost function, and the standard deviation of the distribution of schooling attainment conditional on human capital investment ϑ. The education cost parameters imply a convex form for the monetary costs of parental investment in their children's human capital, reflecting that in the data children from rich families have, on average, higher levels of educational attainment. However, there is substantial heterogeneity in this relationship, reflected in the sizable estimate of ϑ.

Table 2b reports correlations between the estimated parameters of the earnings function and the intrinsic quality of occupations.[27] These patterns of correlation suggest that *(i)* occupations with higher intrinsic qualities display a lower fixed component of earnings and a lower return to parental endowment, but a higher return to schooling and talent, *(ii)* occupations with a lower fixed component of earnings exhibit higher returns to schooling and talent, implying a tradeoff between occupations with high fixed component of earnings and with high returns, and *(iii)* occupations in which the return to education is high also exhibit a high return to talent.

Our maximum likelihood estimation strategy aims to fit the joint distribution of the observed data. Appendix C.3.1 shows that the estimated model also reproduces a number of untargeted moments capturing the observed patterns of educational attainment and occupational choice. In the remainder of this section, we examine the success of the model in accounting for the most important untargeted moments of interest: first, the relationship between intrinsic occupation quality and the occupational choice of rich and poor children, as discussed in the motivating facts in Section 2.3, and second, the observed persistence of earnings in the data.

4.3 Parental Endowment and Occupational Choice

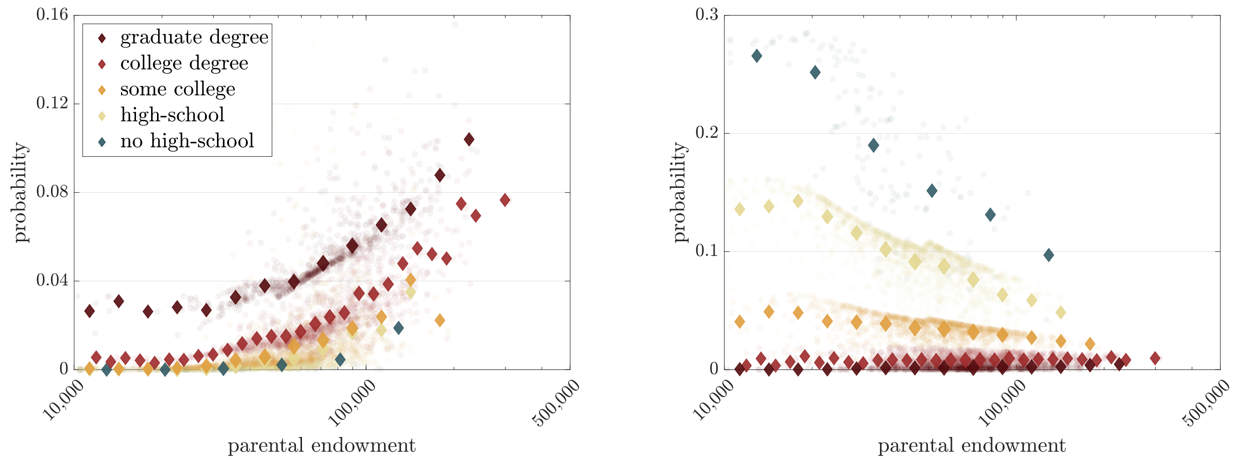
Figure 5 shows the relationship between children's occupational choice and parental endowment as predicted by the model. Panel (a) displays the probability of choosing one of the three occupations with the highest intrinsic quality (post-secondary teachers, librarians, archivists, curators, and architects) as a function of parental endowment and by education group. Panel (b), in turn, displays the probability of choosing one of the three occupations with the lowest intrinsic quality (freight, stock and material handlers, mail distributors, motor vehicle operators). Echoing the argument in Section 3.2.1 and the findings in the PSID data, the probability of choosing an occupation with a high intrinsic quality is increasing in parental endowment. Additionally, the figure also shows that the probability of working in high (low) intrinsic quality occupations increases (decreases) in the level of schooling.

Next, we revisit the correlation between occupational choice elasticities and the intrinsic quality that we saw in Section 2.3 in the context of the estimated model. We take the following strategy. For each observed parent-child pair i in the data, we take the parental endowment y_i as given and draw a talent u_i for the child from the distribution $\mathbb{P}(u_i) = \mathcal{N}(0,1)$. We then re-draw educational attainment s_i, occupational choice o_i, and earnings e_i for each child in the data based on the conditional distribution implied by the model. We generate 10,000 instances of such re-sampled datasets both for the benchmark estimated model and the other estimated

[27] See Table 10 in the online supplemental material for a full list of the estimated parameters of the earnings function.

Figure 5: Occupational Choice and Parental Endowment

(a) High Intrinsic Quality Occupations (b) Low Intrinsic Quality Occupations



Notes: Panel (a) shows the cumulative probability that the child chooses one of the three occupations with the highest intrinsic quality, by educational attainment. Panel (b) shows the cumulative probability that the child chooses one of the three occupations with the lowest intrinsic quality, by educational attainment.

model featuring no variations in intrinsic quality. 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.

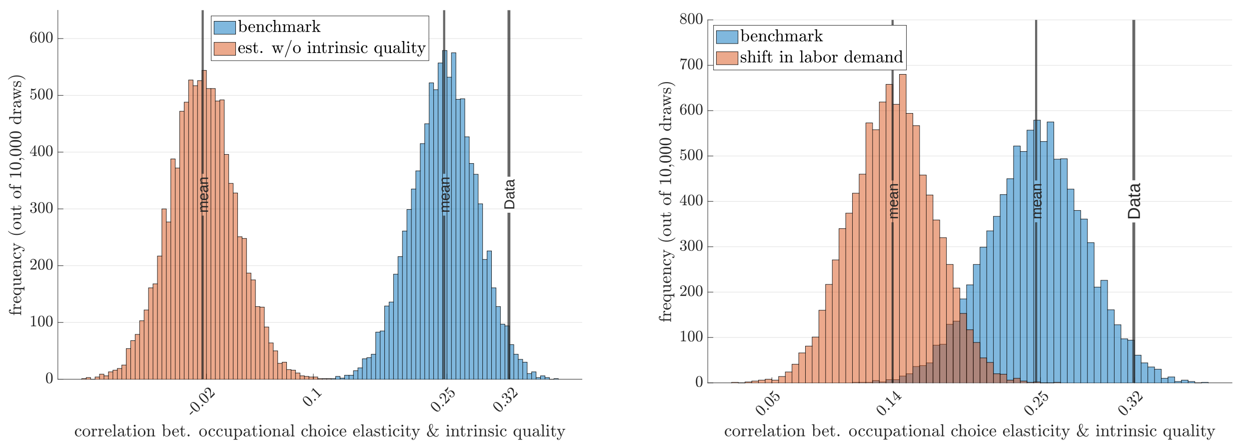
Figure 6a shows the distributions of the resulting correlations across the 10,000 re-sampled datasets, corresponding to the benchmark model and the model without variations in intrinsic qualities. The mean value of these correlations falls from 0.25 ($SE = 0.04$) under the benchmark model to -0.02 ($SE = 0.04$) under the model estimated with no intrinsic qualities. Thus, the presence of intrinsic occupation quality allows us to explain the systematic relationship observed in the data between occupational choice elasticities and intrinsic qualities.

4.4 Intergenerational Mobility in the Estimated Model

Next, we examine the degree of intergenerational persistence of earnings and income under the estimated model. Table 3 contrasts the measures of intergenerational mobility in our PSID sample against their respective average in 10,000 re-sampled datasets based on our estimated model following the procedure discussed in Section 4.3. We calculate four such measures. The first is the intergenerational elasticity between parental endowment and the child's earnings, and

Figure 6: Occupational Choice Elasticticies 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).

is defined as the slope coefficient of a regression of log-child earnings on log-parental endowment (Black and Devereux, 2011). The second is the rank-rank slope between parental endowment and child earnings. Letting $r_{y,i} \in [0,1]$ denote the parent i's rank in the distribution of parental endowment and $r_{e,i} \in [0,1]$ denote their child's rank in the distribution of children earnings, the rank-rank slope is defined as the slope coefficient of a regression of $r_{e,i}$ on $r_{y,i}$. The third is the share of children who are in a higher decile of the child earnings distribution than their parents are in the parental endowment distribution. The fourth is the covariance between log-child earnings on log-parental endowment. As the table shows, the model, despite its parsimony, is able to reproduce between 72 and 100% of the intergenerational persistence in the data. In Appendix C.4, we discuss the drivers of persistence of earnings under the model and provide a decomposition of the persistence into the different channels discussed in Section 3.2.2.

4.5 Demanded Compensation and Compensating Differentials

In Section 3.2.1, we discussed how the occupational sorting of the children depends on the demanded compensation, the amount needed to convince each child to switch to occupations with lower intrinsic quality, and the prevailing equilbrium compensating differentials across occupations. We now turn to examining both these objects in the context of the estimated model.

Table 3: Intergenerational Mobility

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

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

To illustrate the core prediction prediction in Equation (12), we compute for each child i in the PSID data the compensation d_i required to render the child indifferent between remaining in their current occupation and moving to an occupation with intrinsic quality that is $\Delta\nu$ lower than the intrinsic quality of the current occupation. Specifically, d_i is such that

$$V\left(b^*\left(y_i\right)+e_i+d_i\right)-V\left(b^*\left(y_i\right)+e_i\right)=\zeta\Delta\nu, \tag{17}$$

where $\Delta\nu$ is set to equal the difference between the 75^{th} and the 25^{th} percentile of the distribution of intrinsic qualities.[28] Figure 7 shows that, consistent with the prediction of the theory, this compensation is increasing in parental endowment. It represents, on average 10% of earnings in the region of the parental endowment space where the most mass is, but can be as high as 25%, on average, for children of rich parents.

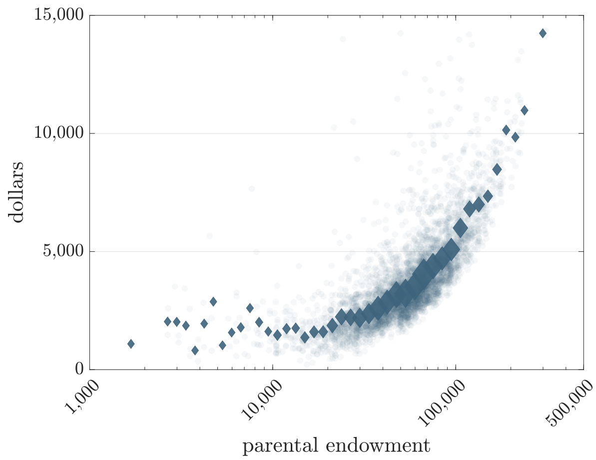
Uncovering Compensating Differentials We take two distinct strategies to provide proxies for the equilibrium compensating differentials through the lens of the estimated model.

