Occupational Choice and the Intergenerational Mobility of Welfare*

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Abstract

If the average worker attributes distinct values to the intrinsic qualities of different occupations, benefitting from those values constitutes part of one’s labor compensation. Based on responses in the General Social Survey (GSS), we construct an index that aggregates positive qualities such as respect, learning, and work hazards, controlling for respondent income and tenure. Using the PSID and NLSY data, we document that children of richer US parents are more likely to select into occupations that rank higher in terms of this index. We rationalize this fact when we introduce 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 size of compensation each worker receives from their choice of occupation. When earnings are adjusted to reflect this additional compensation, we find substantially larger persistence of income from parents to children. Applying this adjustment, our model further predicts that the trends in the composition of labor demand in the US over the past three decades may have decreased intergenerational persistence, while also leading to higher growth in the welfare of the average worker.

Keywords: Intergenerational mobility; Compensating differentials; Occupational choice.

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1 Introduction

Modern economies aspire to offer all individuals, regardless of the economic background they are born into, similar opportunities to acquire skills, develop their talents, and build productive and fulfilling careers. A standard measure of a society’s success in realizing this promise is the persistence of earnings and income from parents to their children. A myriad of different factors that lead to better opportunities for rich children in the labor market ultimately translate into higher earnings for them. Thus, it is commonly argued, the intergenerational mobility of income informs us about the extent of equality of opportunity on the labor market (Black and Devereux, 2011).

Nevertheless, there are important and welfare-relevant aspects of an individual’s labor market outcomes that are not reflected in earnings. Take, for instance, an individual’s choice of occupation. Some occupations are tedious, arduous, even hazardous. Some are rewarding, intellectually stimulating, even entertaining. Some are conducted in isolation, while others involve much social interaction. Despite potential heterogeneity in preferences among workers, the average worker is still likely to distinguish occupations in how much she values the bundle of all such intrinsic qualities. All else equal, the theory of compensating differentials predicts that occupations valued more highly by the average worker should in equilibrium pay lower earnings (Rosen, 1986). Workers who take up such occupations are remunerated in part through the higher intrinsic value they receive from their work throughout their lifetimes.

In this paper, we document that such patterns of compensation through intrinsic value are more common among the children of rich parents. We rely on the General Social Survey (GSS) to construct empirical proxies for how workers value different occupations based on qualities distinct from, and orthogonal to, earnings. We then use micro data from the Panel Study of Income Dynamics (PSID) and the National Longitudinal Survey of Youth 1997 (NLSY) to show that the children of richer parents are more likely to choose occupations that rank higher in terms of our proxies of intrinsic occupational value. We provide evidence that these choices are not explained by the ability of these children to earn higher incomes in such occupations. We then construct a quantitative model of intergenerational mobility and occupational choice that allows us to both rationalize this fact, and to infer the monetary value of the compensation each individual receives from their choice of occupation. Using the resulting estimates, we find substantially higher levels of persistence in the measures of

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1In popular discourse, this idea is often invoked through the observation that in order to afford to take up occupations such as arts or design, one need to come from a rich background (e.g., Bui, 2014, March 18, 2017, Feb 9; Sussman, 2017, Feb 14).
earnings that account for the additional compensation due to occupational intrinsic value. Thus, relying on observed earnings leads us to overestimate the degree of intergenerational mobility of opportunity and welfare.

For our measures of the intrinsic non-pecuniary value of occupations, we rely on the Quality of Work-life Module of the GSS. The intrinsic non-pecuniary value of an occupation should ideally capture the bundle of job amenities that the average worker values and that are thus implicitly priced in the market. We consider a bundle of seven such amenities as reflected in the survey questions in the Module: respect at the workplace, heavy lifting, hand movement, continuous learning, variety of tasks, and opportunity to develop new abilities. We purge the responses for each question from the effect of wages and tenure and combine them into a single index by using principal component analysis. We refer to the first principal component of the residualized values as the intrinsic value of an occupation. We find that being a machine operator, a farmer, or a housekeeper carries relatively low intrinsic value, while artists, librarians, or architects enjoy a relatively high intrinsic value.

As already mentioned, we rely on the PSID and the NLSY micro data 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 the parental income rises. Consistent with the intuition laid out above, the data suggests that having richer parents makes children more likely to become lawyers and judges, architects, social scientists, librarians, archivists, curators, writers, artists, entertainers, athletes, and less likely to become machine operators, farmers, janitors, housekeepers, or material handlers. We find this to be true even after taking into account that having a richer background could influence children’s potential earnings across all occupations.

We use the estimated occupational choice elasticities and intrinsic occupation values to show that the likelihood of choosing intrinsically desirable occupations rises with parental income. In particular, we find a large and positive correlation between occupation specific elasticities and intrinsic values. This relationship is present both in the PSID and in the NLSY, and suggests that the occupations that are more likely to be chosen by richer children are precisely those that yield higher non-pecuniary rewards. This confirms the core hypothesis of this paper that the intergenerational persistence of income only provides a partial picture of the inequality of opportunity stemming from differences in economic backgrounds.

To understand the drivers of this fact, we introduce occupational choice and taste for occupational characteristics into the classical theory of intergenerational transmission of earnings and welfare (Becker and Tomes, 1979, 1986). Our quantitative, dynamic, general
equilibrium model features overlapping generations of individuals who decide on their occupational choice, and altruistically allocate their wealth between own market consumption and human capital investments for and direct transfers to their children. Crucially, before deciding on their occupational choice, young adults receive independent taste shocks for each occupation. We discipline the common mean of these occupational taste shocks to be correlated with our estimated empirical proxies of intrinsic value based on the GSS. In addition, the productivity of each young adult varies across occupations depending on her schooling attainment, an idiosyncratic and unobserved talent shock, and parental income. The latter dependence accounts for all the potential mechanisms through which richer parents may facilitate higher earnings for their children on the labor market, e.g., by endowing their children with tacit know-hows, social skills, or career networks.

Assuming extreme-value distributions for the occupation-level taste shocks, we can derive a simple Bellman equation for the value of the overall endowment (wealth) of an individual, which captures the intergenerational dynamics of income and occupational choice in the model. The educational investment and transfer policy functions only depend on a single state variable, i.e., the endowment, and fully characterize the conditional distributions of occupational choice, earnings, and ultimately welfare of the children. We close the model by a simple CES specification of demand for occupational services, which allow us to endogenize occupational wages.

The model provides a simple explanation for why the children of rich parents are more likely to choose occupations with higher intrinsic values. Under standard assumptions, the value function of income is concave, implying a decreasing marginal value of labor earnings. Since the children of rich parents typically receive higher transfers, they face a lower marginal value for each extra dollar of earnings. In contrast, since the intrinsic value of different occupations is a non-monetary source of welfare, it does not vary with one’s income. Therefore, when rich children compare their potential earnings between two occupations with high and low intrinsic value, they demand a higher compensation to be willing to choose the low-valuation occupation. We assume labor markets do not discriminate in the earnings they offer to workers based on their parental income. As a result, under the equilibrium occupational wage rates, we find a sorting of rich and poor children into high and low valuation occupations, respectively.

The model additionally leads to 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 a cross-section of parent-child pairs in the PSID data. The estimated parameters provide us with the full structure of the potential earnings of each individual given
their schooling, parental income, and inferred talent, across 54 occupations in our data. We show that, despite its parsimony, the model can explain a sizable share of variations in the corresponding moments in the data.

We use the model to derive the effective compensation that each individual in the data receives due to the non-pecuniary value of their occupation. We construct two different such measures depending on whether or not we include the 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. This has important implications for our understanding of intergenerational mobility. First, it suggests that failing to account for differences in the non-pecuniary value of occupations provides too optimistic an assessment of the intergenerational mobility of opportunity and welfare. Second, that we find a higher degree of intergenerational persistence when including idiosyncratic taste shocks implies that richer children not only benefit from choosing occupations with higher intrinsic values, but they also benefit from being able to choose occupations that better reflect their idiosyncratic tastes.

To unpack the role of intrinsic values, we consider a counterfactual experiment in which we eliminate differences in intrinsic values across occupations. We find that, relative to the model with no intrinsic values, in the benchmark economy equilibrium wages are lower precisely in occupations that compensate workers through higher intrinsic values. Removing differences in intrinsic values of occupations substantially weakens the relationship between parental income and the occupational choice of children and increases the intergenerational mobility of welfare.

Lastly, we use the model to study the implications of trends in occupational labor demand observed in the United States over the past three decades. In addition to the overall rise in average earnings, we find that the trends in labor demand also shifted the composition of the labor force towards occupations with higher intrinsic value. Accounting for these trends, our model predicts that parental endowment become a less important determinant of selection into high intrinsic value occupations, leading to a higher intergenerational mobility of earnings and welfare. Finally, through the lens of the model, these trends also imply that a non-trivial component of the rise in average welfare over the period stems from the rise in the monetary evaluation of the higher average intrinsic value of workers’ occupations. Additionally, we show that the growth in welfare over the period may be more equally distributed across workers than the observed gains in earnings.

**Prior Work** Our paper builds on the extensive literature on intergenerational mobility of earnings, income and wealth. Earlier empirical contributions to this literature are summa-
rized by Solon (1999) and Black and Devereux (2011). More recently, Chetty et al. (2014) and Chetty et al. (2017) rely on administrative tax records to document patterns of intergenerational mobility in the United States. These patterns are borne in our main data source of intergenerational linkages, 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). Recent extensions of this model have focused on enriching the original model in terms of different stages of the development of children, the different types of investments in human capital, and different types of cognitive and non-cognitive skills (e.g., Cunha and Heckman, 2007; Cunha et al., 2010; Lee and Seshadri, 2019; Abbott et al., 2019; Daruich, 2020). While we maintain the parsimonious structure of the benchmark model along these dimensions, we introduce occupational choice with non-pecuniary intrinsic value into the model, in a framework that can be quantitatively disciplined by rich data on choices of children in a large set of occupations.

Introducing occupational choice into the benchmark theories of mobility also allows us to unify standard income-based analysis of intergenerational persistence with another strand of empirical work that has instead focused on occupation-based proxies. Due to the lack of availability of detailed individual data, historical studies of mobility typically rely on information on occupations (Ferrie, 2005). For instance, Clark (2015) discusses long-run measures of persistence based on the frequency of representation of different family names among certain high-status occupations. Our index of intrinsic value of occupations is similar in spirit to the Hope-Goldthorpe scores of occupational prestige (Goldthorpe and Hope, 1974) that are occasionally used in lieu of income (e.g., Ermish and Francesconi, 2002). More broadly, our contribution to the literature on intergenerational mobility is to advance the idea that the intergenerational mobility of income need not necessarily translate to intergenerational mobility of welfare if agents face tradeoffs between higher earnings and some non-market goods, which in our case are given by the non-pecuniary and intrinsic value of occupations.

Our paper is thus also related 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)

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2 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).

3 In a recent paper, Lo Bello and Morchio (2019) have studied the role of occupational choice in intergenerational mobility. However, they focus on how children may rely on parental network to enhance their chances in frictional search for jobs on the labor market.

4 Another leading example of such a good is leisure (e.g., Aguiar et al., 2017). However, in contrast to the intrinsic value that workers receive from their occupation, empirical measures of the intensive margin of labor supply, and therefore the consumption of leisure, are widely available.
presents evidence on the non-pecuniary value of jobs and show 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.

Our focus on socioeconomic background and occupational choice speaks to the work of Bell et al. (2018), who show that children’s chances of becoming inventors vary with their parents’ socioeconomic class. Similarly, it also relates to the paper by Hsieh et al. (2019), who find that certain demographic groups face obstacles to accumulating human capital, and such distortions are important drivers of the allocation of talent across occupations and, in turn, economic growth. Our hypothesis that growing up in a rich family makes it more likely for children to choose occupations with a higher intrinsic value, even though these occupations might pay less, 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. Luo and Mongey (2019) show this has implications for welfare in the context of student debt repayment policies.

2 Data and Facts

In this section we document empirically that children from richer families are more likely to choose occupations with a higher intrinsic value, a fact that holds even when controlling for potential earnings in all other occupations.

2.1 Data

We use data from the Panel Study of Income Dynamics (PSID), the National Longitudinal Survey of Youth 1997 (NLSY) and the General Social Survey (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 highlight the key variables for our analysis of income, earnings and occupations.