First, we construct a micro-level proxy for compensating differentials that corresponds to the tradeoffs faced by individuals making occupational choice decisions. For each individual in the data, we consider the top two most likely occupations predicted by the model, and compare the difference in log earnings between the two occupations against the difference between their

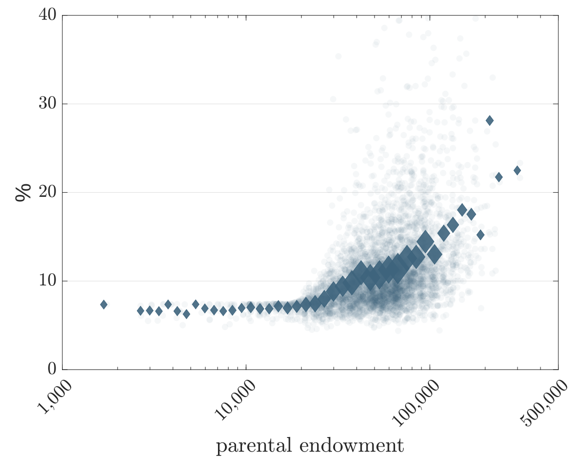
[28] Recall from Equation (12) that this requires the policy function $b^*(y)$ to be increasing in parental endowment y. Appendix C.3.2 shows that the policy function in the estimated model indeed satisfies this condition.

Figure 7: Earnings Compensation and Parental Endowment

(a) Compensation in Dollars



(b) Compensation as Share of Earnings



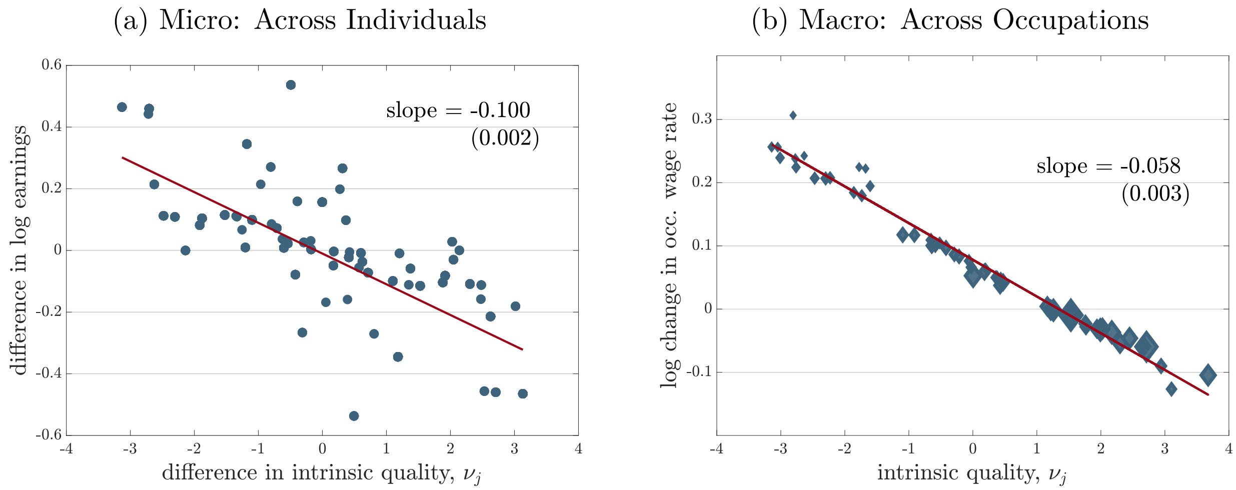
Notes: The figure shows the compensation required to make children indifferent between their current occupation and an occupation with an intrinsic quality that is $\Delta\nu$ lower, as function of the parental endowment. The compensation is expressed in 1996 US dollars in Panel (a) and as a percentage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

intrinsic quality. Figure 8a shows the scatter plot of these differences. The linear fit implies that in the tradeoff between top two choices faced by each individual, a standard deviation gain in intrinsic quality is, on average, associated with a fall of over 17% in earnings.

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

In the environment with removed variations in intrinsic quality, the idiosyncratic taste shocks for occupations still provide a source of heterogeneity for the non-monetary dimension of working across different occupations. However, these idiosyncratic shocks average to zero across the population and only lead to a finite elasticity of occupational labor supply. The only difference

Figure 8: Compensating Differentials



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

between the new environment and our benchmark is the absence of intrinsic qualities. Thus, we may think of the resulting changes in the log occupational wage rates (given by $\boldsymbol{\alpha} - \boldsymbol{\alpha}^n$) as a proxy for the *general equilibrium compensating differentials* that satisfy the constraints imposed by the original levels of occupational wage bill under the benchmark model.

Figure 8b shows that the response of occupational wages is indeed strongly correlated with intrinsic quality: compared to the model with no intrinsic qualities, the benchmark economy reduces the (per efficiency unit) wage rate in occupations that compensate workers through higher intrinsic qualities under the benchmark model. We find that a linear fit captures most of the variations in the occupational wages, providing us an alternative characterization of the trade-off between intrinsic quality and earnings: one standard deviation rise in the intrinsic quality is accompanied by an average fall of around 11.4% in the (per efficiency unit) wage rate.

5 Mobility and the Intrinsic Quality of Occupations

In this section, we study the patterns of mobility in the data in light of our estimated model.

5.1 Welfare and Compensated Earnings

The most comprehensive measure of welfare in the model is V^+ in Equation (2), which accounts for both the pecuniary and non-pecuniary components of welfare. However, we need to transform a cardinal proxy for welfare such as V^+ to a money metric in order to compare the corresponding measure of mobility of welfare with standard measures in terms of income. Here, we face an additional challenge in that we do not observe the idiosyncratic occupation-specific shocks.

To tackle the latter challenge, we take two alternative strategies. Our first strategy relies on the observation that, given parental endowment y, talent u, schooling s, and occupation j of children, the conditional cumulative distribution function of V^+ is independent of the ex-post occupation of the child, and is given by[29]

$$F_v\left(v^+|s,u,y\right) \equiv \mathbb{P}\left(V^+ < v^+|s,u,y,j\right) = \exp\left[-\exp\left(-\frac{v^+ - \overline{V}^+(s,u,y)}{\rho} - \overline{\gamma}\right)\right], \tag{18}$$

where the Euler-Mascheroni constant $\overline{\gamma}$ is defined as in Equation (3) and $\overline{V}^+(s,u,y)$ satisfies Equation (6) and gives the conditional expectation of V^+. This result implies that, conditional on the tuple (s,u,y), the residual inequality of welfare generated by heterogeneity in idiosyncratic occupation-specific taste shocks is the same regardless of the ex-post occupation. In other words, if we know the tuple (s,u,y) for a given agent in the model, we can characterize the welfare of the agent subject to an additional shock that has the same distribution for everyone. Now, recall from Equation (16) that we can infer the talent of each child in the data given their observed earnings, schooling, parental endowment, and occupational choice. Thus, we can infer the expected welfare $\overline{V}_i^+ \equiv \mathbb{E}_{\boldsymbol{\epsilon}}\left[V^+|e_i,o_i,s_i,y_i\right]$ of each child i observed in our data by substituting for unobserved talent u_i from Equation (16) into the expression from Equation (6).

In our second approach, we simply abstract away from the idiosyncratic shock component of welfare V^+ and evaluate the two components corresponding to the market consumption and the intrinsic quality of occupation[30]

$$\widetilde{V}_i^+ \equiv V\left(b^*(y_i) + e_i\right) + \zeta\, \nu_{o_i}. \tag{19}$$

Noting that $\overline{V}_i^+ - \widetilde{V}_i^+ \equiv \rho\mathbb{E}_{\boldsymbol{\epsilon}}\left[\epsilon_{o_i}|e_i,o_i,s_i,y_i\right]$, the two measures above allow us to separate the

[29]See Lemma 3 in Appendix B. Appendix B.1 uses this result to derive the distribution of child welfare conditional on parental endowment, characterizing the persistence of welfare in the model.

[30]Figure 22 in Appendix D shows that the two measures are highly correlated in our data. A regression of $\widetilde{V}_i^+$ on $\overline{V}_i^+$ in our sample leads to a coefficient of 0.9995 ($SE = 0.001$).

contribution of intrinsic qualities and taste shocks in forming our welfare proxy.

In order to compare the intergenerational mobility of income with the corresponding mobility in terms of these measures of welfare, we rely on the concept of *compensating variation*. The issue is that we observe the earnings of children across distinct occupations, which in turn generate varying degrees of intrinsic quality for them. We therefore perform a hypothetical exercise in which each child i is moved from their observed occupation o_i to a common benchmark occupation, which we choose to be the one with the lowest intrinsic quality $\underline{\nu}$. We then compute the corresponding compensating variation that makes each child indifferent between remaining in their original occupation o_i and moving to this benchmark occupation.

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

$$V\left(b^*\left(y_i\right)+e_i+\overline{d}_i\right)+\zeta\underline{\nu}=\overline{V}_i^+, \tag{20}$$

where in the left hand side of the equation we have used the fact that the expected taste shock for the child under the benchmark occupation is zero. Similarly, for the second measure $\widetilde{V}_i^+$ defined in Equation (19), we can define the compensation $\widetilde{d}_i$ such that it satisfies

$$V\left(b^*\left(y_i\right)+e_i+\widetilde{d}_i\right)-V\left(b^*\left(y_i\right)+e_i\right)=\zeta\left(\nu_{o_i}-\underline{\nu}\right). \tag{21}$$

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

$$\overline{ce}_i\equiv e_i+\overline{d}_i,\qquad \widetilde{ce}_i\equiv e_i+\widetilde{d}_i, \tag{22}$$

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

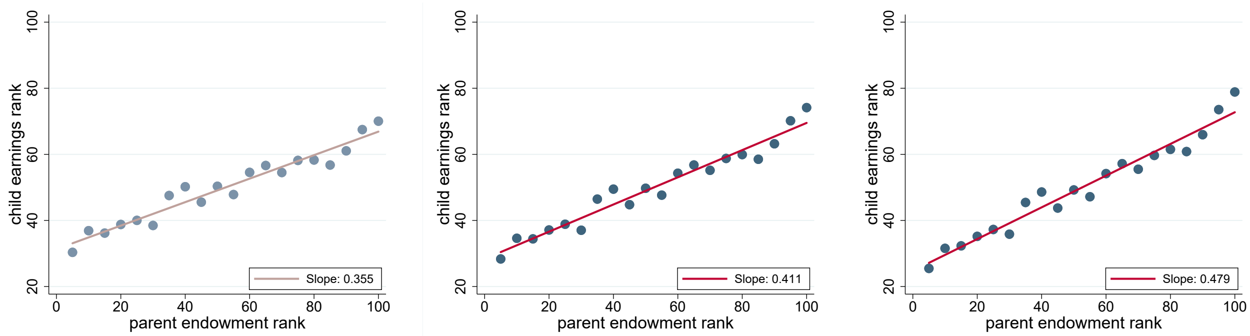
5.2 Mobility and Compensation of Earnings

The procedure discussed in Section 5.1 allows us to compute the compensated earnings for each child in the data, given uncompensated (observed) earnings, schooling attainment, occupational choice, and parental endowment. We find the ranks $r_{\overline{ce},i}$ and $r_{\widetilde{ce},i}\in[0,1]$ of the child in the respective distributions of compensated earnings for the two measures of compensated earnings defined in Equations (22). To examine the implications of the model regarding the intergenerational mobility of income versus welfare, we compare rank-rank slopes between parental endowment and the realized and compensated earnings of the child.