PSID. The PSID is a longitudinal survey of a representative sample of US individuals and families. The survey started in 1968, collecting information on a sample of approximately 5,000 households. We employ all surveys from 1968 to 2015 in our analysis. Our

5 Other recent contributions to the estimation of compensating differentials include Lavetti and Schmutte (2015).
sample reflects the PSID’s nationally representative core sample and PSID sample extensions to better represent dynasties of recent immigrants. Over the years both the original families and their split-offs (children moving out of the parent household) have been followed. This is an essential feature of the survey that makes it suitable for the analysis in this paper. We match parents and children in the survey using the PSID Family Identification Mapping System, resulting in a panel of parent-child pairs. Our analysis focuses on career choices, so we transform the panel into a cross-section of parent-child pairs 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 (i.e. the career) as the most frequently held occupation between age 22 and age 55 and consider an occupation classification with 54 occupations, listed in Table 5 in Appendix A. Education is defined as the highest level of education attained, for both parents and children. 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 are allowed to 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 patterns of intergenerational mobility of earnings, as well as occupational choice as a function of parental income.

NLSY. 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 define parental income in the cross-section as the average over parental family income over this period, net of time effects.
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 all GSS respondents who are working in a given year and includes questions on hours worked, workload, worker autonomy, layoffs and job security, job satisfaction/stress, and worker well-being. As we discuss below, we use a subset of these questions and principal component analysis (PCA) to create a measure of the intrinsic value of occupations.

2.2 Intergenerational Mobility in PSID

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

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

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

We also calculate a measure of absolute intergenerational mobility, namely the fraction of children who move to a higher earnings decile than their parents. On average, 43% of children move to a higher decile of the lifetime earnings distribution than their parents. This fraction is however declining over time, consistent with the findings of Chetty et al. (2014) and Chetty et al. (2017). Figure 21a and Figure 21b in Appendix D offer a depiction of these statistics.
2.3 What Occupations are Rich Children More Likely to Choose?

In this section we document simple relationships between occupational choice, parental income and the intrinsic value of occupations using data from the PSID. We also show robustness with respect to the NLSY data.

2.3.1 Occupational Choice and Parental Income

We begin our analysis 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 \(o_i = j\), for \(j \in \{2, \ldots, 54\}\) to depend on the logarithm of lifetime parental income and the educational attainment of child \(i\), expressed in years of schooling. Letting \(P(o_i = j)\) 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

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

where \(\beta_j^g\) is the occupation \(j\) specific coefficient on log parental income in the multinomial logit model.

Figure 1a 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, farm managers, architects, social scientists, urban planners, health diagnosticians, librarians, archivists, curators, writers, artists, entertainers, and athletes. Conversely, growing up in a rich family makes children less likely to become farm workers, janitors, housekeepers, or material handlers.

Figure 22 in Appendix D shows that estimates of occupational choice elasticities based on the PSID data correlate positively with those based on the NLSY. Specifically, the correlation coefficient of occupational choice elasticities across the two datasets is 0.601 (SE=0.111).

2.3.2 The Intrinsic Value of Occupations

We next describe our measure of the intrinsic value of occupations. The intrinsic value of an occupation should ideally capture a bundle of amenities associated with the occupation that
Figure 1: Occupational Choice Elasticities and Intrinsic Values

Notes: Bars are estimated occupations choice elasticities for each occupation in Panel (a) and indices of intrinsic values of occupations represented by the first principal component of the occupation characteristics we consider in Panel (b).

From the list of questions asked in the Quality of Worklife module of the GSS, we select 7 job characteristics that we believe most workers would regard as representing desirable or undesirable amenities. These work characteristics are listed in the first column of Table 1. In

6Such a technique has been used, for example, in the spatial economics literature to measure the variations in amenities across cities (Diamond, 2016) or in the trade literature to reduce the dimensionality of tasks associated to occupations (Traiberman, 2019).
the remainder of the analysis we use standardized values of these worklife characteristics. Some of the characteristics we focus on are likely to be correlated with tenure at the job, wages or the number of hours worked. For example, tenured workers are arguably more likely to be treated with respect. Similarly, higher paid workers are likely to have higher-rank positions and are thus also more likely to be treated with respect. Therefore, we first purge respondents’ assessment of the quality of their worklife along these dimensions from confounding factors such as tenure, wages and hours worked. Specifically, for each occupation characteristic $v^x$ listed in the first column of Table 1, where $x = 1, \ldots, 7$, we estimate

$$v^x_{it} = \alpha^x X_{it} + \delta^x_j + \epsilon^x_{it},$$

(1)

where $i$ denotes the respondent and $t$ denotes the wave of the survey module (2002, 2006, 2010 or 2014). Here, $X_{it}$ 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 $\alpha^x$ is the corresponding vector of coefficients.\(^7\) The coefficients $\delta^x_j$ are occupation specific fixed effects and $\epsilon^x_{it}$ are the residuals.

Our measure of the intrinsic value of an occupation, which we denote by $v_j$, is an overall worklife quality index represented by the first principal component of all occupation characteristics $\delta^x_j$ listed in the first column of Table 1. The second column of Table 1 reports loadings on each occupation amenity. The occupation valuation 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. This suggests that a simple one-dimensional index is able to capture the bundle of job amenities that workers value. Additionally, the first component alone explains 51% of the total variance in the 7 job characteristics. The last column of Table 1 reports the variance that remains unexplained in each characteristic and suggests that our measure of the intrinsic value 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 1b displays the measured intrinsic values of occupations. The figure reveals substantial heterogeneity in the intrinsic value of occupations. Occupations with low intrinsic value are freight, stock and material handlers, mail distributing occupations, motor vehicle operators, non-managerial firm occupations, and machine operators. At the other end of the spectrum, occupations with high intrinsic value are teachers, librarians, archivists and curators, architects, lawyers and judges, architects, writers, artists, entertainers and athletes.

\(^7\)Unfortunately, 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

<table>
<thead>
<tr>
<th>Occupation characteristic $v^X$</th>
<th>Loading</th>
<th>Unexplained variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treated with respect</td>
<td>0.38</td>
<td>0.49</td>
</tr>
<tr>
<td>Little hand movement</td>
<td>0.41</td>
<td>0.40</td>
</tr>
<tr>
<td>Little heavy lifting</td>
<td>0.36</td>
<td>0.52</td>
</tr>
<tr>
<td>Keep learning new things</td>
<td>0.47</td>
<td>0.21</td>
</tr>
<tr>
<td>Do numerous different things</td>
<td>0.40</td>
<td>0.43</td>
</tr>
<tr>
<td>Opportunity to develop abilities</td>
<td>0.41</td>
<td>0.40</td>
</tr>
<tr>
<td>Do not need to work fast</td>
<td>0.11</td>
<td>0.95</td>
</tr>
</tbody>
</table>

social scientists, and urban planners. While the cardinal information in the estimated values may not be readily interpretable, the relative ranking of occupations is meaningful, and is what we exploit next.

We explore how our measure of the intrinsic value of occupations correlates with a general measure of job satisfaction using 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?", and applying the same treatment described above in Equation (1). Figure 2a shows that our measure of the intrinsic value of occupations correlates strongly with job satisfaction: the correlation coefficient is 0.524 ($SE=0.118$). However, this general measure of job satisfaction may be a reflection of amenities that are valued by workers and but are not necessarily priced in the market. For this reason, we proceed in the remainder of the analysis with the PCA-based measure of occupation values 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 intrinsic value of occupations correlates with other characteristics of occupations. We consider several such characteristics. First, we use six dimensions of feelings about work collected in the American Time Use Survey in 2010, 2012 and 2013. Respondents in the survey 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 value 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
Figure 2: Intrinsic Value of Occupations and Other Occupation Characteristics

(a) Job Satisfaction

(b) Other Characteristics of Occupations

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

of Occupational Titles, and the measure of social skill intensity of occupations by Deming (2017), based on O*NET.

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

2.3.3 Occupational Choice Elasticities and The Intrinsic Value of Occupations

We now turn to the joint analysis of occupational choice elasticities and the intrinsic value of occupations. Figure 3a depicts the correlation between occupational choice elasticities and the intrinsic value of occupations. We find a large and positive correlation between occupational choice elasticities and the intrinsic value of occupations, 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 values and highlights a channel through which 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 values explains 35% of the variation in occupational choice elasticities.

Figure 23 in Appendix D shows that this finding is robust with respect to the occupation
Figure 3: Occupational Choice Elasticities and the Intrinsic Value of Occupations

(a) Without Earnings Controls

(b) Controlling for Potential Earnings

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

classification and the number of job characteristics we include in measuring the intrinsic value of occupations. Figure 24 in Appendix D shows that the relationship also holds in the NLSY data. Lastly, Table 10 in Appendix D shows that the intrinsic value of occupations correlates positively with occupational choice elasticities and continues to explain a sizable share of their variation when controlling for how risky occupations are. 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).

2.4 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. In particular, it is possible that children of richer parents are more productive and earn higher earnings exactly in those occupations that feature higher estimates of intrinsic values. If that is the case, we cannot readily interpret higher likelihood of choosing occupations with higher proxies of intrinsic value as indicative of the fact that children indeed attribute higher values to such occupations.
In this section, we explore the extent to which growing up in a rich family affects the realized earnings of individuals in different occupations and revisit occupational choice elasticities and their relationship with the intrinsic value of occupations, factoring in the effect of parental income on occupational efficiency. To that end, we first estimate a flexible earnings equation that allows the annual earnings of the child to depend on their parent’s lifetime income, their occupation, as well as covariates (years of schooling, age, gender and race) whose effect on earnings is allowed to vary by occupation.\footnote{See Appendix A.3 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.} Using this earnings equation we can predict potential earnings that children in our sample would earn in each occupation $j \in \{1, \ldots, 54\}$. This allows us to re-estimate the occupational choice elasticities controlling for (counterfactual) potential earnings for each individual across all occupations. 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 (alternative) specific characteristics, which in our case are potential earnings across all occupations. Figure 25 in Appendix D compares the new occupational choice elasticities estimated that control for potential earnings against those without such controls. The two sets of elasticities are very similar: the correlation between the two is high and equal to 0.806 ($SE=0.082$). This suggests that the estimation of endowment elasticities is robust to factoring in the effect that parental income has on differential occupation efficiency.

Finally, Figure 3b shows that the relationship between occupational choice elasticities and the intrinsic value of occupations is qualitatively and quantitatively 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, and statistically significant at the 1% confidence level in both cases.\footnote{With the more flexible earnings function mentioned in footnote 17 the correlation coefficient is 0.51 and not statistically different from the one reported in Figure 3b.} Additionally, the $R^2$ from projecting occupational choice elasticities on intrinsic occupations values is 0.295, suggesting that differences in the intrinsic value of occupations explains 29.5% of the variation in occupational choice elasticities.

### 3 Model

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

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 is indexed by the period \( t \) in which they are adults. An adult starts period \( t \) in one occupation \( j_t \in \{1, \cdots, J\} \) with total endowment of \( y_t = b_t + e_t \), comprised of her own (lifetime) earnings \( e_t \) as well as a direct transfer \( b_t \) that she has received from her parent. She bears one child, and then chooses how to allocate her total endowment \( y_t \) between own market consumption \( c_t \) and the resources to offer her child, in the form either of a human capital investment \( h_t+1 \) or a direct transfer \( b_{t+1} \geq 0 \).

After the decisions on human capital investment and direct transfer are made, three components of uncertainty about the child’s outcomes are resolved. First, the child receives an idiosyncratic talent \( u_{t+1} \), drawn independently of other outcomes from a distribution \( P_u(\cdot) \). Second, the child receives an idiosyncratic human capital shock that leads to her observed schooling \( s_{t+1} \) based on a distribution \( P_s(\cdot|h_{t+1}) \) conditional on parental investment \( h_{t+1} \). Third, the child draws a \( J \)-dimensional vector \( \epsilon_{t+1} \equiv (\epsilon_{j_{t+1}}) \) of taste shocks across different occupations, drawn as i.i.d. samples from a distribution \( P_{\epsilon}(\cdot) \).

Given talent and schooling, the earnings of the child as an adult the next period in occupation \( j \) depend on her occupation-specific ability \( A_j \) and the occupation-specific wage rate per efficiency units of ability \( w_{jt+1} \) for generation \( t + 1 \). We allow the occupation-specific abilities to be functions of schooling, talent, and the endowment of the parent as \( e_{jt+1}(s_{t+1}, u_{t+1}, y_t) = w_{jt+1}A_j(s_{t+1}, u_{t+1}, y_t) \). The dependency of occupation-specific ability on parental endowment \( y_t \) accounts for potential channels for the intergenerational persistence of income besides educational investment.