Figure 9a depicts the relationship between the parent's rank r_y in the distribution of parental

Figure 9: Intergenerational Mobility of Compensated Earnings in the Data

(a) Realized Earnings (b) Compensated Earnings, $\widetilde{ce}$ (c) Compensated Earnings, $\overline{ce}$



Notes: Panel (a) shows the relationship between the parent's rank r_y in the distribution of parental endowment and the child's rank r_e in the distribution of child earnings. Panels (b) and (c) show the relationship between the parent's rank r_y in the distribution of parental endowment and the child's ranks $r_{\widetilde{ce}}$ and $r_{\overline{ce}}$, respectively, in the distribution of compensated earnings.

endowment and the child's rank r_e in the distribution of child earnings. Figures 9b and 9c show the relationship between the parent's rank r_y and the child's ranks $r_{\widetilde{ce}}$ and $r_{\overline{ce}}$. Accounting for the intrinsic quality of occupations lowers intergenerational mobility relative to what is predicted by earnings alone. Specifically, the rank-rank slope between parental endowment and compensated earnings $\widetilde{ce}$ ($\overline{ce}$) of the child is 16% (35%) larger than that between parental endowment and the realized earnings of the child.[31]

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

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

Expected Mobility under the Model In the next section, we will study changes in the environment that affect wages and parental investments. In the exercise above, we evaluated

[31] If, instead, we consider the hypothetical exercise of moving each child i from their observed occupation o_i to a common benchmark occupation that is the one at the 25^{th} percentile of the intrinsic quality distribution we obtain $r_{\widetilde{ce}}$=0.39 and $r_{\overline{ce}}$=0.47, so that the intergenerational mobility of compensated earnings is, respectively, 11% and 18% lower than the intergenerational mobility of realized earnings.

the degree of intergenerational persistence for the individuals in the PSID sample, taking the observed earnings and occupational choice as given in the data. However, in order to evaluate the effects of these changes on mobility, we need to compare the *expected* degrees of persistence given the conditional distributions of earnings and occupational choice predicted by the model. To build measures of expected persistence as a benchmark for these comparisons, we follow the strategy introduced in Sections 4.3 and 4.4 and re-sample 10,000 datasets, re-drawing the occupation and earnings for each individual conditional on their observed parental endowment. We do this separately under the benchmark model, as well as *(i)* under the model estimated without intrinsic qualities, and *(ii)* the benchmark model with removed intrinsic qualities.

Table 4 presents the results for the three models in the first three rows. In line with the results we saw in the case of observed data, the benchmark model predicts that the mobility is on average the highest in terms of uncompensated earnings, and the lowest in terms of the compensated measure accounting for both intrinsic qualities and taste shocks. Under the two cases with no variations in intrinsic qualities, the mobility of uncompensated earnings is slightly lower than that in the data.[32] More importantly, the mobility in terms of the compensated measure $\widetilde{ce}$, which accounts for the intrinsic quality of occupations, falls under the benchmark model relative to the mobility of the uncompensated earnings. The two models without intrinsic qualities, mechanically, lead to the same predictions about mobility for the uncompensated earnings and this measure of uncompensated earnings. Finally, in all models, the mobility is lower in terms of the compensated measure $\overline{ce}$, that additionally accounts for idiosyncratic taste shocks, compared to the mobility of the uncompensated earnings.

6 Trends in Occupational Labor Demand

A large literature has documented substantial shifts in the occupational composition of the labor force in the US, including an expansion of occupations that require non-routine, abstract and social skills, and a shrinkage of those that are intensive in routine tasks (Autor et al., 2006, Acemoglu and Autor, 2011, Jaimovich and Siu, 2012, Autor and Dorn, 2013). Following the common approach, we use data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) to calculate, for each occupation, the change in the wage bill share over three decades. We restrict attention to workers between 16 and 64 and we calculate, for each occupation, the average wage bill share between 1980 and 1985 and between

[32]See Appendix C.4 for a discussion of the drivers of the change in the mobility of uncompensated earnings compared to the benchmark.

Table 4: Mobility of Uncompensated and Compensated Earnings under the Model

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

2010 and 2015.[33] Figure 10a shows a substantial rise in the share of occupations with high intrinsic quality: the slope of the linear fit suggests that an increase of one standard deviation in the intrinsic quality of occupations has been associated with a rise in the wage bill of around 40%. In this section, we examine the implications of this fact for the welfare of workers, in terms of intergenerational mobility, inequality, and earnings growth.

Figure 4b provides an intuitive account of the rise in the compensating differentials as a result of the shift in labor demand. This shift moves the transformed demand curve $\widetilde{\mathcal{D}}_L$ to the left, since the demand for low-intrinsic quality occupations falls. In the absence of any supply response, this would lead to a fall in the compensating differentials, and a modest expansion of the labor supply of the high intrinsic-quality occupations toward the children of relatively poorer parents.

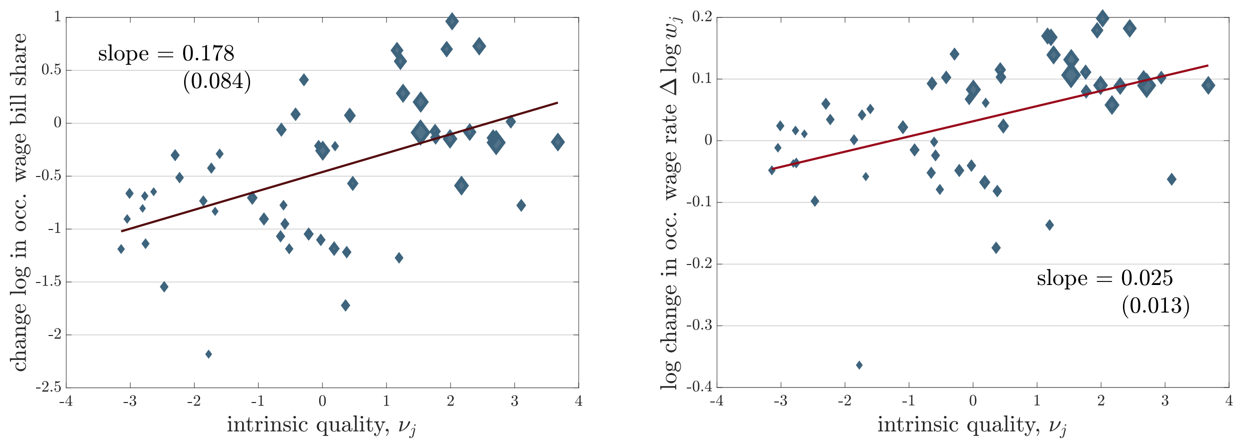
However, the core mechanism of the model implies an additional general equilibrium response in occupational labor supply. Recall from Equation (11) that the shape of the demanded compensation curve $\mathcal{C}(\cdot)$ is driven by the dependence of the marginal value function on the sum of parental transfers and earnings. Since the shift in the demand curve $\widetilde{\mathcal{D}}_L$ leads to a response in occupational earnings, we need to account for the full general equilibrium structure to determine the predictions of the model with regard to compensating differentials and occupational choice.

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

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

Figure 10: Shifts in Occupational Labor Demand

(a) Shifts in Occupational Labor Demand (b) Response in Occupational Wage Rate



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

Statistics (BLS). We let $\tau \equiv d$ denote this variation in the environment.[34] Equalizing occupational labor supply and demand in Equation (13) then allows us to solve for fixed components of the earnings function $\boldsymbol{\alpha}^d$ that characterize the new occupational wage rates w_j, as well as the corresponding value function V^d and stationary distribution of endowments F_y^d.[35]

To study the effects on long-run labor supply, Figure 11a shows the response in the compensation required to make children indifferent between two occupations at the 25th and 75th percentile of the intrinsic quality distribution, as a function of parental endowment. The figure shows the change in the mean logarithm of the demanded compensation in the model with shifted labor demand relative to the benchmark, across 10,000 re-sampled datasets from each model. The shifts in labor demand lead to a rise of approximately 4% in the 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 and is stronger among the children of poorer parents, for which the rise in earnings e_i has a stronger effect as their receive a lower transfer $b^*(y_i)$.

Figure 4b shows that if the upward shift in the demanded compensation curve $\mathcal{C}(\cdot)$ is strong

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

[35] For comparison, we also compute the effects of the same change in labor demand under a model without variations across occupations in intrinsic qualities, i.e., when we set $\nu_j \equiv 0$ for all j. We indicate this latter variation, corresponding to both no variations in intrinsic qualities and the shifts in labor demand, with $\tau \equiv nd$.

enough, equilibrium compensating differentials may grow. Figure 11b confirms this is the case in our quantitative exercise. The figure shows the response of occupational wages if we remove the variations in intrinsic qualities under the model with shifted labor demand, which we interpret as equilibrium compensating differentials. We find this relationship to become stronger.[36]

6.1 Response in Earnings, Occupational Choice, and Mobility

Combining the changes in both supply and demand in general equilibrium, Figure 10b shows the response of occupational wages to the shifts in occupational labor demand. The model predicts that rise in demand for occupations with high intrinsic quality translates into higher earnings for occupations with higher intrinsic quality.[37] Note, in addition, that the mean occupational wage rate also rises by approximately 2.5%, to account for the component of the shift in labor demand capturing the growth in average earnings.

Next, we examine the effect of the shifts in occupational labor demand on the relationship between parental endowment and the likelihood of choosing occupations with high intrinsic qualities, following the same sampling strategy as in Section 4.3. We perform linear regressions of occupational choice on parental endowment and educational attainment, and compute the correlation between the coefficient on parental endowment and the intrinsic quality of occupations. Figure 6b 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.