A vector \( v \equiv (v_j)_{j=1}^J \) characterizes the mean intrinsic values of different occupations. The child chooses her own adulthood occupation \( j_{t+1} \), having observed her talent \( u_{t+1} \), schooling attainment \( s_{t+1} \), taste shocks \( \epsilon_{t+1} \), as well as the direct transfers \( b_{t+1} \) from the parent, in order

---

\(^{10}\)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.

\(^{11}\)We can offer an alternative rendition of our model by characterizing the conditional distribution of a multi-dimensional ability vector \( a_t \in \mathbb{R}^J \) 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 17 below.
to maximize her future adulthood utility

\[ V_t^+ (s_{t+1}, u_{t+1}, \epsilon_{t+1}, b_{t+1}, y_t) \equiv \max_j V_{t+1} (b_{t+1} + \epsilon_{jt+1} (s_{t+1}, u_{t+1}, y_t)) + \zeta v_j + \rho \epsilon_{jt+1}, \] (2)

where \( V_{t+1}(\cdot) \) denotes the pecuniary component of utility as an adult of generation \( t+1 \), which is a function of future endowment as we will characterize below. The last two terms in Equation (2) account for the non-pecuniary value derived from working in occupation \( j \).

The parameter \( \zeta \) characterizes the weight of intrinsic values and the parameter \( \rho \) controls the dispersion of the zero-mean, occupation-specific taste shocks \( \epsilon_{t+1} \).

We assume that the distribution \( P_\epsilon \) of idiosyncratic, occupation-specific taste shocks is a normal Type-I extreme-value distribution with zero-mean, that is,

\[ P_\epsilon(\epsilon) = \exp(-\exp(-\epsilon - \bar{\gamma})), \] (3)

where \( \bar{\gamma} \equiv \int_{-\infty}^{\infty} u \exp(-u \exp(-u))du \) 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 parent, an adult in generation \( t \), depends on the intrinsic value \( v_{jt} \) of her own occupation, as well as on her market consumption and expected future dynastic utility (with a corresponding weight \( \beta < 1 \)). More specifically, the pecuniary component of the utility of a member of generation \( t \) with total endowment \( y_t \) in occupation \( j_t \) is given by

\[ V_t(y_t) \equiv \max_{c_t, h_{t+1}, b_{t+1}} \log c_t + \beta \mathbb{E}_{s_t, u_t, \epsilon_t, V_{t+1}} [V_{t+1}^+ (s_{t+1}, u_{t+1}, \epsilon_{t+1}, b_{t+1}, y_t) | h_{t+1}], \] (4)

\[ y_t \geq c_t + \frac{b_{t+1}}{1 + r_t} + \varphi_t (h_{t+1}), \] (5)

where \( \varphi_t(\cdot) \) is a function that characterizes the cost for different levels of human capital investment \( h_t \) and \( r_t \) is the real rate of interest from generation \( t \) to \( t+1 \). The parent values the expected utility of the child \( \mathbb{E}[V_{t+1}^+] \), and accordingly decides on human capital investment \( h_{t+1} \) and direct transfer \( b_{t+1} \) depending on the available endowment \( y_t \).

Adults and children in generation \( t \) take the future paths of occupation-specific wages \( (w_{t'})_{t'-t}^\infty \), interest rate \( (r_{t'})_{t'-t}^\infty \) and schooling costs \( (\varphi_{t'})_{t'-t}^\infty \) as given, and make decisions regarding the consumption, transfers, schooling investments and occupational choice.\(^{13}\)

\(^{12}\)Alternatively, we can define the taste shocks as \( \frac{\zeta}{\rho} v_j + \epsilon_{jt+1} \), where \( \frac{\zeta}{\rho} v_j \) gives the mean of taste shocks for occupation \( j \) across the population.

\(^{13}\)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 Lemma 1 in Appendix B.
3.1.2 Production and Occupational Labor Demand

Next, we endogenize the vector of occupation-specific wages $w_t$ by constructing the aggregate demand for occupation-specific labor. Competitive firms produce a final good using a Cobb-Douglas production function $X_t = K_t^\chi L_t^{1-\chi}$ combining capital $K_t$ and a composite aggregate $L_t$ of different types of labor. The composite $L_t$ is a CES aggregator of different occupations, given by

$$L_t \equiv \left( \sum_{j=1}^{J} \Psi_{jt}^{\frac{1}{\psi}} (Z_{jt} L_{jt}) \right)^{\frac{1}{1-\psi}},$$

where the parameter $\psi$ is the elasticity of substitution in occupational labor demand, $\Psi_{jt}$ is an occupational demand shifter, and where $Z_{jt}$ and $L_{jt}$ denote the productivity and the total efficiency units employed in occupation $j$ in period $t$. Capital depreciates at rate $\xi$ and accumulates according to $K_{t+1} = K_t (1 - \xi) + I_t$ where $I_t$ is the level of investment by generation $t$, denoted in units of final goods.

We normalize the price of final goods to unity, implying $1 = \left( \frac{R_t}{\chi} \right)^{\chi} \left( \frac{W_t}{1-\chi} \right)^{1-\chi}$, where $W_t$ is the price index corresponding to the CES aggregator (6). The labor demand for occupation-$j$ in generation $t$ is then given by

$$w_{jt} L_{jt} = (1 - \chi) X_t \frac{w_{jt} L_{jt}}{\sum_{j'} w_{j't} L_{j't}} = (1 - \chi) X_t \Psi_{jt} \left( \frac{w_{jt}}{Z_{jt} W_t} \right)^{1-\psi}.$$

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

3.2 Stationary Equilibrium

In this section, we focus on characterizing a steady state along which wage rates $w \equiv (w_j)$, interest rate $r$, and schooling costs $\varphi(\cdot)$ are constant.

3.2.1 Parental Income and Occupational Choice

In such a steady state, the pecuniary component of the utility of an individual in occupation $j$ with endowment $y$ is given by $V(y)$ in all periods, where the steady state value function

\footnote{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 $L_t = L_t(Z_{1t} L_{1t}, \cdots, Z_{Jt} L_{Jt})$.}
$V(\cdot)$ satisfies the following Bellman equation:

$$
V(y) = \max_{h,b} \log \left( y - \frac{b}{1+r} - \varphi(h) \right) \\
+ \beta \rho \mathbb{E}_{s,u} \left[ \log \left( \sum_{j=1}^{J} \exp \left( \frac{\zeta}{\rho} v_j + \frac{1}{\rho} V(b + e_j(s,u,y)) \right) \right) \right], \quad (8)
$$

where the expression on the second line accounts for the term $\beta \mathbb{E}_{s,u,\epsilon} [V^+]$ under the stationarity assumption.$^{15}$ The resulting transfer and educational investment policy functions $b^*(\cdot)$ and $h^*(\cdot)$ are time-invariant functions of parental endowment.

The policy functions $b^*(\cdot)$ and $h^*(\cdot)$ that solve the Bellman equation (8) allow us to find the conditional occupational choice decisions of the children. Relying on the properties of the extreme value distribution, we can show that the probability that the child of a parent total endowment $y$, schooling $s$, and talent $u$ chooses occupation $j$ is given by$^{16}$

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

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

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 ratios of choosing two occupations: high-intrinsic value occupation $H$ and low-intrinsic value occupation $L$ for this child satisfy

$$
\rho \log \frac{\mu_H}{\mu_L} = \zeta v_H - \zeta v_L + V(b^*(y) + e_H) - V(b^*(y) + e_L). \quad (10)
$$

Letting $\Delta v \equiv v_H - v_L > 0$ denote the difference in intrinsic values between the two occupations, we ask how much higher should the earnings in occupation $L$ be, compared to occupation $H$, in order for the child to be equally as likely to choose this occupation as to choose the one with higher intrinsic value? Equation (10) suggests that this demanded com-

$^{15}$See Lemma 2 in Appendix B for the derivation.

$^{16}$See Lemma 3 in Appendix B.
Notes: The diagram represents the determination of equilibrium compensating 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 \( \mathcal{D} \) 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-intrinsic value occupation is given by the sorting condition \( y < y^* \).

The intuition behind the result above is simple. Equation (2) shows that the market consumption component of utility for a child making her occupation decision is captured by

\[
V (b^* (y) + e_H) - V (b^* (y) + e_H + d) = \zeta \Delta v. \tag{11}
\]

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

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

which is positive valued whenever the value function is concave and the transfer policy function is monotonically increasing. Equation (12) shows that the compensation required to make a child equally as likely to choose the occupation with a lower intrinsic value rises in the endowment of the parent. This result explains the evidence presented in Section 2.3, since it implies that children of richer parents in equilibrium sort into occupations with higher intrinsic values.

The intuition behind the result above is simple. Equation (2) shows that the market consumption component of utility for a child making her occupation decision is captured by
the value function, evaluated at the sum of the transfer from the parents \(b\) and the earnings \(e\). The marginal value of an extra dollar in earnings for the utility of the child is given by the derivative of this value. Since this value function is concave under standard assumptions, higher levels of parental transfers 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 compared to the child of poorer parents to compensate them for the same loss in intrinsic valuation to accept a worse occupation. Since rich children demand higher compensating differentials, otherwise identical rich and poor children may sort into occupations with high and low levels of intrinsic valuations, respectively.

Figure 4 provides a visual representation of how the demanded compensation defined in Equation (11) and the labor demand together determine equilibrium compensating differentials. Here, we consider a simplified setting with only two occupations \(\{L, H\}\) where the only relevant source of heterogeneity among workers is parental endowment, i.e., \(\delta_j \equiv \kappa_j \equiv \theta_j \equiv \rho \equiv 0\). The curve \(d = \mathcal{C}(y)\) shows the demanded compensation, or the wage premium \(d \equiv e_L - e_H\) for each worker with parental endowment \(y\) to become indifferent between the two occupations. Since we have assumed that the labor market does not differentiate based on parental endowment, the prevailing compensating differentials \(d\) under equilibrium leads to a sorting pattern whereby workers with parental endowment \(y < \mathcal{C}^{-1}(d)\) choose occupation \(L\). Thus, the labor supply of occupation \(L\) is simply given by \(S_L(d) \equiv F_y(\mathcal{C}^{-1}(d))\), where \(F_y(\cdot)\) is the cumulative distribution of parental endowment. Accordingly, if we define a monotonic transformation \(\tilde{D}_L(\cdot) \equiv F_y^{-1}(D_L(\cdot))\) of the labor demand \(D_L(\cdot)\) for occupation \(L\), the equilibrium compensating differentials \(d^*\) is the intersection between the demanded compensation curve \(\mathcal{C}\) and the transformed labor demand curve \(\tilde{D}_L\).

3.2.2 Intergenerational Mobility

In order to facilitate the characterization of intergenerational mobility in the model, let us make an additional parametric assumption on the occupation-specific ability function \(A_j\). Consider the following log-linear form for the earnings function:

\[
\log e_j(s, u, y) \equiv \log \left[ w_j A_j(s, u, y) \right] = \alpha_j + \kappa_j s + \theta_j u + \delta_j \log y. \tag{13}
\]

We can see that the constant term \(\alpha_j\) absorbs the log wage rate \(\log w_j\) 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, which is constant along a steady-state equilibrium. Exogenous parameters \(\kappa_j\) and \(\theta_j\) capture the returns to education and talent in occupation-specific ability, respectively. Finally, the exogenous parameter \(\delta_j\) accounts for all potential
mechanisms through which parental endowment may impact occupation-specific ability.\textsuperscript{17}

**Equilibrium Mobility of Earnings and Income** Examining Equation (13), we can find three potential channels for the persistence of earnings across generations. First, to the extent that the human capital investment policy function $h^*(y)$ implies larger investments by richer parents, the distribution of schooling for the children of richer parents shifts to the right. Thus, in the presence of positive returns $\kappa$ to schooling, children of rich parents typically earn higher incomes compared to the children of poor parents. 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 positive values for returns $\delta$, leading to positive associations between parental endowment and children earnings.

The third and final channel for persistence may stem from the patterns of occupational choice. In particular, the children of rich parents may choose occupations that give them a higher fixed component of income $\alpha_j$ or higher returns to schooling $\kappa_j$. Moreover, they may also display stronger patterns of sorting of schooling and talent, meaning that rich children with higher levels of schooling and talent may be more likely to choose occupations with higher returns to schooling and talent, respectively.

To illustrate the three channels above, we can write the cumulative distribution function for the earnings of the children of parents with endowment $y$ as

$$F_e(e|y) = \mathbb{E}_s [F_e(e|s,y) \mid h^*(y)],$$

where we have defined the cumulative distribution function $F_e(e|s,y)$ of the earnings of children with schooling $s$ and parental endowment $y$ as\textsuperscript{18}

$$F_e(e|s,y) \equiv \sum_{j=1}^J \int_{-\infty}^{\log e_j - \alpha_j - \kappa_j s - \delta_j \log y} \mu_j(s,u,y) \, d\mathbb{P}_u(u),$$

\textsuperscript{17}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 the log earnings of the child is given by $\log e_j(s_i,a_{ij}) = \alpha_j + \kappa_j s_i + a_{ij}$. We assume that the vector of abilities has a multivariate Gaussian distribution with the following conditional expected value and covariances:

$$\mathbb{E}[a_{ij}|y_i] = \delta_j y_i, \quad \forall j \in \{1, \cdots, J\},$$

$$\mathbb{C}[a_{ij}, a_{ij'}|y_i] = \theta_{jj'}^2, \quad \forall j, j' \in \{1, \cdots, J\}.$$

\textsuperscript{18}Equation (15) assumes $\theta_j > 0$ for all $j \in \{1, \cdots, J\}$. 

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and where the conditional occupational choice function \( \mu_j \) satisfies Equation (9). Equation (15) accounts for the second and the third effects of the parental endowment on child earnings discussed above. The second effect, that higher parental endowment may raise the earnings within the occupation, is reflected in the upper bound on the integral. The third effect, that parental endowment shapes the patterns of occupational choice, is reflected through the dependence of the term \( \mu_j \) on parental endowment. Finally, Equation (14) 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 cumulative distribution function of total endowment \( y \) has to satisfy the following fixed point condition

\[
F_y(y^+) = \int_0^{\infty} F_e(y^+ - b^*(y)|y) \, dF_y(y),
\]

where the conditional distribution of earnings \( F_e(\cdot|y) \) satisfies Equations (14) and (15). 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 \( b^*(y) \).

All in all, rich parents help influence the material consumption of their children, and their respective descendants, through three channels: \( i \) affecting their occupational choice, \( ii \) investing in their human capital, and \( iii \) transferring income directly through transfers.

Equilibrium Mobility of Welfare

Recall that the welfare of a child in the model is captured by Equation (2), which we denote simply by \( V^+ \) along the stationary equilibrium

\[
V^+(s, u, \epsilon, b^*(y), y) = \max_j V \left( b^*(y) + e_j(s, u, y) \right) + \zeta v_j + \rho \epsilon_j,
\]

and accounts for both the material and non-material components of welfare, as well as the expected utility of the respective descendants of the child. We can show that, conditional on the parental endowment \( y \), talent \( u \), schooling \( s \), and occupation \( j \) of children, the conditional cumulative distribution function for this measure of welfare is independent of the ex-post occupation of the child, and is given by\(^{19}\)

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

where the Euler-Mascheroni constant \( \overline{\gamma} \) is defined as in Equation (3) and where, in line with Equation (8), we have defined the expected utility of a child with schooling \( s \), talent \( u \), and

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\(^{19}\)See Lemma 4 in Appendix B.
parental endowment $y$ as

$$V^+(s,u,y) \equiv E \left[ V^+ | s,u,y \right] = \rho \log \left( \sum_{j=1}^{J} e^{V_j} \exp \left[ \frac{1}{\rho} \psi \left( \psi \left( b^+ (y) + \epsilon_j (s,u,y) \right) \right) \right] \right). \quad (19)$$

This means that the residual inequality of welfare generated by heterogeneity in idiosyncratic occupation-specific taste shocks is the same across all occupations in our model.

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

$$F_{v} (v^+ | y) = E_{s,u} \left[ F_{v} \left( v^+ | s,u,y \right) \mid h^*(y) \right]. \quad (20)$$

Equation (20) 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 (20) as $F_{v}(v) \equiv \int F_{v}(v | y) dF_{y}(y)$. We revisit the quantitative differences between the mobility in welfare and income in the context of the estimated model in Section 5.1 below.

### 3.2.3 Aggregation and General Equilibrium

To study the general equilibrium aspects of our model, we focus attention on endogenizing the vector of occupational wages along a stationary equilibrium. The supply of occupation-specific efficiency units of labor is given by

$$w_{j}L_{j} = \int_{0}^{\infty} E_{s,u} \left[ \epsilon_{j}(s,u,y) \mu_{j}(s,u,y) \mid h^*(y) \right] \ dF_{y}(y). \quad (21)$$

Equating the supply function above with the labor demand Equation (7) yields $J - 1$ constraints on the vector of wage rates $\mathbf{w} \equiv (w_{j})$.

We assume that the interest rate $r$ is exogenous to the model, pinning down the steady state rental price of capital as $R = r + \bar{\zeta}$, where $\bar{\zeta}$ is the depreciation rate of capital. From the fact that final good is the numeraire, we find that $W = (1 - \chi) \left( (r + \bar{\zeta}) / \chi \right)^{\chi}$, which yields an additional constraint on the vector of wage rates $\mathbf{w}$. Having determined the wage rate, we can find the aggregate labor supply $L$ by summing Equation (21) across all occupations.\(^{20}\)

\(^{20}\)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.
4 Model Estimation

In this section, we discuss our approach to the estimation of 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

Prior to the estimation, we first calibrate two model parameters, the altruism parameter $\beta$ and the exogenous interest rate $r$, based on prior work. A period in the model corresponds to a generation, which we set to a span of 30 years. We set $r$ equal to 2.21% per year, as in Kaplan and Violante (2014). We assume that $\beta$ is equal to 0.5, a value that is within the range of estimates in the literature.\footnote{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).}

Our data is composed of a sample of 4,637 parent-child observations. For each parent-child pair $i$, we observe the earnings $e_i$, occupation $o_i$ and schooling $s_i$ of the child, as well as parental endowment $y_i$.\footnote{See Section 2.1, as well as Appendix A for a discussion of the construction of each variable.} The schooling in the data takes one of the five potential 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 5 in Appendix A.

We rely on the log-linear specification of the earnings function in Equation (13). In addition, we assume that underlying distribution of talent is a normal distribution with unit variance $P(u) = \mathcal{N}(0; 1)$. For the distribution of schooling attainment conditional on human capital investment, we assume a truncated and discretized Gaussian distribution:

$$
P_{s|h}(s|h) \equiv \frac{\exp \left( -\frac{1}{2} \left( \frac{s-h}{\varphi} \right)^2 \right)}{\sum_{s' = 0}^{4} \exp \left( -\frac{1}{2} \left( \frac{s'-h}{\varphi} \right)^2 \right)}. \tag{22}
$$

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 $\varphi \equiv (\varphi_1, \cdots, \varphi_4)$ such that $\varphi_k$ corresponds to the slope of the function between $k - 1$ and $k$.

Let $\varsigma \equiv (\rho, \zeta, \theta, \varphi, \alpha, \kappa, \delta, \theta)$ denote all the model parameters to be estimated, and let $d \equiv (e_i, o_i, s_i, y_i)_{i=1}^{N}$ denote the data described above. Using Equation (13), we can infer the
unobserved talent of the individual given the model parameters according to

\[ u_i = \mathcal{U}(e_i, o_i, s_i, y_i, \varsigma) \equiv \frac{1}{\theta_{o_i}} \left[ \log e_i - (\alpha_{o_i} + \kappa_{o_i}s_i + \delta_{o_i}\log y_i) \right]. \] (23)

This observation allows us to write down the joint probability of data \( d \) 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 values, i.e., setting \( \nu_j \equiv 0 \) for all occupations. We will use the resulting estimates in some of the experiments below to contrast the predictions of the benchmark model against the same model without variations in intrinsic values.

### 4.2 Estimation Results

Table 2a reports the estimated preference parameters \( \zeta \) and \( \rho \), representing the weights on the intrinsic occupation value and the dispersion of the idiosyncratic occupation taste shock, respectively. In addition, it presents the parameters characterizing the human capital investment cost function, and the standard deviation of the distribution of schooling attainment conditional on human capital investment \( \theta \). We note that the estimated weight \( \zeta \) on the intrinsic value of occupations is positive, suggesting that agents value the non-material aspect of occupations. The parameter \( \rho \) is informative about how strongly occupational choice responds to wage differentials, rather than simply reflecting the realization of idiosyncratic taste shocks. A small estimated value for this parameter 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 education cost parameters imply a convex form for the monetary costs of parental investment in their children’s human capital. As we show below, this is a reflection of the fact that in the data children from rich families have, on average, higher levels of educational attainment. However, the data shows substantial heterogeneity in terms of schooling as a function of parental endowment, reflected in the sizable estimate for the standard deviation of the distribution of schooling conditional on human capital investment \( \theta \).

Table 2b reports correlations between the estimated parameters of the earnings function and the intrinsic value of occupations introduced in Section 2.3.2.\(^{23}\) The patterns of correlations among the estimated parameters of the earnings function across occupations allow us

\(^{23}\)See Appendix A for a full list of the estimated parameters of the earnings function.
Table 2: Estimation Results

(a) Preference and Education Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>weight on occ. intrinsic value</td>
<td>ζ</td>
</tr>
<tr>
<td>dispersion in occ. taste shocks</td>
<td>ρ</td>
</tr>
<tr>
<td>education cost</td>
<td></td>
</tr>
<tr>
<td></td>
<td>φ₁</td>
</tr>
<tr>
<td></td>
<td>φ₂</td>
</tr>
<tr>
<td></td>
<td>φ₃</td>
</tr>
<tr>
<td></td>
<td>φ₄</td>
</tr>
<tr>
<td>dispersion in schooling shocks</td>
<td>θ</td>
</tr>
</tbody>
</table>

(b) Estimated Earnings Function

<table>
<thead>
<tr>
<th></th>
<th>ν</th>
<th>α</th>
<th>κ</th>
<th>δ</th>
<th>θ</th>
</tr>
</thead>
<tbody>
<tr>
<td>ν</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>α</td>
<td>-0.75</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>κ</td>
<td>0.91</td>
<td>-0.81</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.08)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>δ</td>
<td>-0.70</td>
<td>0.26</td>
<td>-0.68</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(0.13)</td>
<td>(0.10)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>θ</td>
<td>0.47</td>
<td>-0.61</td>
<td>0.50</td>
<td>-0.33</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.11)</td>
<td>(0.12)</td>
<td>(0.13)</td>
<td></td>
</tr>
</tbody>
</table>

to make several observations. First, occupations with higher intrinsic values display a lower fixed component of earnings and a lower return to parental endowment, but a higher return to schooling and talent. Second, occupations with a lower fixed component of earnings exhibit higher returns to schooling and talent. This implies that individuals face a tradeoff choosing occupations with high fixed component of earnings and those with high returns, and is what allows the model to explain the sorting of individuals with higher schooling and talent to those occupations with higher returns to schooling and talent. Lastly, 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.4.1 shows that the estimated model provides a reasonable quantitative account of 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, i.e, first, the relationship between intrinsic values 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) of the figure displays the probability of choosing one of the three occupations with the highest intrinsic value (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 value (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 value is increasing in parental endowment. Additionally, the figure also shows that the probability of working in high intrinsic value occupations increases in the level of schooling and, conversely, the probability of working in low intrinsic value occupations decreases with educational attainment.

Next, we revisit the correlation between occupational choice elasticities and the intrinsic values 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 \( P(u_i) = N(0, 1) \). 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 model featuring no variations in intrinsic values. For each re-sampled dataset, we run a linear regression of occupational choice \( I\{o_i = j\} \) 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 values \( \nu_j \) across occupations.

Figure 6 shows the distributions of the resulting correlations across the 10,000 resampled
Figure 6: Occupational Choice Elasticities and Intrinsic Values

![Histogram of correlation values between occupational choice elasticities and intrinsic values](image)

Notes: The figure shows the histograms of the correlation values between occupational choice elasticities and the intrinsic value of occupation across 10,000 re-sampled datasets under the benchmark model (blue) and the model estimated with no variations in intrinsic values (red).

Datasets, corresponding to the benchmark model and the model without variations in intrinsic values. The mean value of these correlations across all re-sampled datasets falls from 0.25 ($SE = 0.04$) under the benchmark model to -0.02 ($SE = 0.04$) under the model estimated with no intrinsic values. Thus, the presence of intrinsic values allows us to explain the systematic relationship observed in the data between occupational choice elasticities and intrinsic values. When we remove the variations in intrinsic occupation values, parental endowment does not predict the likelihood of choosing occupations with high intrinsic values (controlling for the effect of education).

4.4 Demanded Compensation and Compensating Differentials

In Section 3.2.1, we discussed the mechanism through which the model predicts that children of richer parents demand higher levels of earnings compensation to be willing to switch to occupations with lower valuations. Recall from Equation (12) that this requires the policy function $b^*(y)$ to be increasing in parental endowment $y$. As expected, appendix C.4.2 shows that the policy function in the estimated model indeed satisfies this condition.