Turning to intergenerational mobility, the last row of Table 4 shows the mean persistence of earnings under the model with shifted labor demand, proxied by the rank-rank slope of a child's earnings on parental endowment. We find that the persistence in terms of realized earnings falls compared to the benchmark model. The main driver of this rise in mobility of earnings is the rise in the expected returns to schooling as the children of poorer parents switch to occupations with high intrinsic qualities that also offer higher returns to schooling κ.[38]

The mobility in terms of compensated earnings measures $\widetilde{ce}_i$ and $\overline{ce}_i$ also rises. Two distinct

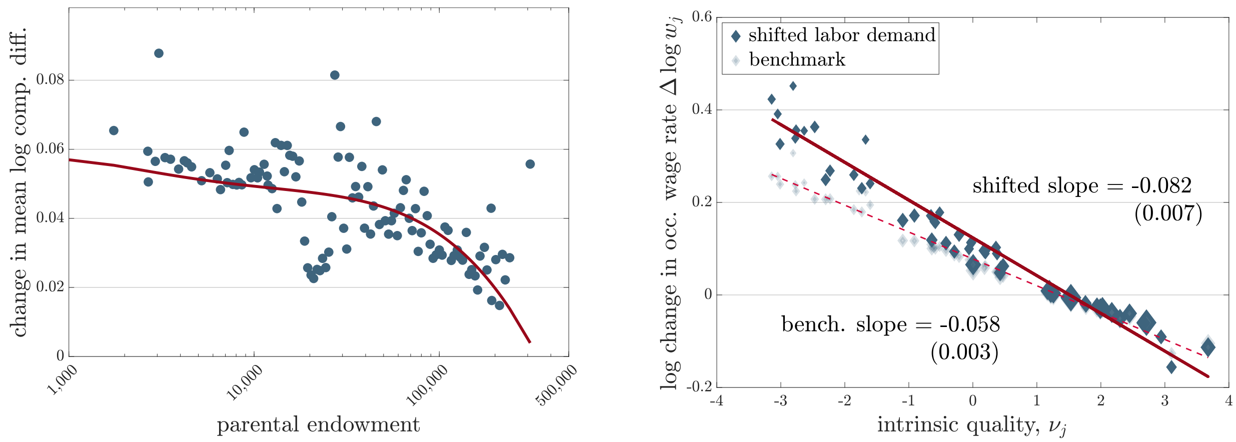
[36] The linear fit implies that one standard deviation rise in the intrinsic quality is now accompanied by a fall of around 14.2% in the wage rate (from a baseline of 10.3%), corresponding to a rise of over 38% in terms of this proxy for compensating differentials

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

[38] See Table 2b for the correlations between different parameters of the earnings function and the intrinsic qualities across occupations. See Appendix C.4 for a discussion of the drivers of the change in the mobility of uncompensated earnings compared to the benchmark.

Figure 11: Compensating Differentials with Shifts in Occupational Labor Demand

(a) Response in Demanded Compensation (b) Wage Response Removing Intrinsic Quality



Notes: Panel (a) shows the binscatter plot of the change in the mean logarithm of the compensation required to make the child indifferent between two occupations at the 25th and 75th of instrinsic values, from Equation (17), in the model with shifted labor demand relative to the benchmark, across 10,000 resampled datasets from each model. Panel (b) plots the change in the log occupational wage rates $\alpha_j^d - \alpha_j^{nd}$ against occupational intrinsic qualities ν_j, where nd represents the counterfactual experiment of eliminating differences in intrinsic occupation values under the model with shifted labor demand, and d represents the model with shifted demand.

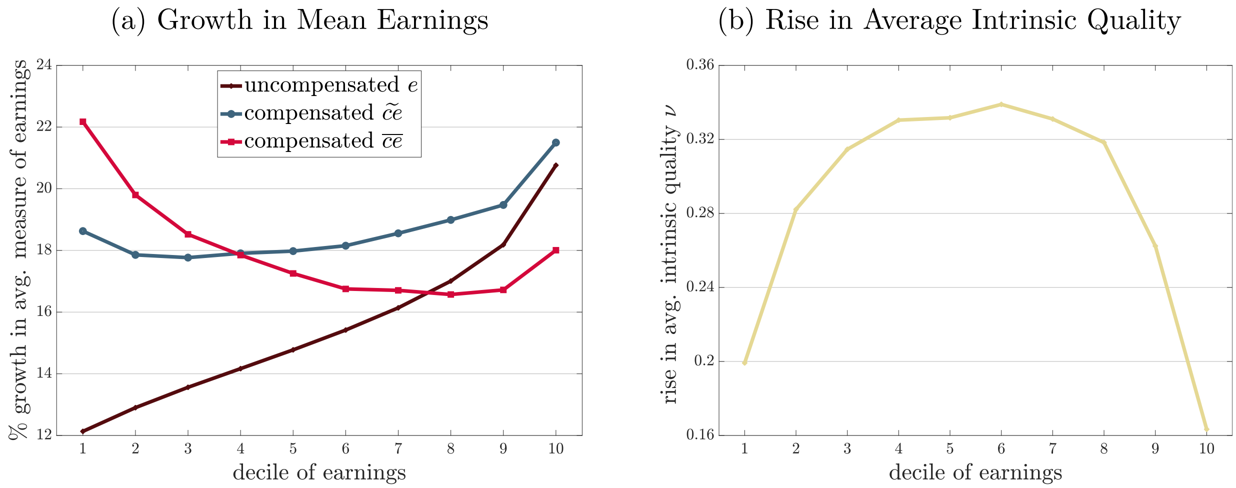
forces shape the contribution of the compensation $\widetilde{d}_i$ from Equation (21) to the mobility in terms of this measure of compensated earnings: *(i)* the dependence of occupational intrinsic qualities ν_{o_i} on parental endowment y_i and *(ii)* the dependence of own endowment $b^*(y_i) + e_i$ on parental endowment y_i. Both components in fact show the weakening of the intergenerational link: the former as seen in Figure 6b and the latter as seen in Table 4. Together, these two forces lead to a rise in the mobility of welfare: the children of poor parents shift to occupations with higher intrinsic quality and also the value that these children attribute to this intrinsic quality rises as they become relatively richer. The overall effect is a fall in the correlation between compensation $\widetilde{d}_i$ and parental endowment y_i, which in turn leads to the patterns in Table 4.

6.2 Growth in Compensated Earnings

As we saw, the trends in labor demand have shifted the composition of the labor force toward occupations with higher intrinsic quality. Since workers value this rise in the intrinsic occupational quality in ways that are not reflected in their earnings, the observed rise in workers' earnings does not fully capture all welfare-relevant aspects of their job market outcomes.

We use our model to calculate the growth in compensated earnings, which account for the

Figure 12: Change in Welfare Across Deciles of Earnings



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

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

$$\mathbb{E}[ce] \equiv \sum_j \int_0^\infty \mathbb{E}_{s,u}\left[\left(e_j(s,u,y) + d_j(s,u,y)\right)\mu_j(s,u,y) \,|\, h^*(y)\right] dF_y(y)\,, \tag{23}$$

where $d_j(s,u,y)$ either satisfies Equation (21) or Equation (20). As before, the first case compensates agents only for the intrinsic quality of their respective occupation, and the second for the additional value of their conditional expected idiosyncratic taste shock.

The growth in the average earnings from shifting labor demand is 17.1%. The corresponding growth in the measures $\mathbb{E}[\widetilde{ce}]$ and $\mathbb{E}[\overline{ce}]$ defined in Equation (23) is 19.2% and 17.7%, respectively. Thus, accounting for the role of taste for occupation *raises* our estimates of growth by 0.6 to 2.1 percentage points over a baseline of around 17 percentage points, or around 4-12 percent of the measured growth. The intuition for this upward correction is straightforward: the economy has shifted labor toward occupations that workers enjoy more. Therefore, a larger share of worker compensation comes from the intrinsic qualities occupations, leading to an underestimation of growth in worker welfare if we merely rely on observed earnings.

Figure 12a shows how the growth in uncompensated and compensated earnings varies across earnings deciles. Uncompensated earnings growth is larger for higher deciles. While the shifts in labor demand *raise the mobility* in uncompensated earnings, as discussed in Section 6.1, they also *increase the inequality* in uncompensated earnings. We also find that the contribution of non-monetary components of work is larger for the median (compared to the average) worker: the growth in earnings in the two measures of compensated earnings $\widetilde{ce}$ and $\overline{ce}$ are 14.8%, 18.0%, and 17.3%, respectively, implying an additional contribution of around 2.5-3.2 percentage points.

The two measures of compensated earnings display distinct patterns. Accounting only for the intrinsic quality of occupations ($\widetilde{ce}$), most additional gains are disproportionately accrued to workers in the lower deciles of earnings. This result is driven by a combination of two factors: *(i)* the change in the intrinsic quality of the occupations chosen by individuals in each decile, and *(ii)* the change in the value attributed to these changes in intrinsic qualities. Figure 12b examines the first factor, showing that the expected intrinsic quality of the occupations chosen by the workers in the middle deciles of earnings sees the highest gains. Comparing Figure 12a and Figure 12b, we infer that workers in the lowest deciles of earnings witness only modest increases in the mean intrinsic quality of their occupations, but attribute substantially larger monetary values to these gains. This measure of compensated earnings suggests that the welfare improvements stemming from the shifts in occupational labor demand have been more equally distributed across workers than is suggested by the uncompensated earnings measures.

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

7 Conclusion

In this paper, we use micro data from the Panel Study of Income Dynamics (PSID), the National Longitudinal Survey of Youth 1997 (NLSY) and the General Social Survey (GSS) to document that children of rich parents are more likely to choose occupations with a higher intrinsic quality.

The intrinsic quality of an occupation captures welfare-relevant aspects of the occupation that go beyond earnings. We proxy this by the first principal component of a bundle of job amenities that the average worker values and that are implicitly priced in the market in the form of compensating differentials. We characterize the effect of growing up in a rich family on occupational choice in the form of an occupational choice elasticity that captures the change in the likelihood of choosing a given occupation as parental income increases. We find a positive correlation between occupational choice elasticities and intrinsic occupation quality that is robust across datasets, occupation classifications and measures of intrinsic occupation quality.

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

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

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

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Online Appendix

A Data Appendix

A.1 PSID Data and Sample Selection

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

1. *Occupation*: defined, for both parents and children, as the most frequenty held occupation between age 22 and age 55. To study occupational choice and characteristics of occupations, we map detailed (and changing) occupation classifications in the PSID into 54 occupations, listed in Table 8 in the online supplemental material. In robustness exercises, we also consider a finer occupation classification, with the 80 occupation groups listed in Table 9.

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

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

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

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

5. *Parental endowment*: defined as the sum between parental earnings and annualized parental inherited wealth. Parental earnings is 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 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.

A.2 NLSY Data and Sample Selection

The NLSY 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 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 frequenty held occupation between age 22 and age 36.

The oldest respondents in the NLSY 1997 are 36.

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

3. *Earnings*: defined as the average earnings in the most frequently held occupation between age 22 and 36. Prior to constructing earnings in the cross-section, in the panel we remove age and time trends by projecting earnings on a quadratic age term, a quadratic time trend and an interaction term between age and year, all of which are allowed to vary by occupation. We then evaluate earnings at age 30 and in year 2010, to ensure comparability across years when averaging over time. We evaluate earnings at a different age and in a different year than in the PSID data because the NLSY sample covers a more recent period than the PSID. The earnings variable in the cross-section is then obtained by averaging over the earnings in the most frequently held occupation. Since the earnings variable thus constructed nets out age and time effects, in all regressions that use this variable we do not control for age and time.

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

A.3 General Social Survey

The GSS is a survey that assesses attitudes, behaviors, and attributes of a representative sample of US residents. The survey began in 1972, collecting information on a sample between 1,500 and 4,000 respondents. We use seven topics/questions from the Quality of Working Life module, administered in 2002, 2006, 2010 and 2014. These topics/questions are: *(i)* At the place where I work, I am treated with respect, *(ii)* Does your job regularly require you to perform repetitive or forceful hand movements or involved awkward postures?, *(iii)* Does your job require you to do repeated lifting, pushing, pulling or bending?, *(iv)* My job requires that I keep learning new things, *(v)* I have an opportunity to develop my own special abilities, *(vi)* I get to do a number of different things on my job, and *(vii)* My job requires that I work very fast. We recode answers to topics/questions *(i)*, *(iv)*-*(vii)* to range from 1-Strongly disagree, 2-Disagree, 3-Agree to 4-Strongly agree and answers to topics/questions *(ii)* and *(iii)* to 1-Yes and 2-No. We standardize these answers before estimating Equation 1, so that each ν_{it}^{x} is a number between 0 and 1.

A.4 Estimating Potential Earnings

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

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

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

B Model Appendix

B.1 The Stationary Distribution of Endowment and Intergenerational Mobility

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

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

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

$$F_e(e|y) = \mathbb{E}_s \left[F_e(e|s, y) \,\middle|\, h^*(y) \right], \tag{24}$$

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

$$F_e(e|s, y) \equiv \sum_{j=1}^{J} \int^{\widetilde{E}_j^{-1}(e;s,y)} \mu_j(s, u, y)\, d\mathbb{P}_u(u), \tag{25}$$

where the conditional occupational choice function μ_j satisfies Equation (9). Equation (25) accounts for two distinct effects of the parental endowment on child earnings discussed above.

The first effect, that higher parental endowment may raise the earnings within the occupation, is reflected in the upper bound on the integral. The second effect, that parental endowment shapes the patterns of occupational choice, is reflected through the dependence of the term μ_j on parental endowment. Finally, Equation (24) 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

$$F_y\left(y^+\right) = \int_0^\infty F_e(y^+ - b^*(y)|y)\, dF_y(y), \tag{26}$$

where the conditional distribution of earnings $F_e(\cdot|y)$ satisfies Equations (24) and (25). The dispersion in total endowment is shaped by two distinct forces: the dependence of child earnings on parental total income $F_e(\cdot|y)$ as well as the direct parental transfer policy $b^*(y)$.

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

$$F_v\left(v^+|y\right) = \mathbb{E}_{s,u}\left[F_v\left(v^+|s,u,y\right) | \, h^*(y)\right], \tag{27}$$

where $F_v\left(v^+|y\right)$ satisfies Equation (18). Equation (27) additionally accounts for the contribution of parental endowment to the welfare of the children through its effect on schooling attainment. Conditional on attained schooling, Equation (18) shows the welfare effect of parental endowment through its direct effect on earnings and its indirect effect on the patterns of occupation choice. Finally, the long-run stationary distribution of welfare in the model immediately follows from Equation (27) as $F_v(v) \equiv \int F_v(v|y)\, dF_y(y)$.

B.2 Proofs and Derivations

Sequential Formulation of the Problem of Generation t The problem laid out in Section 3.1.1 corresponds to the recursive formulation of the the following sequential problem faced by each generation t:

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

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

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

Lemma 1. *The expected utility of children in Equation (4) is given by Equation (6).*

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. Consider a child with schooling s, talent u, parental transfer b, and parental income y, and let $\vartheta_j \equiv V\left(b + e_j\left(s, u, y\right)\right) + \zeta\,\nu_j$,to simplify the expressions. The probability that the expected adult utility of this child is below v is given by

$$\begin{aligned}
F_v(v) &\equiv \mathbb{P}\left[V^{+}\left(s, u, \boldsymbol{\epsilon}, b, y\right) < v\right], \\
&= \mathbb{P}\left[\max_{j}\ \vartheta_j + \rho\,\epsilon_j < v\right], \\
&= \prod_{j=1}^{J} \mathbb{P}\left(\epsilon_j \leq \tfrac{1}{\rho}\left(v - \vartheta_j\right)\right), \\
&= \prod_{j=1}^{J} F\left(\tfrac{1}{\rho}\left(v - \vartheta_j\right)\right), \\
&= \prod_{j=1}^{J} \exp\left(-\exp\left(-\tfrac{1}{\rho}\left(v - \vartheta_j\right) - \overline{\gamma}\right)\right), \\
&= \exp\left(-\exp\left[-\tfrac{1}{\rho}v + \log\left(\sum_{j=1}^{J} e^{\frac{1}{\rho}\vartheta_j}\right) - \overline{\gamma}\right]\right).
\end{aligned}$$

This allows us to calculate

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

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

$$\begin{aligned}
\mathbb{E}_{\boldsymbol{\epsilon}}\left[V^{+}\left(s,u,\boldsymbol{\epsilon},b,y\right)\right] &= \rho\sum_{j=1}^{J}\int_{-\infty}^{\infty}\left(x-\overline{\gamma}+\log\sum_{j'=1}^{J}\exp\left(\tfrac{1}{\rho}\vartheta_{j'}\right)\right)\ \exp\left(-x\right)\ \exp\left(\exp\left(-x\right)\right)dx,\\
&= \rho\ \log\sum_{j'=1}^{J}\exp\left(\tfrac{1}{\rho}\vartheta_{j'}\right).
\end{aligned}$$

□

Lemma 2. *The probabilities of occupational choice under a stationary distribution is given by Equation (9).*

Proof. We use the same notation as in the proof of Lemma 1 above. Dropping the time subscripts to simplify the expressions, the probably of choosing occupation j for a child with schooling s, talent u, parental transfer b, and parental income y is given by

$$\begin{aligned}
\mu_j\left(s,u,b,y\right) &\equiv \mathbb{P}\left(j=\operatorname*{argmax}_{j'}\ \vartheta_{j'}+\rho\,\epsilon_{j'}\right),\\
&= \int_{-\infty}^{\infty} F'\left(\epsilon_j\right)\times\prod_{j'\neq j}\mathbb{P}\left(\epsilon_{j'}\leq\epsilon_j+\tfrac{1}{\rho}\left(\vartheta_j-\vartheta_{j'}\right)\right)d\epsilon_j,\\
&= \int_{-\infty}^{\infty}\exp\left(-\epsilon_j-\overline{\gamma}\right)\exp\left(-e^{-\epsilon_j-\overline{\gamma}}\right)\\
&\qquad\times\prod_{j'\neq j}\exp\left(-e^{-\left(\epsilon_j+\frac{1}{\rho}\left(\vartheta_j-\vartheta_{j'}\right)\right)-\overline{\gamma}}\right)d\epsilon_j,\\
&= \int_{-\infty}^{\infty}\exp\left(-\epsilon_j-\overline{\gamma}\right)\exp\left(-e^{-\epsilon_j-\overline{\gamma}}\left(1+\sum_{j'\neq j}e^{-\frac{1}{\rho}\left(\vartheta_j-\vartheta_{j'}\right)}\right)\right)d\epsilon_j,
\end{aligned}$$

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

$$= \frac{e^{\frac{1}{\rho}\vartheta_j}}{\sum_{j'} e^{\frac{1}{\rho}\vartheta_{j'}}},$$

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

Lemma 3. *For a stationary equilibrium, define V^+ as in Equation (2). We then have $\mathbb{P}\left(V^+ < v | y, s, u, j\right) = \mathbb{P}\left(V^+ < v | y, s, u\right)$, where we have defined the distribution of utility conditional on the selected occupation j as*

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

Proof. We use the same notation as in the proof of Lemma 2 above. The distribution of utilities, conditional on a given occupation j is given by:

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

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

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

$\square$

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

$$\mathbb{P}\left(\boldsymbol{d};\boldsymbol{\varsigma}\right) = \prod_{i=1}^{N} \left\{ \frac{\exp\left[\frac{\zeta}{\rho}\nu_{o_i} + \frac{1}{\rho}V\left(b^*\left(y_i\right) + e_{o_i}\left(s_i, \mathcal{U}\left(e_i, s_i, o_i, y_i; \boldsymbol{\varsigma}\right), y_i\right)\right)\right]}{\sum_j \exp\left[\frac{\zeta}{\rho}\nu_j + \frac{1}{\rho}V\left(b^*\left(y_i\right) + e_j\left(s, \mathcal{U}\left(e_i, s_i, o_i, y_i; \boldsymbol{\varsigma}\right), y\right)\right)\right]} \right.$$
$$\left. \times \frac{1}{\sqrt{2\pi\,\theta_{o_i}^2}} \exp\left(-\frac{1}{2}\mathcal{U}\left(e_i, s_i, o_i, y_i; \boldsymbol{\varsigma}\right)^2\right) \times \frac{\exp\left(-\frac{1}{2}\left(\frac{s_i - h^*(y_i)}{\vartheta}\right)^2\right)}{\sum_{s'=0}^{4}\exp\left(-\frac{1}{2}\left(\frac{s' - h^*(y_i)}{\vartheta}\right)^2\right)} \right\}, \tag{28}$$

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

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

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

where we have perform the change of variables $x \equiv u_i/\theta_{o_i}$ in the fourth equality. Equation (28) immediately follows. $\square$

C Estimation Appendix

C.1 Log-Likelihood Function

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

$$
\begin{aligned}
\mathcal{L}(\boldsymbol{d};\boldsymbol{\varsigma}) &\equiv \sum_{i=1}^{N} \log \mathbb{P}(e_i, o_i, s_i | y_i), \\
&= \frac{\zeta}{\rho}\left(\sum_{i=1}^{N} \nu_{o_i}\right) + \frac{1}{\rho}\sum_{i=1}^{N} V\left(b^*(y_i) + e_j\left(s_i, y_i, \mathcal{U}(e_i, o_i, s_i, y_i; \boldsymbol{\varsigma})\right)\right) \\
&\quad - \sum_i \log\left(\sum_j \exp\left[\frac{\zeta}{\rho}\nu_j + \frac{1}{\rho}V\left(b^*(y_i) + e_j\left(s_i, y_i, \mathcal{U}(e_i, o_i, s_i, y_i; \boldsymbol{\varsigma})\right)\right)\right]\right) \\
&\quad - \frac{1}{2}\sum_i \mathcal{U}(e_i, o_i; \boldsymbol{\varsigma})^2 - \tfrac{1}{2}\sum_i \log\theta_{o_i} \\
&\quad - \frac{1}{2}\sum_i \left(\frac{s_i - h^*(y_i)}{\vartheta}\right)^2 - \sum_i \log\sum_{s'=0}^{4}\exp\left(-\frac{1}{2}\left(\frac{s' - h^*(y_i)}{\vartheta}\right)^2\right).
\end{aligned}
\tag{29}
$$

The second and third lines of Equation (29) characterize the conditional distribution of occupational choice, given schooling, earnings, and parental endowment. The fourth and fifth lines characterize the conditional distribution of talent and schooling, given parental endowment. We find the set of parameters $\boldsymbol{\varsigma}$ maximizing the log likelihood function above for the observed data. For the derivation, see Lemma 4 in Appendix B.