To illustrate the core prediction in Equation (12) in the context of the predicted model, we can now 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 that carries an intrinsic value that is $\Delta v$ lower than the intrinsic value of the current occupation. Specifically, $d_i$ is such that
Notes: The figure shows the compensation required to make children indifferent between remaining in their current occupation and an occupation with an intrinsic value 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 the current occupation in Panel (b). $\Delta \nu$ is equal to the difference between the 75th and the 25th percentile of the distribution of intrinsic values.

$$V (b^* (y_i) + e_i + d_i) - V (b^* (y_i) + e_i) = \zeta \Delta \nu,$$

(24)

where $\Delta \nu$ is set to equal the difference between the 75th and the 25th percentile of the distribution of intrinsic values. Figure 7 displays this compensation, expressed in 1996 US dollars in Panel (a) and as a share of earnings $e_i$ in Panel (b). 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 whose parents are at the top of the parental endowment distribution.

**Uncovering Compensating Differentials** In the discussion of our mechanism in Section 3.2.1, we considered the stylized rendition of the model with two occupations, stripped of all sources of worker heterogeneity other than parental endowment. Our estimated model includes 54 occupations and additional sources of heterogeneity among workers in schooling, talent, and idiosyncratic taste for occupations. We take two distinct strategies to provide proxies for the extent of 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 the intrinsic value of the two occupations. Figure 8a shows the scatter plot of the differences in log earnings and intrinsic values, where the linear fit yields a slope of \(-0.101\) \((SE = 0.002)\). On average, in the tradeoff individuals face between their top two choices, a standard deviation gain in intrinsic value is 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 intrinsic values. How much do we have to increase the wage rate for occupations with higher benchmark intrinsic values to recover the original supply of labor for these occupations? Let \(\tau\) denote such a variation in the environment faced by agents, when compared to the benchmark set of parameters uncovered in Section 4. 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 \(\tau \equiv n\). To solve for general equilibrium response to this variation, we jointly solve for the new vector of fixed components of the earnings function \(\alpha^\tau\), the corresponding value function \(V^\tau\), and stationary distribution of endowments \(E^\tau_y\) that satisfy conditions in Equation (21) for the same original levels of occupational wage bill.

In the environment with removed variations in intrinsic values, the idiosyncratic occupation-specific shocks still provide a source of heterogeneity for the non-monetary value of working across different occupations. However, these idiosyncratic shocks average to zero across the population and only lead to a finite elasticity of occupational labor supply. The only difference between the new environment and our benchmark is the absence of intrinsic values. Thus, we may think of the resulting changes in the log occupational wage rates (given by \(\alpha - \alpha^n\)) 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 values: compared to the model with no intrinsic values, the benchmark economy reduces the (per efficiency unit) wage rate in occupations that compensate workers through higher intrinsic values under the benchmark model. We find that a linear fit with a semi-elasticity of wages to intrinsic values (where each occupation is weighted by its wage bill) with slope of \(-0.058\) \((SE = 0.003)\) captures most of the variations in the occupational wages. This provides us with an alternative way of characterizing the trade-off between intrinsic values and earnings: one standard deviation rise in the intrinsic value is accompanied by an average fall of around 10.9% in the (per efficiency unit) wage rate.
Figure 8: Compensating Differentials

(a) Micro: Across Individuals

(b) Macro: Across Occupations

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

4.5 Intergenerational Mobility in the Estimated Model

Finally, 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 resampled 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 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%
Table 3: Intergenerational Mobility

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intergenerational elasticity</td>
<td>0.339</td>
<td>0.272</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>Rank-rank slope</td>
<td>0.356</td>
<td>0.258</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>Share at higher decile than parents</td>
<td>0.432</td>
<td>0.439</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>Covariance log $e$ and log $y$</td>
<td>0.119</td>
<td>0.095</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td></td>
</tr>
</tbody>
</table>

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.

of the intergenerational persistence in the data. In Appendix C.5, 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.

5 Mobility and the Intrinsic Value of Occupations

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

5.1 Welfare and Compensated Earnings

As we discussed in Section 3.2.2, the most comprehensive measure of the welfare of a young individual along a stationary distribution of the model is given by Equation (17). However, we need to transform a cardinal proxy such as $V^+$ for welfare to a money metric in order to compare to compare the corresponding measure of mobility and inequality of welfare with standard measures in terms of earnings and income. Here, we face an additional challenge in that we also do not observe the idiosyncratic occupation-specific shock in Equation (17).

To tackle the latter challenge, we take two alternative strategies. Our first strategy relies on the results of Section 3.2.2, where we showed in Equation (18) that the conditional distribution of $V^+$ given schooling $s$, talent $u$, parental endowment $y$, and occupational choice $j$ is independent of latter. Moreover, we found that the distribution of $V^+ - \overline{V}^+(s, u, y)$ is the same for all $(s, u, y)$, where the expected conditional value $\overline{V}^+(s, u, y)$ is given by Equation (19). Thus, if we know the tuple $(s, u, y)$ for a given agent in the model, we can characterize
the welfare of the individual subject to an additional shock that has the same distribution for everyone. Now, recall from Equation (23) that we can uncover 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 $V_i \equiv \mathbb{E}_\epsilon [V^+ | e_i, o_i, s_i, y_i]$ of each child $i$ observed in our data by substituting for unobserved talent $u_i$ from Equation (23) into the expression from Equation (19).

Even if theoretically appealing, the strategy above comes with the caveat that deriving the expression for $V_i^+$ in Equation (19) heavily relies on our distributional assumption about the taste shocks. In order to examine the robustness of our results, we also adopt a second strategy. In this alternative 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 value of occupation:\footnote{Figure 26 in Appendix D shows that the two measures are highly correlated in our data. A regression of $\tilde{V}_i^+$ on $V_i^+$ in our sample leads to a coefficient of 0.9995 ($SE = 0.001$).}

$$\tilde{V}_i^+ \equiv V (b^*(y_i) + e_i) + \zeta v_{0i}. \quad (25)$$

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 core problem is that we observe the earnings of children across distinct occupations, which in turn generate varying degrees of intrinsic values 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 value $v$. 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 $V_i^+$ defined above. The corresponding compensation $\tilde{d}_i$ for this measure satisfies

$$V \left( b^*(y_i) + e_i + \tilde{d}_i \right) + \zeta v = V_i^+, \quad (26)$$

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 $\tilde{V}_i^+$ defined in Equation (25), we can define the compensation $\tilde{d}_i$ such that it satisfies

$$V \left( b^*(y_i) + e_i + \tilde{d}_i \right) - V \left( b^*(y_i) + e_i \right) = \zeta (v_{0i} - v). \quad (27)$$
We then define two measures of compensated earnings $\bar{ce}_i$ and $\tilde{ce}_i$ as
\begin{equation}
\bar{ce}_i \equiv e_i + \bar{d}_i, \quad \tilde{ce}_i \equiv e_i + \tilde{d}_i,
\end{equation}
to be the measures of earnings that account for the welfare of working in an occupation that carries an intrinsic value.

5.2 Mobility and Compensation of Earnings

The procedure discussed in Section 5.1 allows us to compute measures of earnings compensation for each child in the data, given observed earnings, schooling attainment, occupational choice, and parental endowment. We find the ranks $r_{\bar{ce},i}$ and $r_{\tilde{ce},i} \in [0, 1]$ of the child in the respective distributions of compensated earnings for the two measures of compensated earnings defined in Equations (28). 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 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 endowment rank $r_y$ and the child’s ranks $r_{\tilde{ce}}$ and $r_{\bar{ce}}$ in the respective distributions of compensated earnings. The figure reveals that accounting for the intrinsic value of occupations lowers intergenerational mobility relative to what is predicted by earnings alone. Specifically, the rank-rank slope between parental endowment and compensated earnings $\tilde{ce}$ of the child is 16% larger than that between parental endowment and the realized earnings of the child. Similarly, the rank-rank slope between parental endowment and compensated earnings $\bar{ce}$ of the child is 35% larger than that between parental endowment and realized earnings.

The fact that the former measure implies lower levels of mobility than the latter has an important implication. Recall that the measure $\bar{ce}$ compensates individuals based on their expected level of welfare, accounting both for the intrinsic value and the idiosyncratic component of their preferences over occupations. In contrast, the measure $\tilde{ce}$ only compensates individuals based on the intrinsic value of their occupation. Thus, we learn that not only richer children benefit from choosing occupations with higher intrinsic values, but they also benefit from being able to better choose occupations that reflect their idiosyncratic tastes.

Overall, these results suggest that failing to account for differences in the quality of work-life across occupations leads us to overestimate the degree of intergenerational mobility of opportunity and welfare.
Figure 9: Intergenerational Mobility of Compensated Earnings in the Data

(a) Realized Earnings  (b) Compensated Earnings, $\tilde{c}$  (c) Compensated Earnings, $c$

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 $r_{\tilde{c}}$ and $r_c$, respectively, in the distribution of compensated earnings.

Expected Mobility under the Model  In the exercise in Section 5.2 above, we took the observed levels of earnings and occupational choice for each individual as given in the data. We can further examine the predictions of our model regarding intergenerational mobility based on the conditional distributions of earnings and occupational choice predicted by the model. To this end, we follow the strategy introduced in Sections 4.3 and 4.5 and re-sample 10,000 datasets conditional only on the parental endowment for each individuals. We do this separately under the benchmark model, as well as (i) under the model estimated without intrinsic values, and (ii) the benchmark model with removed intrinsic values introduced in Section 4.4.

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 values and taste shocks. Under the two cases with no variations in intrinsic values, the mobility of uncompensated earnings is slightly lower than that in the data. More importantly, the mobility in terms of the compensated measure $\tilde{c}$, which accounts for the intrinsic values, falls under the benchmark model relative to the mobility of the uncompensated earnings. The two models without intrinsic values, 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 $c$, that additionally accounts for idiosyncratic

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\[25\text{See Appendix C.5 for a discussion of the drivers of the change in the mobility of uncompensated earnings compared to the benchmark.}\]
Table 4: Mobility of Uncompensated and Compensated Earnings under the Model

<table>
<thead>
<tr>
<th>Rank-rank slope of endowment $y$ and Earnings</th>
<th>Earnings</th>
<th>Compensated earnings, $\tilde{ce}$</th>
<th>Compensated earnings, $\tilde{ce}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark</td>
<td>0.260</td>
<td>0.332</td>
<td>0.442</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Estimated w/o Intrinsic Values</td>
<td>0.279</td>
<td>0.279</td>
<td>0.428</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Benchmark w. Removed Intrinsic Values</td>
<td>0.269</td>
<td>0.269</td>
<td>0.396</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Shifts in Labor Demand</td>
<td>0.210</td>
<td>0.267</td>
<td>0.362</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.005)</td>
</tr>
</tbody>
</table>

taste shocks, compared to the mobility of the uncompensated earnings.

6 Trends in Occupational Labor Demand

In this section, we perform a quantitative exercise to explore the consequences of the recent trends in occupational labor demand for inequality and intergenerational mobility of income and welfare through the lens of the estimated model. In addition to accounting for the observed changes in the occupational composition of labor demand, in this exercise we also account for the observed rise in average earnings over the same period.

A prominent approach to measuring the change in occupational labor demand is to study the change in employment or wage bill shares across occupations (Autor et al., 2006, Acemoglu and Autor, 2010, Jaimovich and Siu, 2012, Autor and Dorn, 2013). The literature has documented an expansion of occupations that require non-routine, abstract and social skills, and a shrinkage of those that are intensive in routine tasks. Following the approach in this literature, we use data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) to calculate, for each occupation, the change in the wage bill share over three decades. We restrict attention to workers between 16 and 64 and we calculate, for each occupation, the average wage bill share between 1980 and 1985 and between 2010 and 2015.26 We then calculate the difference in wage bill shares between these two time periods and use it to calibrate occupational demand shifters in the model.