C.2 Details of the Estimation Procedure

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

In turn, we initialize the values of parameters of the restricted model in this first stage estimation by applying the following strategy. First, note that Equations (14) and (9) together imply that the conditional expected log earnings of children based on the model satisfies

$$\mathbb{E}\left[\log\left(e\right)\Big| j,s,y\right]=\alpha_j+\kappa_j\log s+\delta_j\log y+\theta_j\underbrace{\frac{\int u\times\mu_j\left(s,u,y\right)d\mathbb{P}(u)}{\int\mu_j\left(s,u,y\right)d\mathbb{P}(u)}}_{\equiv\overline{u}_j(s,y)},\tag{30}$$

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

$$\mathbb{V}\left[\log\left(e\right)\Big| j,s,y\right]=\theta_j^2\,\frac{\int\left(u-\overline{u}_j\left(s,y\right)\right)^2\times\mu_j\left(s,u,y\right)d\mathbb{P}(u)}{\int\mu_j\left(s,u,y\right)d\mathbb{P}(u)}.\tag{31}$$

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

We consider a set of bins for the values of parental endowment $Y=\left\{\bar{y}^1,\bar{y}^2,\bar{y}^3,\bar{y}^4,\bar{y}^5\right\}$ and map each observed parental endowment in the data to one of the bins, setting $\bar{y}_i\equiv\arg\min_{\bar{y}\in Y}\Big|\log\,y_i-\bar{y}\Big|$. Inspired by Equations (30) and (31), we find an initial estimate for the coordinates of returns to schooling $\boldsymbol{\kappa}$ by relying on an observation-weighted least-squares regression of log earnings $\widehat{\mathbb{E}}\Big[\log e\Big|j,s,\bar{y}\Big]$ on schooling s while attempting to control for the selection term by $\widehat{\mathbb{V}}\Big[\log\,e\Big|j,s,\bar{y}\Big]^{1/2}$. Using the resulting estimates, we recover initial guesses for occupation-specific fixed earnings and returns to talent $(\boldsymbol{\alpha},\boldsymbol{\theta})$ as

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

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

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

Optimization. We perform the maximization of the log likelihood objective function in two stages. In the first stage, we perform an iterative, block-wise scheme, in which we iterate over maximizing the objective function only over one of the following three partitions of the model parameters (keeping all other components at their current levels): 1) the taste parameters (ζ, ρ), 2) the human capital cost parameters $(\widetilde{\boldsymbol{\phi}}, \vartheta)$,[39] and 3) the parameters of the earnings function $(\boldsymbol{\alpha}, \boldsymbol{\kappa}, \boldsymbol{\theta}, \boldsymbol{\delta})$.[40] After a few rounds of this block-wise optimization, we then perform a joint maximization of the objective function over the entire parameter space using a SQP-type algorithm.

54-Occupations Environment. We use the estimates found on the data with 14 occupational codes to initialize the parameters of the model for the main data with 54 occupational codes. We rely on a crosswalk between the two levels to initialize all the parameters of the earnings function at the 54-occupation level that belong to the same 14-occupation level code with the values estimated in the first stage for the latter. We then apply another iterative, block-wise optimization scheme similar to the one discussed above across the implied 14 blocks of occupational codes. For each block, we separately update the parameters of the earnings function corresponding to the occupations within each of the 14-occupation codes. After a few rounds of applying this block-wise strategy, we follow the same strategy as that discussed above for the 14-code level to gradually extend the search to the joint space including other model parameters. We finally introduce the returns to parental endowment parameters $\boldsymbol{\delta}$, before applying a final round of joint optimization in the space of all model parameters.[41]

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

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

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

C.3 Additional Estimation Results

C.3.1 Untargeted Moments

Table 5 compares the predictions of the model regarding children's schooling attainment as a function of parental endowment with the corresponding patterns in the data. Consistent with the data, children of poor parents (i.e. those with log parental endowment below the median) in the model are more likely not to graduate from high-school or to only obtain a high-school degree. Conversely, children of rich parents have a higher educational attainment and are more likely to obtain a college or a graduate degree.

Table 6 assesses the model's performance in terms of predicting the dependence of occupational choice on parental endowment and schooling attainment. To that end, the table reports correlation coefficients between occupational choice probabilities conditional on parental endowment and schooling predicted by the model and their counterpart in the PSID data. These correlation coefficients are positive and high, suggesting that the model is able to capture what occupations are more likely to be chosen by children with a given educational attainment and parental endowment.

C.3.2 Policy Functions

Figure 13 displays the policy functions for education investment $h^* (y)$ and direct transfers $b^* (y)$. As Panel (a) of the figure shows, both direct transfers and education investment are increasing in parental endowment. Panel (b) shows that poor parents transfer resources to their children

Table 5: Schooling Attainment Conditional on Parental Endowment

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

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

Table 6: Occupational Choice Conditional on Parental Endowment and Schooling

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

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

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. In summary, the policy function under the estimated model broadly satisfies the main condition of the theory.

C.4 The Decomposition of Persistence in Earnings

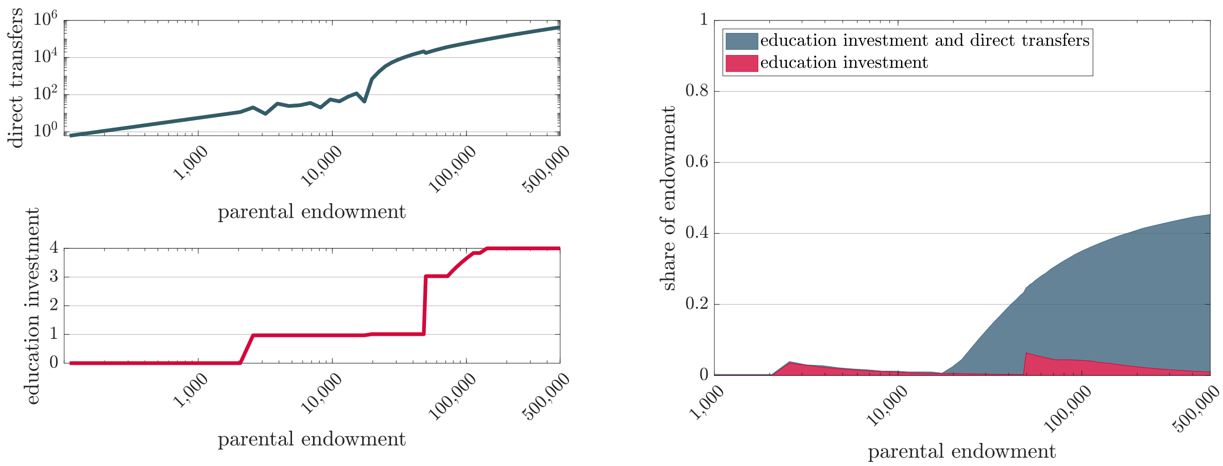
In this appendix, we provide a decomposition that characterizes the channels through which the model generates intergenerational persistence. Our model offers a simple characterization for the last measure in Table 3, i.e., the covariance between child earnings and parental endowment y. Let $\mathbb{C}_{ey}(\log e, \log y)$ denote the covariance between log earnings and log parental endowment:

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

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

Figure 13: Investment in Education and Direct Transfers

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



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

first define the conditional joint probability of occupational choice, talent, and schooling given parental endowment as

$$\mathbb{P}\,(j,s,u|y) \equiv \mu_j(s,u,y)\,\mathbb{P}_u(u)\,\mathbb{P}_{s|h}(s|h^*(y)), \tag{32}$$

where the conditional probabilities of occupational choice are given by Equation (9). Using this joint distribution, and with slight abuse of notation, we can define a number of marginal conditional distributions. For instance, the conditional distribution of occupational choice given parental endowment is given by $\mathbb{P}(j|y) \equiv \int \sum_s \mathbb{P}\,(j,s,u|y)\,du$ and the conditional distribution of schooling given parental endowment is $\mathbb{P}(s|y) \equiv \int \sum_j \mathbb{P}\,(j,s,u|y)\,du = \mathbb{P}_{s|h}(s|h^*(y))$.

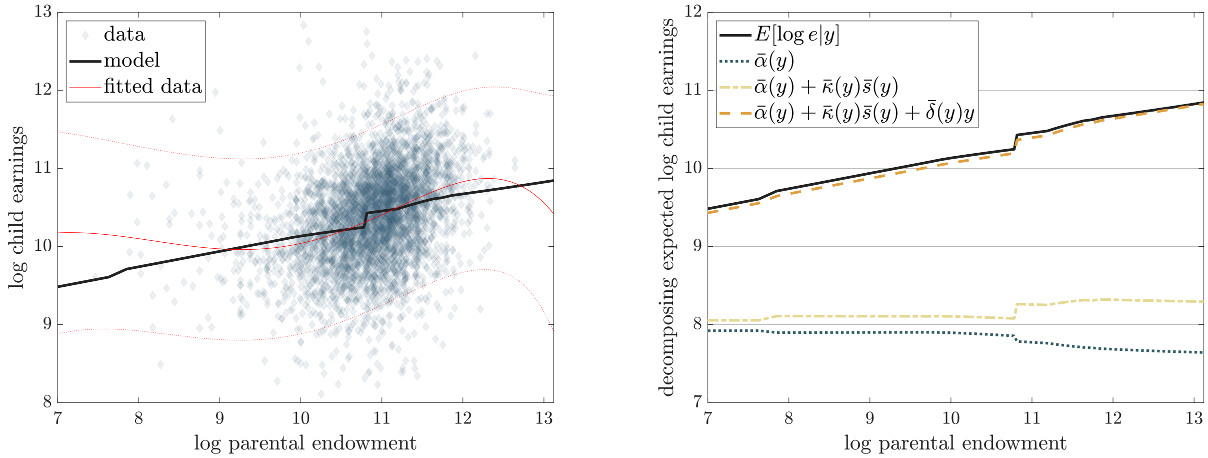
Based on the definitions above, Equation (14) implies that we can write the expected value of child earnings conditional on parental endowment as

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

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

Figure 14: 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).

parental endowment y:

$$\mathbb{C}_{js}\left(\kappa_j, s|\, y\right) \equiv \mathbb{E}_{j,s}\left[\kappa_j\left(s - \bar{s}(y)\right)|y\right], \tag{34}$$

$$\mathbb{C}_{ju}\left(\theta_j, u|\, y\right) \equiv \mathbb{E}_{j,u}\left[\theta_j u\,|\, y\right]. \tag{35}$$

The first term in Equation (33) captures the variations in the fixed component of earnings as a function of parental endowment, which captures the earnings of an agent with no schooling ($s = 0$), a unit parental endowment ($y = 1$), and a mean level of talent ($u = 0$). As we saw in Section 4.2, the fixed component of earnings varies negatively with the returns to schooling and talent across occupations. The second term in Equation (33) accounts for the product of the conditional mean return to schooling and conditional mean schooling given parental endowment. This term captures two distinct forces: the patterns of occupational choice through which the children of rich parents may sort into occupations with higher returns to schooling, and the patterns of schooling attainment through which the children of rich parents receive higher educational investment and schooling. Similarly, the third term accounts for the mean return to parental endowment, capturing the potential sorting of the children of rich parents into occupations with higher returns to parental endowment.