The exercise follows the structure of the comparison between the benchmark model and the model without intrinsic values in Section 4.3. We consider moving from the benchmark

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26Our 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: Wage Response to 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 values $\nu_j$. Panel (b) plots the predictions of models with and without variations in the intrinsic value for the change in the log occupational wage rates $\alpha^d_j - \alpha_j$, 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.

environment to one with occupational wage bill shares corresponding to the changes observed in the CPS data from 1980-1985 to 2010-2015. In addition, we assume a change in total wage bill $\sum_j w_jL_j$ corresponding to the 17.2% growth observed in average earnings over the same period based on the Bureau of Labor Statistics (BLS) data.\(^{27}\) We let $\tau \equiv d$ denote this variation in the environment that corresponds to the new vector of occupational wage bills $w_jL_j$ that characterize the shifted occupational labor demand.\(^{28}\) Equalizing occupational labor supply and demand in Equation (21) then allow us to solve for fixed components of the earnings function $\alpha^d_j$ that characterize the new occupational wage rates $w_j$, as well as the corresponding value function $V^d$ and stationary distribution of endowments $F^d_y$. For comparison, we also compute the effects of the same change in labor demand under a model that does not include variations across occupations in intrinsic values, i.e., when we set $\nu_j \equiv 0$ for all $j$. We indicate this latter variation, corresponding to both no variations in intrinsic values and the shifts in labor demand, with $\tau \equiv nd$.

\(^{27}\)Note that the sum of aggregate earnings $\sum_j w_jL_j$ in the model maps to average earnings in the data since the aggregate population is normalized to unity under the model.

\(^{28}\)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 $\Psi_{jt}$ in the aggregator (6).
6.1 Response in Wages, Occupational Choice, and Mobility

Figure 10 shows the general equilibrium response of occupational wages to the shifts in occupational labor demand under the benchmark model. First, the figure shows a rise in demand for occupations with high intrinsic values over the three decades.\textsuperscript{29} The model predicts that these trends in turn translate into higher earnings for occupations with higher intrinsic value.\textsuperscript{30} Note, in addition, that the mean log occupational wage rate also rises by around 0.025 to account for the component of the shift in labor demand capturing the growth in average earnings.

We revisit the relationship between intrinsic values and the dependence of occupational choice on parental endowments. We follow the same strategy as that used in Section 4.3 to perform the comparison between our benchmark and the model with shifts in occupational labor demand. We again re-sample datasets based on the conditional distributions implied by the latter model, just as we did for the benchmark model before. We then perform linear regressions of the occupational choice on parental endowment and educational attainment, and compute the correlation between the coefficient on parental endowment and the intrinsic value of occupations. Figure 11 shows the distributions of the resulting correlations.

\textsuperscript{29}The slope of the linear fit is 0.18, implying that an increase of one standard deviation in the intrinsic value of occupations has on average been associated by a rise in wage bill of around 40%.

\textsuperscript{30}In particular, the linear fit in the figure has a slope of 0.025 ($SE = 0.014$), implying that a standard deviation increase in the intrinsic value of occupation is predicted by the model to lead to a rise in wage rates of around 4.7% in response to the observed shifts in the composition of labor demand over this period.
Figure 12: Compensating Differentials with Shifts in Occupational Labor Demand

(a) Response in Demanded Compensation  (b) Wage Response to Removing Intrinsic Values

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 intrinsic values, from Equation (24), 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 $\alpha^d_j - \alpha^{nd}_j$ against occupational intrinsic values $\nu_j$, 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.

across the 10,000 resampled data, corresponding to the benchmark model and the model with shifts in labor demand. The mean value of these correlations across all resampled datasets 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.

Next, we explore the drivers of the fall in the relationship between parental endowment and the intrinsic value of occupations chosen by the children. Figure 12a shows the effect of the shifts in labor demand on the relationship between parental endowment and the compensation required to make the child indifferent between two occupations at the 25th and 75th percentile of the intrinsic value distribution, as defined by Equation (24). 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 resampled datasets from each model. We find that the shifts in labor demand lead to a rise of approximately 4% in the demanded compensation, which falls with the income of the parents. The rise is simply due to the overall rise in the earnings of the children, who now focus relatively more on the intrinsic value of occupations. As we can see in Equation (24), the rise in earnings $e_i$ has a stronger effect for the children of poorer parents who receive a lower transfer $b^*(y_i)$.

The rise in the compensation demanded by the children of poorer parents we saw in
Figure 13: Demanded Compensation and Compensating Differentials

Notes: The diagram represents the change in equilibrium compensating differentials in moving from the benchmark to the model with shifts in labor demand, following the same assumptions as in Figure 4.

Figure 12a reduces the labor supply for low-intrinsic value occupations. Figure 12b repeats the exercise we already saw for the benchmark model in Figure 8b, but now comparing the response of occupational wages if we remove the variations in intrinsic values under the model with shifted labor demand. Again, we interpret the relationship between the response in occupational wages in Figure 12b and intrinsic values as equilibrium compensating differentials. We find this relationship to become stronger: it is well approximated by a linear fit with a slope of -0.082 ($SE = 0.007$), compared to the benchmark value of -0.058 ($SE = 0.002$), implying that one standard deviation rise in the intrinsic valuation is now accompanied by a fall of around 14.3% in the wage rate. Relying on the slopes of these two fits as our proxies for the size of compensating differentials, the equilibrium compensating differentials are approximately 41% higher under the model with shifted labor demand compared to that of the benchmark.

Figure 13 provides an intuitive account of the rise in the compensating differentials as a result of the shift in labor demand, following the same assumptions as that of Figure 4 in Section 3.2.1. The shift in labor demand shifts the transformed demand curve $\tilde{D}_L$ to the left, since the demand for low-intrinsic value occupations falls. In the absence of any supply response, we would expect this to lead to a fall in the compensating differentials, and a modest expansion of the labor supply of the high intrinsic-value occupations toward the children of relatively poorer parents. However, as we saw in Figure 12a, the demanded
compensation curve shifts upward, especially for the children of the poorer parents. If this response is strong enough, then equilibrium compensating differentials in fact rise, as we witness in Figure 12b. As Figure 13 shows, this may lead to a stronger shift in the labor supply of the children of poorer parents toward high intrinsic-value occupations.

Next, we examine the impact of the shifts in occupational labor demand on the intergenerational mobility of earnings and welfare. The last row of Table 4 shows the mean persistence of earnings under the model with shifted labor demand, as proxied by the rank-rank slope of a child’s earnings on parental endowment across 10,000 resampled datasets. 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 values that also offer higher returns to schooling $\kappa$ (see Table 2b).

The table additionally makes the same comparison instead using the compensated earnings measure $\tilde{c}_i$ and $\bar{c}_i$ defined by Equations (27) and (28). The mobility in terms of these measure of welfare also rises. Note that two distinct forces work together to shape the contribution of intrinsic value compensation $\tilde{d}_i$ from Equation (27) to the mobility in terms of this measure of compensated earnings: (i) the dependence of occupational intrinsic values $\nu_o$ 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 11 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 values and also the value that these children attribute to this intrinsic value rises as they become relatively richer. The overall effect is a fall in the correlation between compensation $\tilde{d}_i$ and parental endowment $y_i$, which in turn leads to the patterns in Table 4.

### 6.2 Growth in Welfare

As we have seen, the trends in labor demand over the past three decades, in addition to the overall rise in average earnings, have also shifted the composition of the labor force toward occupations with higher intrinsic value. If workers indeed attribute higher values to working in such occupations, it follows that there is an additional component of the rise in welfare that is not fully reflected in our measures of earnings growth. In this section, we account for the intrinsic value and idiosyncratic taste for occupation in our measurement of welfare growth.

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31See Appendix C.5 for a discussion of the drivers of the change in the mobility of uncompensated earnings compared to the benchmark.
Figure 14: Change in Welfare Across Deciles of Earnings

(a) Growth in Mean Earnings

(b) Rise in Average Intrinsic Value

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 value of the occupation for people in each decile of earnings when moving from the benchmark to the model with shifted labor demand.

We rely on the money metrics that we developed in Section 5.1 to quantify the magnitude of the additional contribution of the taste for occupations to our measures of welfare growth. In particular, 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 $E \equiv \sum_j w_j L_j$ given by Equation (21) 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. In particular, define

$$E[\tilde{c}] \equiv \sum_j \int_0^\infty E_{s,u} \left[ \left( e_j(s,u,y) + \tilde{d}_j(s,u,y) \right) \mu_j(s,u,y) \right] dF_y(y), \quad (29)$$

where $\tilde{d}_j(s,u,y)$ satisfies Equation (27) for $s_i = s, y_i = y, o_i = j,$ and $e_i = e(s_i, u_i, y_i)$. This measure corresponds to the mean of earnings where each agent is compensated for the intrinsic value of their respective occupation. Similarly, we can define

$$E[c] \equiv \sum_j \int_0^\infty E_{s,u} \left[ \left( e_j(s,u,y) + \bar{d}(s,u,y) \right) \mu_j(s,u,y) \right] dF_y(y), \quad (30)$$

where $\bar{d}(s,u,y)$ satisfies Equation (26) for $s_i = s, y_i = y,$ and $e_i = e(s_i, u_i, y_i).$ This measure
corresponds to the mean measure of earnings where each agent is compensated both for the intrinsic value of their respective occupation and the corresponding expected idiosyncratic taste shock.

The growth in the average earnings in moving from the benchmark model to the one with shifted labor demand is 17.1%. The corresponding growth in the measures $E[\tilde{ce}]$ and $E[\bar{ce}]$ defined in Equations (29) and (30) are 19.2% and 17.7%, respectively. Thus, accounting for the role of taste for occupation in our measurement of welfare in this exercise 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 growth measured in terms of uncompensated earnings. The intuition for this upward correction is straightforward: the economy has shifted labor toward occupations that the workers enjoy more. Therefore, a larger share of worker compensation comes from the intrinsic values of worker occupations, leading to an underestimation of welfare growth if we merely rely on observed earnings.

Figure 14a shows how the growth in mean uncompensated and compensated earnings varies across different deciles of earnings. The fact that the growth is larger for higher deciles suggests that the model does indeed capture the observed rise in the inequality of uncompensated earnings, based on the compositional shifts in labor demand across occupations. While the shifts in labor demand raise the mobility in uncompensated earnings, as we discussed in Section 6.1, they also increase the inequality in uncompensated earnings.

Accounting for the compensation that workers receive based on the intrinsic value and the taste for their occupations, we observed distinct patterns for our two measures of compensation $\tilde{ce}$ and $\bar{ce}$ in Equations (29) and (30). First, we observe that accounting only for the intrinsic value of occupations, using our measure $\tilde{ce}$, 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 level of the intrinsic value of the occupations chosen by individuals in each decile, and (ii) the change in the compensation attributed to the same level of intrinsic values. Figure 14b examines the first factor, showing that the expected intrinsic value of the occupations chosen by the workers in the middle deciles of earnings sees the highest gains. Comparing Figure 14a and Figure 14b, we conclude that the compensation associated with the same level of intrinsic value rises most workers in the lowest deciles of earnings. Overall, this measure of compensated earnings suggests that the overall welfare gains from the shifts in occupational labor demand have been more

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Note that the individual’s own earnings plays a similar role in determining the demanded compensation in Equation (11) as does the transfers from their parents. Since the individual’s in the lowest deciles typically receive very little in the way of transfers from their parents, the growth in their uncompensated earnings leads to an upward shift in their demanded compensation. In other words, they attribute a higher compensation to the same level of intrinsic value that they receive from their occupation.
equally distributed across workers than the uncompensated earnings.

Figure 14a further shows that using the compensated measure $\bar{v}$ even tilts the balance in favor of the workers in the lowest deciles of earnings. Recall that this measure additionally accounts for the value of the conditional expectation of the occupation-specific idiosyncratic taste shocks. The growth in terms of this measure for the workers in the highest deciles are even lower than that measured using uncompensated earnings. These workers earn the highest earnings working in occupations with the highest intrinsic values. As a result, they become less likely to be swayed by their idiosyncratic tastes toward occupations with lower earnings and intrinsic values. 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.  

All in all, the results of this section suggest that accounting for the intrinsic value and the taste for occupations changes our predictions about the effects of the trends in labor demand over the last three decades on mobility and the unequal distribution of gains in welfare. In particular, we find that mobility in welfare terms rises and the growth in welfare over the period may be more equally distributed across workers than the observed gains in 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 that carry a higher intrinsic value. The intrinsic value 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 intrin-

\[\text{Figure 27 in Appendix D shows how the growth in mean uncompensated and compensated earnings vary across occupations with different levels of mean earnings under the benchmark model. That shifts in labor demand have a convex form in terms of occupational earnings, growing particularly among the occupations with the highest initial levels of mean earnings. The growth in mean uncompensated mean earnings inherits this convex pattern, reaching to over 30 percent among the highest paying occupations. Compensation for the taste for occupations leads to a U-shape pattern for measured growth. Except among the initially highest paying occupations, accounting for the value of taste for occupations raises our measured growth in welfare of workers in different occupations.}\]
sic occupation values that is robust across datasets, occupation classifications and measures of intrinsic occupation values.