The last two terms in Equation (33) account for the patterns of sorting of children with higher schooling and talents toward occupations with higher returns to schooling and talent, respectively, *conditional* on parental endowment. The two covariances defined by Equations (34) and (35) capture how these two patterns of sorting vary across children with different levels of parental endowment. The stronger each of these two sorting patterns, the higher the conditional expected value of the log earnings of the children.

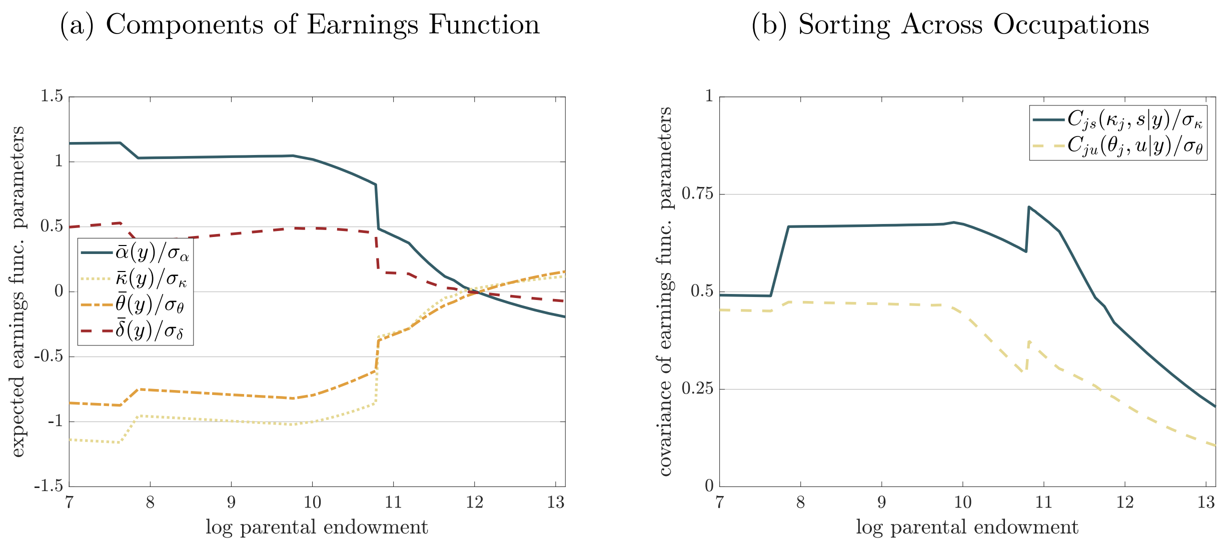
The Decomposition under the Benchmark Model Figure 14a compares the conditional expected earnings of children $\mathbb{E}_e[\log e|\, y]$ implied by the model with the observed relationship in our PSID sample. The model illustrates that the expected log earnings based on the model closely resembles that in the data. Accordingly, as reported in the last row of Table 3, the model comes very close to the observed covariance in the data. Figure 14b decomposes the expected log earnings in the model into different components following Equation (33). We find that the first three terms of the equation together explain the lion's share of the expected relationship between log earnings and parental endowment.

We find that the conditional expectation of fixed earnings $\overline{\alpha}(y)$ falls in parental endowment due to the fact that the children of richer parents sort into occupations with higher returns to schooling and talent and lower fixed earnings. Next, we find that the contribution of schooling $\overline{\kappa}(y)\overline{s}(y)$ increases in parental endowment, due to both the rise in the expected returns to schooling and the expected schooling attainment.[42] However, the estimation results suggest that through the lens of the model the main driver of the *variations* in expected log earnings as a function of parental endowment is the direct effect of parental endowment on earnings through the term $\overline{\delta}(y)\, y$. Despite sizable variations in the patterns of sorting across occupations conditional on parental endowment, Figure 14b shows that these variations make quantitatively negligible contributions to the overall dependence of expected log earnings on parental endowment.

Figure 15b focuses on the two relevant patterns of sorting: the covariance of schooling and returns to schooling, and the covariance of talent and returns to talent. Both these two covariances are initially stable as parental endowment rises, but then eventually fall as parental endowment continues to rise. The reason is that the children of very rich parents become relatively more responsive to their idiosyncratic taste shocks and intrinsic quality of occupations and thus do not respond as strongly to the earnings incentives in their occupational choice.

[42] Figure 15a in Appendix D shows how the conditional expected value of each component of the earnings function varies with parental endowment. We find that the expected returns to schooling $\overline{\kappa}(y)$ and to talent $\overline{\theta}(y)$ rise in parental endowment, while the returns to parental endowment $\overline{\delta}(y)$ fall in parental endowment.

Figure 15: Drivers of Persistence in Earnings



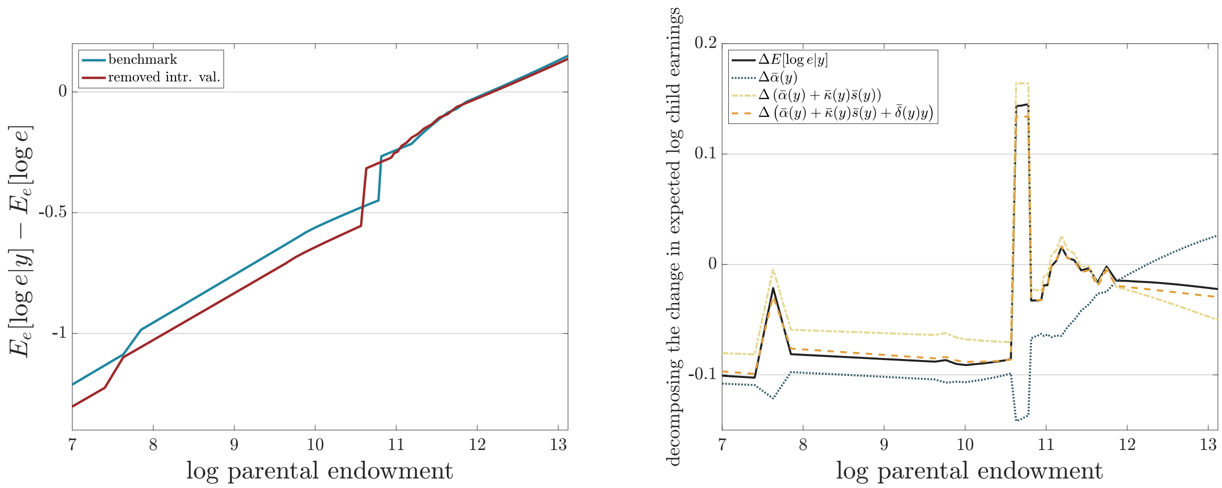
Notes: Panel (a) shows how the conditional expectation of different components of the earnings function across occupations vary with parental endowment. Each component is normalized by its corresponding standard deviation across the entire population, e.g., $\sigma_\alpha \equiv \mathbb{V}_j[\alpha_j]$ 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.

Persistence of Earnings without Intrinsic Qualities As we saw in Table 4, the persistence in earnings slightly rises relative to the benchmark model when we remove the variations in the intrinsic qualities. Several forces together help shape this change in persistence. First, the most pronounced effect of removing intrinsic qualities for the children of the poorest and richest households is on the generate equilibrium response in the fixed component of their earnings. As we saw in Figure 8b, the wage rates fall in low-intrinsic quality occupations, chosen mostly by the children of the poorest parents under the benchmark, and rise in high-intrisic quality occupations, chosen by the children of the richest. To the extent that the children of poor children switch to occupations with higher intrinsic qualities, this further lowers the fixed component of their earnings due to the negative correlation between the intrinsic qualities and the fixed components of income α under the benchmark (see Table 2b). The most pronounced effect on the earnings of the children of middle class parents is through their schooling. These children are those most likely to switch to occupations with high intrinsic qualities, which happen to also have higher returns to schooling κ (see Table 2b). Their expected earnings rise due to higher schooling investment and attainment.

Figure 16a compares the conditional expected log earnings as a function of parental en-

Figure 16: Expected Log Earning vs. Parental Endowment, Removed Intrinsic Qualities

(a) Benchmark vs. Removed Intr. Val.   (b) Decomposition of the Change



Notes: Panel (a) compares the relationship between conditional expected log earning and log parental endowment between the benchmark model and that with removed variations in intrinsic qualities. Panel (b) decomposes the the change in the conditional expected log earnings of the children given parental endowment to different components based on Equation (33), in going from the benchmark model to the one with removed variations in intrinsic qualities.

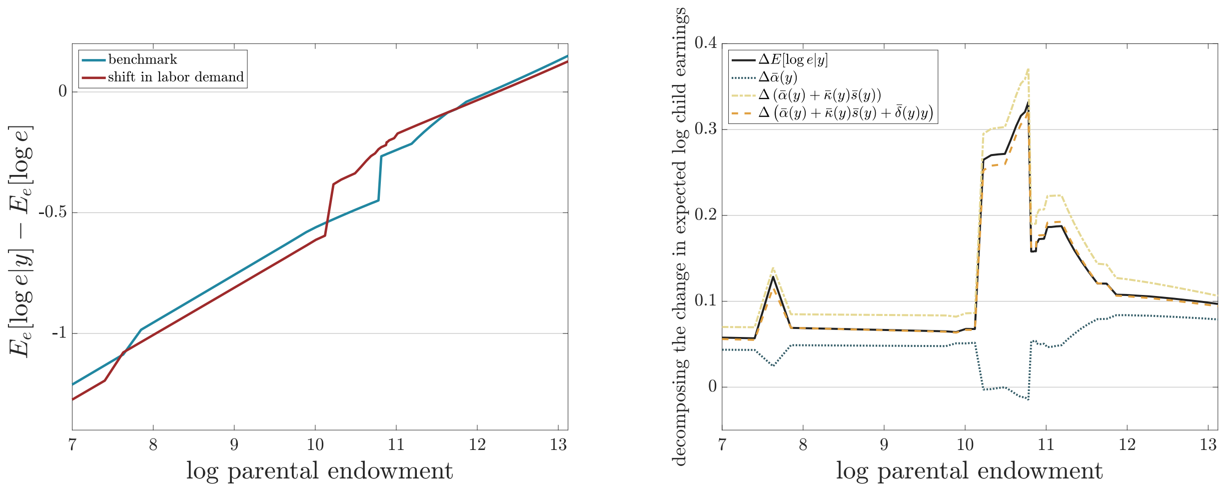
dowment under the benchmark with that under the model with removed variations in intrinsic qualities. Therein, Figure 16b decomposes the changes between the two conditional expectations to the different components based on Equation (33). We can see that the conditional expectation of the fixed component of log earnings $\overline{\alpha}(y)$ explains most of the differences between the children of the poorest and the richest parents, while the term involving the expected returns to schooling $\overline{\kappa}(y)\overline{s}(y)$ explains the change for the children of the middle class.

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 16b 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.

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.

D Additional Figures and Tables

Figure 18a compares occupational choice elasticities estimates with controls for potential earnings and the occupation of the parent with those without such controls.

Figure 19 displays the correlation between elasticities estimated with the PSID and NLSY data.

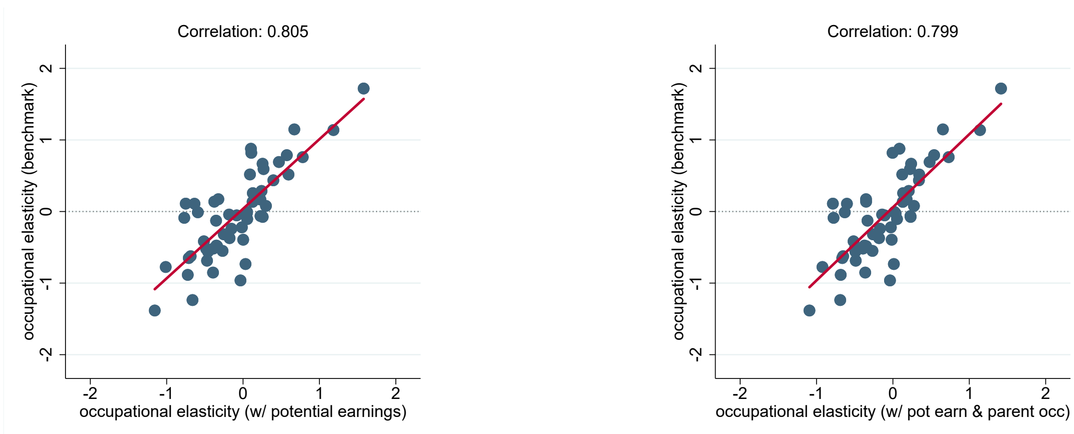
Figure 20 displays the relationship between occupational choice elasticities estimated with the NLSY data and the intrinsic quality of occupations.

Figure 21 displays the relationship between occupational choice elasticities estimated with the PSID data and the intrinsic quality of occupations under two alternative specifications. In the left panel, occupational choice elasticities and the intrinsic quality of occupations are estimated for the 80 occupation groups in Table 9. In the right panel, we maintain the occupation classification with 54 groups in Table 8, but define the intrinsic quality of occupations to be the first principal component of 5 job characteristics only: treated with respect, little hand movement, little heavy lifting, keep learning new things, do numerous different things. In both cases, the correlation remains positive, high (0.52 and 0.58, respectively) and statistically significant.

Table 7 examines whether controlling for the risk of occupations alters the relationship be-

Figure 18: Occupational Choice Elasticities Controlling for Potential Earnings and Parent's Occupation

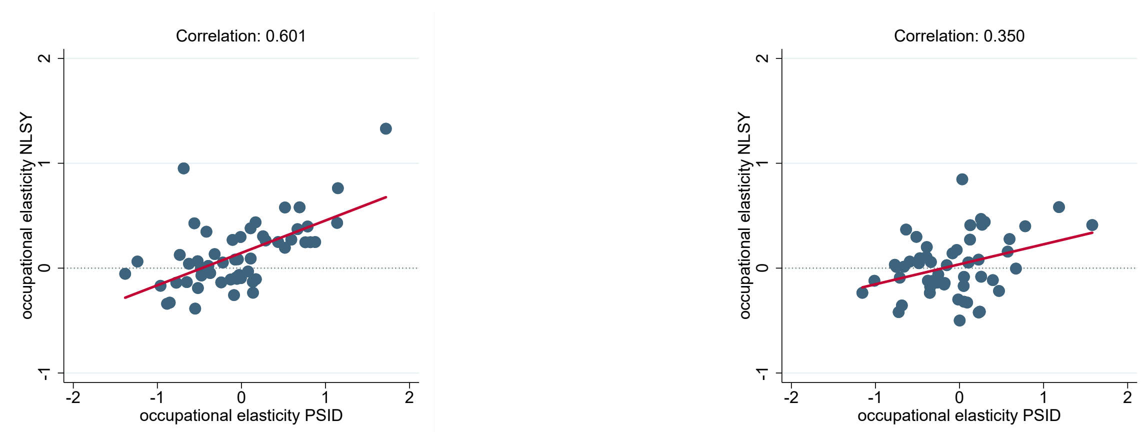
(a) Potential Earnings (b) Potential Earnings and Parent's Occ



Notes: The left panel depicts the benchmark occupational choice elasticities against elasticities from the conditional logit estimation controlling for potential earnings across all occupations. The right panel depicts the benchmark occupational choice elasticities against elasticities from the conditional logit estimation controlling both for potential earnings and a dummy variable that is equal to one if the parent works in the given occupation.

Figure 19: Occupational Choice Elasticities, PSID vs NLSY

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

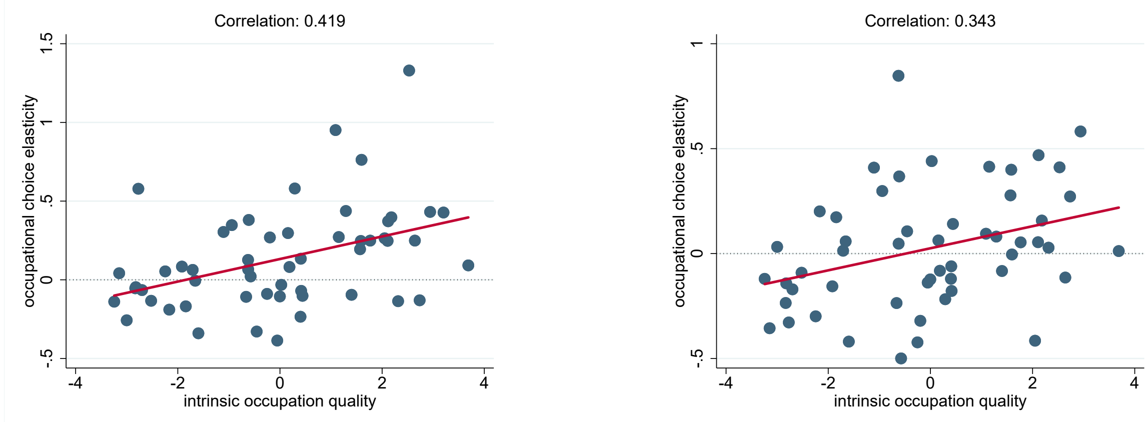


Notes: The left panel depicts the benchmark occupational choice elasticities. The right panel depicts the occupational choice elasticities estimated controlling for potential earnings in all occupations. The standard error of the correlation in the left panel is 0.111 and that of the correlation in the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

tween occupational choice elasticities and intrinsic qualities. Column (1) reports results from projecting occupational choice elasticities on the intrinsic qualities of occupations. Columns (2)

Figure 20: Occupational Choice Elasticities and the Intrinsic Quality of Occupations, NLSY

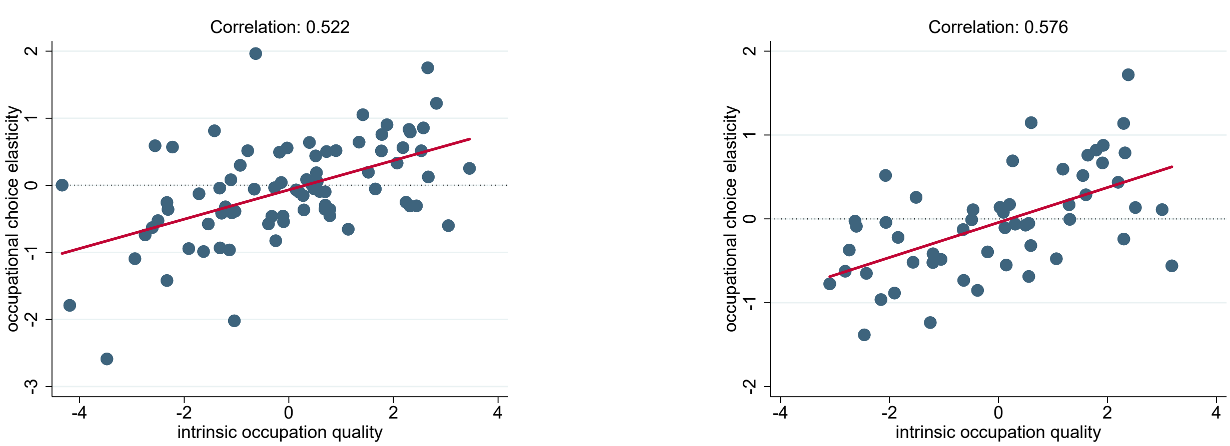
(a) Without Earnings Controls (b) Controlling for Potential Earnings



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

Figure 21: Occupational Choice Elasticities and The Intrinsic Quality of Occupations, Robustness

(a) Alternative Occupation Classification (b) PCA 5 Job Characteristics



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

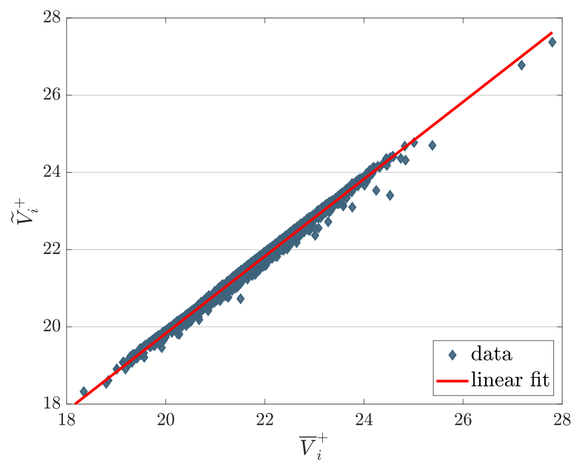
and (3) add to this projection a control for the coefficient of variation of log earnings by occupation, measured as the ratio between the standard deviation and the average log earnings by

Table 7: Occupational Choice Elasticities, Risk and the Intrinsic Quality of Occupations

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

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

Figure 22: Comparison Between the Two Welfare Measures $\overline{V}^+$ and $\widetilde{V}^+$



Notes: The figure displays a scatter plot of our two proxies for welfare of each child in our sample.

occupation. In column (2) the coefficient of variation of log earnings by occupation is calculated based on the pooled sample of the ASEC waves from 1976 to 2017. In column (3) the coefficient of variation of log earnings by occupation is calculated controlling for age (16-25, 26-35, 36-45, 46-55, 56-64), sex, race (white, Black, other) and year.