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. In consequence, rich children demand a higher earnings compensation than poor children for working in low intrinsic value occupations.

We use to model to assign a monetary value to the non-pecuniary compensation that each individual receives from their choice of occupation and revisit standard measures of intergenerational mobility. We find that accounting for the additional compensation due to occupational intrinsic value 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 and welfare.

We also examine the impact of changes in occupational labor demand over the past three decades on earnings and welfare growth, as well as 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 value 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.

References


Bui, Quoc trung, “Who had richer parents, doctors or artists?,” Planet Money. NPR (https://www.npr.org/sections/money/), 2014, March 18. 2


Clark, Gregory, The son also rises: Surnames and the history of social mobility, Princeton University Press, 2015. 6


Ermish, John and Francesconi, “Intergenerational mobility in Britain: new evidence from BHPS,” in Miles Corak, ed., Generational income mobility in North America and Europe, Cambridge, UK: Cambridge University Press, 2002. 6


Heckman, James J. and Stefano Mosso, “The economics of human development and social mobility,” Annual Review of Economics, 2014, 6, 689–733. 6, 17


Lo Bello, Salvatore and Iacopo Morchio, “Like father, like son: occupational choice, intergenerational persistence and misallocation,” 2019. 6


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Sussman, Anna Louie, “Can only rich kids afford to work in the art world?,” *Artsy* (https://www.artsy.net), 2017, Feb 14. 2


A Data Appendix

A.1 PSID Data and Sample Selection

We use all waves of the PSID from 1968 to 2015. The PSID started in 1968, collecting information on a sample of approximately 5,000 households. In subsequent years both the original families and their splitoffs (i.e., children who moved out of the parent household) have been followed. This is an essential feature of the data that makes it suitable for the analysis in this paper. To match parents and children we use the PSID Family Identification Mapping System, resulting in a panel of parent-child pairs. We drop pairs for which the age difference between parents and children in less than 15 years and larger than 65 years, as well as pairs with missing occupation of the child in all years.

We transform the panel of parent-child pairs into a cross-section of parent-child pairs with the following variables:

1. Occupation: defined, for both parents and children, as the most frequently held occupation between age 22 and age 55. To study occupational choice and characteristics of occupations, we map detailed (and changing) occupation classifications in the PSID into 54 occupations, listed in Table 5.

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<th>Occ</th>
<th>Description</th>
<th>% children in occ</th>
<th>% parents in occ</th>
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</thead>
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<td>1</td>
<td>Executive, Administrative, and Managerial Occupations</td>
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<td>2</td>
<td>Management Related Occupations</td>
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<td>3</td>
<td>Architects</td>
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<td>4</td>
<td>Engineers</td>
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<td>Mathematical and Computer Scientists</td>
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<td>6</td>
<td>Natural Scientists</td>
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<td>Health Diagnosing Occupations</td>
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<td>Health Assessment and Treating Occupations</td>
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<td>Therapists</td>
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<td>Adjusters and Investigators</td>
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<td>Private Household Occupations</td>
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<td>Machine Operators</td>
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In robustness exercises, we also consider a finer occupation classification, with the 80 occupation groups listed in Table 6.

Table 6: Occupation Groups, Robustness

<table>
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<tr>
<th>Occ</th>
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<td>Therapists</td>
</tr>
<tr>
<td>10</td>
<td>Teachers, Postsecondary</td>
</tr>
<tr>
<td>11</td>
<td>Teachers, Except Postsecondary</td>
</tr>
<tr>
<td>12</td>
<td>Librarians, Archivists, and Curators</td>
</tr>
<tr>
<td>13</td>
<td>Social Scientists and Urban Planners</td>
</tr>
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<td>14</td>
<td>Social, Recreation, and Religious Workers</td>
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<td>15</td>
<td>Lawyers and Judges</td>
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<tr>
<td>16</td>
<td>Writers, Artists, Entertainers, and Athletes</td>
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<tr>
<td>17</td>
<td>Health Technologists and Technicians</td>
</tr>
<tr>
<td>18</td>
<td>Engineering and Related Technologists and Technicians</td>
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<tr>
<td>19</td>
<td>Science Technicians</td>
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<td>20</td>
<td>Technicians, Except Health, Engineering, and Science</td>
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<tr>
<td>21</td>
<td>Supervisors and Proprietors, Sales Occupations</td>
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<td>22</td>
<td>Sales Representatives, Finance and Business Services</td>
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<tr>
<td>23</td>
<td>Sales Representatives, Commodities Except Retail</td>
</tr>
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<td>24</td>
<td>Sales Workers, Retail, Personal Services and Sales Related Occupations</td>
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25 Supervisors, Administrative Support Occupations
26 Computer Equipment Operators
27 Secretaries, Stenographers, and Typists
28 Information Clerks
29 Records Processing Occupations, Except Financial
30 Financial Records Processing Occupations
31 Duplicating, Mail, and Other Office Machine Operators
32 Communications Equipment Operators
33 Mail and Message Distributing Occupations
34 Material Recording, Scheduling, and Distributing Clerks
35 Adjusters and Investigators
36 Miscellaneous Administrative Support Occupations
37 Private Household Occupations
38 Supervisors, Protective Service Occupations
39 Firefighting and Fire Prevention Occupations
40 Police and Detectives
41 Guards
42 Food Preparation and Service Occupations
43 Health Service Occupations
44 Cleaning and Building Service Occupations, Except Household
45 Personal Appearance Occupations
46 Recreation and Hospitality Occupations
47 Child Care Workers
48 Misc. Personal Care and Service Occupations
49 Farm Operators and Managers
50 Farm and Agricultural Occupations, Except Managerial
51 Forestry and Logging Occupations
52 Fishers, Hunters, and Trappers
53 Supervisors, mechanics and repairers
54 Vehicle and Mobile Equipment Mechanics and Repairers
55 Electrical and Electronic Equipment Repairers
56 Miscellaneous Mechanics and Repairers
57 Supervisors, Construction Occupations
58 Construction Trades, Except Supervisors
59 Extractive Occupations
1. **Education**: defined, for both parents and children, as the highest level of education attained.

2. **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.

3. **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.

4. **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

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

where \( \theta \) is a vector of parameters and \( \lambda \) is the penalty level, both to be estimated. The penalty level \( \lambda \) 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 $\theta$, 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 in the cross-section and $\hat{e}_i$ denote parental earnings in the cross-section, both constructed as discussed above, we defined parental endowment $y_i$ as

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

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

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

1. **Occupation**: defined as the most frequently held occupation between age 22 and age 36. The oldest respondents in the NLSY 1997 are 36. We use the occupation classification in Table 5.

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 Empirical Analysis

#### A.3.1 Estimating Potential Earnings

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

\[
\ln e_{ij} = \alpha_{1j} \ln \bar{y}_i + \tilde{X}_i' \alpha_j + \delta_j + \epsilon_{ij},
\]

where \( e_{ij} \) are the annual earnings of child \( i \) working in occupation \( j \), \( \bar{y}_i \) is their parent’s lifetime income, \( \tilde{X}_i \) is a vector of covariates including years of schooling, age, gender and race whose effect on earnings is allowed to vary by occupation, and \( \delta_j \) are occupation fixed effects. The coefficients of interest are \( \alpha_{1j} \), which capture the effect of parental income on occupational efficiency.

Figure 15 displays the estimates of \( \alpha_{1j} \) for the 54 occupations we consider. The elasticity of potential earnings with respect to parental income is positive for most occupations. However, a visual inspection of Figure 1b and Figure 15 reveals a mixed relationship between this elasticity and the intrinsic value of occupations. For example, children are more likely to earn more as social scientists, urban planners, writers, artists, entertainers or athletes, all occupations with a relatively high intrinsic value, if they have richer parents. At the same time, children with rich parents are less likely to earn high earnings as architects or teachers, also occupations with a relatively high intrinsic value. More formally, the correlation between \( \alpha_{1j} \), the elasticity of earnings with respect to parental income, and \( v_j \), the intrinsic value of occupations, is small (−0.047) and not statistically significant (\( SE=0.139 \)).
Figure 15: Effect of Parental Income on Child’s Earnings

Notes: Bars are elasticities capturing the effect of parental income on earnings across occupations.

B Model Appendix

Lemma 1. The problem laid out in Section 3.1.1 corresponds to the recursive formulation of the following sequential problem faced by each generation $t$:

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

where $c_t$, $j_t$, $b_{t+1}$, and $h_{t+1}$ represent the choice variables, and $\mathbb{E}_t$ denotes the expectation at time $t$. The terms inside the expectation capture the discounted future earnings, adjusting for parental income $c_{t'}$, job-specific productivity $v_{j_{t'}}$, and other factors $\epsilon_{j_{t'}}$. The recursive formulation allows for the continuous evaluation of the optimal choices at each generation, considering the impact of parental income on future earnings.
\[ y_t' \geq c_t' + \frac{b_{t+1}}{1+r_{t'}} + \varphi_t'(h_{t+1}), \quad t' \geq t, \]
\[ y_t' = b_t' + e_{j,t'} (s_{t'}, u_{t'}, y_{t' - 1}), \]

facing a sequence of i.i.d. shocks \((\epsilon_t')_{t'=t}^\infty, s_t,\) 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 ancestral 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 2.** The expected utility of generation-\((t+1)\) children in Equation (4) is given by Equation (19).

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

\[ F(x) \equiv P(\epsilon_j \leq x) = \prod_{j=1}^J \exp(-\exp(-x - \bar{\gamma})), \]

where \(\bar{\gamma} \equiv \int_{-\infty}^{\infty} u \exp(-u \exp(-u)) du\) is the Euler-Mascheroni constant. Consider a child with schooling \(s,\) talent \(u,\) parental transfer \(b,\) and parental income \(y,\) and let

\[ \vartheta_j \equiv V(b_{t+1} + e_{j,t+1} (s_{t+1}, u_{t+1}, y_t)) + \zeta_{v_j}, \]

to simplify the expressions. The probability that the expected adult utility of this child is below \(v\) is given by

\[ F_v(v) \equiv P[V^+_t(s, u, \epsilon, b, y) < v], \]
\[ = P[\max_j \vartheta_j + \rho \epsilon_{j,t+1} < v], \]
\[ = \prod_{j=1}^J P(\epsilon_{j,t+1} \leq \frac{1}{\rho} (v - \vartheta_j)), \]
\[ = \prod_{j=1}^J F\left(\frac{1}{\rho} (v - \vartheta_j)\right), \]
\[ = \prod_{j=1}^J \exp\left(-\exp\left(-\frac{1}{\rho} (v - \vartheta_j) - \bar{\gamma}\right)\right), \]
This allows us to calculate

\[
E_{\epsilon} [V_t^+ (s, u, b, y)] = \frac{1}{\rho} \sum_{j=1}^{l} \int_{-\infty}^{\infty} v f \left( \frac{1}{\rho} (v - \vartheta_j) \right) \prod_{j' \neq j} F \left( \frac{1}{\rho} (v - \vartheta_{j'}) \right) dv,
\]

\[
= \frac{1}{\rho} \sum_{j=1}^{l} \int_{-\infty}^{\infty} v e^{-\frac{1}{\rho} (v - \vartheta_j - \bar{\gamma})} \prod_{j'=1}^{l} \exp \left( -\exp \left( -\frac{1}{\rho} (v - \vartheta_{j'}) - \bar{\gamma} \right) \right) dv,
\]

\[
= \frac{1}{\rho} \int_{-\infty}^{\infty} v \left( e^{-\frac{1}{\rho} v - \bar{\gamma}} \sum_{j=1}^{l} e^{\vartheta_j} \right) \exp \left( e^{-\frac{1}{\rho} v - \bar{\gamma}} \sum_{j'=1}^{l} e^{\vartheta_{j'}} \right) dv.
\]

Defining \( x \equiv \frac{1}{\rho} v + \bar{\gamma} - \log \sum_{j'=1}^{l} e^{\vartheta_{j'}} \), we find:

\[
E_{\epsilon} [V_t^+ (s, u, b, y)] = \rho \sum_{j=1}^{l} \int_{-\infty}^{\infty} \left( x - \bar{\gamma} + \log \sum_{j'=1}^{l} \exp \left( \frac{1}{\rho} \vartheta_{j'} \right) \right) \exp (-x) \exp (\exp (-x)) dx,
\]

\[
= \rho \log \sum_{j'=1}^{l} \exp \left( \frac{1}{\rho} \vartheta_{j'} \right).
\]

**Lemma 3.** 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 2 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

\[
\mu_j (s, u, b, y) \equiv P \left( j = \arg \max_{j'} \vartheta_{j'} + \rho \epsilon_{j'} \right),
\]

\[
= \int_{-\infty}^{\infty} F' (e_j) \times \prod_{j' \neq j} P \left( \epsilon_{j'} \leq e_j + \frac{1}{\rho} \left( \vartheta_j - \vartheta_{j'} \right) \right) d\epsilon_j,
\]

\[
= \int_{-\infty}^{\infty} \exp (-e_j - \bar{\gamma}) \exp \left( -e^{-e_j - \bar{\gamma}} \right) \times \prod_{j' \neq j} \exp \left( -e^{-\left( e_j + \frac{1}{\rho} (\vartheta_j - \vartheta_{j'}) - \bar{\gamma} \right)} \right) d\epsilon_j,
\]

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\[= \int_{-\infty}^{\infty} \exp \left( -e_j - \gamma \right) \exp \left( -e_j - \gamma \left( 1 + \sum_{j' \neq j} e^{-\frac{1}{\rho} (\theta_j - \theta_{j'})} \right) \right) d\epsilon_j,\]

\[= \frac{1}{1 + \sum_{j' \neq j} e^{-\frac{1}{\rho} (\theta_j - \theta_{j'})}} \int_{0}^{\infty} \exp (-x) dx,\]

\[= \frac{1}{e^{\rho \theta_j}} \sum_{j'} e^{\rho \theta_{j'}}.\]

where in the last equality, we have used the change of variables \( x \equiv e^{-e_j - \gamma} \left( 1 + \sum_{j' \neq j} e^{-\frac{1}{\rho} (\theta_j - \theta_{j'})} \right) \).

**Lemma 4.** For a stationary equilibrium, define \( V^+ \) as

\[V^+(s, u, \epsilon, b, y) \equiv \max_j V \left( b + e_j (s, u, y) \right) + \zeta v_j + \rho \epsilon_j.\]

We then have \( \mathbb{P} (V^+ < v | y, s, u, j) = \mathbb{P} (V^+ < v | y, s, u) \), where we have defined the distribution of utility conditional on the selected occupation \( j \) as

\[\mathbb{P} (V^+ < v | y, s, u, j) \equiv \mathbb{P} \left( V^+ < v \left| y, s, u, j = \text{argmax}_{j'} \left( b + e_{j'} (s, u, y) \right) + \zeta v_{j'} + \rho \epsilon_{j'} \right. \right).\]

**Proof.** We use the same notation as in the proof of Lemma 3 above. The distribution of utilities, conditional on a given occupation \( j \) is given by:

\[F_v (v|j) \equiv \mathbb{P} \left( V^+ (s, u, \epsilon, b, y) < v \left| j = \text{argmax}_{j'} \theta_{j'} + \rho \epsilon_{j'} \right. \right),\]

\[= \mathbb{P} \left( V^+ (s, u, \epsilon, b, y) < v, j = \text{argmax}_{j'} \theta_{j'} + \rho \epsilon_{j'} \right) \]

\[= \mathbb{P} \left( j = \text{argmax}_{j'} \theta_{j'} + \rho \epsilon_{j'} \right),\]

\[= \frac{1}{\mu_j} \times \int_{-\infty}^{\frac{1}{\rho} (v - \theta_{j})} F' (\epsilon_j) \prod_{j' \neq j} \mathbb{P} \left( \epsilon_{j'} \leq \epsilon_j + \frac{1}{\rho} (\theta_j - \theta_{j'}) \right) d\epsilon_j,\]

\[= \frac{1}{\mu_j} \int_{-\infty}^{\frac{1}{\rho} (v - \theta_{j})} \exp (-\epsilon_j - \gamma) \exp \left( -e_{j} - \gamma \left( 1 + \sum_{j' \neq j} e^{-\frac{1}{\rho} (\theta_j - \theta_{j'})} \right) \right) d\epsilon_j,\]
\[
\frac{1}{\mu_j} \times \frac{1}{1 + \sum_{j' \neq j} e^{-\frac{1}{\rho} (\varphi_j - \varphi_{j'})}} \int_{-\infty}^{\infty} e^{-\frac{1}{\rho} (v - \varphi_j)} \left( 1 + \sum_{j' \neq j} e^{-\frac{1}{\rho} (\varphi_j - \varphi_{j'})} \right) \exp (-x) \, dx,
\]

\[
= \exp \left( -e^{-\frac{1}{\rho} v - \tau} \left( \sum_j e^{\varphi_j} \right) \right),
\]

\[
= F_v(v),
\]

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

\[
x \equiv e^{-\varphi_j - \tau} \left( 1 + \sum_{j' \neq j} e^{-\frac{1}{\rho} (\varphi_j - \varphi_{j'})} \right).
\]

\[\square\]

**Lemma 5.** The joint distribution of the observed data based on the model is given by

\[
P (d; \varsigma) = \prod_{i=1}^N \left\{ \frac{\exp \left[ \frac{\xi}{\rho} v + \frac{1}{\rho} V \left( b^\ast (y_i) + e_{o_i} (s_i, U (e_i, s_i, o_i, y_i; \varsigma), y_i) \right) \right]}{\sum_j \exp \left[ \frac{\xi}{\rho} v + \frac{1}{\rho} V \left( b^\ast (y_i) + e_j (s, U (e_i, s_i, o_i, y_i; \varsigma), y_i) \right) \right]} \times \frac{\exp \left( -\frac{1}{2} U (e_i, s_i, o_i, y_i; \varsigma) \right)^2}{\sum_{s'=0}^4 \exp \left( -\frac{1}{2} (s' - h^\ast(y_i))^2 \right)} \right\},
\]

where \( U (e_i, s_i, o_i, y_i; \varsigma) \) is defined by Equation (23).

**Proof.** The observations are independent, thus we have \( P (d; \varsigma) = \prod_i P (e_i, o_i, s_i | y_i) \). Based on the model, we have:

\[
P (e_i, o_i, s_i | y_i) = E_{u_i} [P (e_i, o_i, y_i, s_i, u_i)],
\]

\[
= \int P (o_i | y_i, s_i, u_i) \delta \left( e_i - (\alpha_{o_i} + \kappa_0 s_i + \delta_0 y_i + \theta_0 u_i) \right) P (u_i) P (s_i | y_i) \, du_i,
\]

\[
= P (s_i | y_i) \int P (o_i | y_i, s_i, u_i) \delta \left( e_i - (\alpha_{o_i} + \kappa_0 s_i + \delta_0 y_i + \theta_0 u_i) \right) e^{-u_i^2/2} \sqrt{2\pi} \, du_i,
\]

\[
= P (s_i | y_i) \int P \left( o_i | y_i, s_i, \frac{x}{\theta_{o_i}} \right) \delta \left( e_i - (\alpha_{o_i} + \kappa_0 s_i + \delta_0 y_i) - x \right) e^{-x^2/2\theta_{o_i}^2} \, dx \sqrt{2\pi} \theta_{o_i},
\]

\[
= P (s_i | y_i) \left[ h^\ast(y_i) \right] P \left( o_i | y_i, s_i, \frac{e_i - (\alpha_{o_i} + \kappa_0 s_i + \delta y_i)}{\theta_{o_i}} \right) e^{-\left( e_i - (\alpha_{o_i} + \kappa_0 s_i + \delta y_i) \right)^2/2\theta_{o_i}^2} \sqrt{2\pi} \theta_{o_i},
\]

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C Estimation Appendix

C.1 Log-Likelihood Function

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

\[
L(d; \zeta) \equiv \sum_{i=1}^{N} \log P(e_i, o_i, s_i | y_i),
\]

\[
= \frac{\zeta}{p} \left( \sum_{i=1}^{N} v_o i \right) + \frac{1}{p} \sum_{i=1}^{N} V(b^*(y_i) + e_j(s_i, y_i, U(e_i, o_i, s_i, y_i; \zeta)))
- \sum_{i} \log \left( \sum_{j} \exp \left[ \frac{\zeta}{p} v_j + \frac{1}{p} V(b^*(y_i) + e_j(s_i, y_i, U(e_i, o_i, s_i, y_i; \zeta))) \right] \right)
- \frac{1}{2} \sum_{i} U(e_i, o_i; \zeta) \frac{1}{2} \sum_{i} \log \theta_{o_i}
- \frac{1}{2} \sum_{i} \left( \frac{s_i - h^*(y_i)}{\theta} \right)^2 - \sum_{i} \log \sum_{s' = 0}^{4} \exp \left( -\frac{1}{2} \left( \frac{s' - h^*(y_i)}{\theta} \right)^2 \right). \tag{32}
\]

The second and third lines of Equation (32) 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 \( \zeta \) maximizing the log likelihood function above for the observed data. For the derivation, see Lemma 5 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 endowments in occupation-specific ability to zero, i.e., \( \delta \equiv 0 \).

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 (13) and (9) together

where we have perform the change of variables \( x \equiv u_i/\theta_o \) in the fourth equality. Equation (31) immediately follows. \( \Box \)
imply that the conditional expected log earnings of children based on the model satisfies:

$$
E \left[ \log(e) \mid j, s, y \right] = \alpha_j + \kappa_j \log s + \delta_j \log y + \theta_j \frac{\int u \times \mu_j(s,u,y) \, d\mu(u)}{\int \mu_j(s,u,y) \, d\mu(u)} = \pi_j(s,y),
$$

where \( \pi_j(s,y) \) 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:

$$
\mathbb{V} \left[ \log(e) \mid j, s, y \right] = \theta_j^2 \frac{\int \left(u - \pi_j(s,y)\right)^2 \times \mu_j(s,u,y) \, d\mu(u)}{\int \mu_j(s,u,y) \, d\mu(u)}.
$$

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 \( Y = \{\bar{y}_1, \bar{y}_2, \bar{y}_3, \bar{y}_4, \bar{y}_5\} \) and map each observed parental endowment in the data to one of the bins, setting \( \bar{y}_i \equiv \arg \min_{y \in Y} |\log y_i - \bar{y}| \). Inspired by Equations (33) and (34), we find an initial estimate for the coordinates of returns to schooling \( \kappa_j \) by relying on an observation-weighted least-squares regression of log earnings \( \hat{E}[\log e \mid j, s, \bar{y}] \) on schooling \( s \) while attempting to control for the selection term by \( \hat{V}[\log e \mid j, s, \bar{y}]^{1/2} \). Using the resulting estimates, we recover initial guesses for occupation-specific fixed earnings and returns to talent \( (\alpha, \theta) \) as

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

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

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 \( (\tilde{\varphi}_1, \tilde{\varphi}_2, \tilde{\varphi}_3, \tilde{\varphi}_4) \) such that \( \varphi_k \equiv \exp(\tilde{\varphi}_k) \) gives the slope of the cost function in the interval \( h \in [k-1,k] \). We consider a convex form characterized by \( \tilde{\varphi} = (5, 6, 7, 8) \). Finally, we initialize the remain-
ing 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 (ϕ̃, ϑ), and 3) the parameters of the earnings function (α, κ, θ, δ). 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 δ, before applying a final round of joint optimization in the space of all model parameters.

**C.3 Estimated Earnings Function**

Table 7 reports the estimated parameters of the earnings function for each occupation.

---

34In 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.

35Since we rely on a discretization of the state space to solve the Bellman equation to compute the objective function, the numerical evaluation of the gradients and the Jacobians of the objective function often leads to discontinuities. In order to smooth out these discontinuities, we steer the optimization routine by providing initially large-step approximations to the gradients and gradually lowering the step-size for the evaluation of the gradients.

36We initialize the values of these returns parameters as the slopes corresponding to auxiliary regressions of θ, μ_i on y_i for all i such that o_i = j.
<table>
<thead>
<tr>
<th>Occ</th>
<th>Description</th>
<th>$\alpha$</th>
<th>$\kappa$</th>
<th>$\theta$</th>
<th>$\delta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Executive, Administrative, and Managerial Occupations</td>
<td>7.876</td>
<td>0.203</td>
<td>0.540</td>
<td>0.188</td>
</tr>
<tr>
<td>2</td>
<td>Management Related Occupations</td>
<td>7.704</td>
<td>0.233</td>
<td>0.549</td>
<td>0.190</td>
</tr>
<tr>
<td>3</td>
<td>Architects</td>
<td>7.478</td>
<td>0.241</td>
<td>0.579</td>
<td>0.188</td>
</tr>
<tr>
<td>4</td>
<td>Engineers</td>
<td>7.515</td>
<td>0.251</td>
<td>0.578</td>
<td>0.194</td>
</tr>
<tr>
<td>5</td>
<td>Mathematical and Computer Scientists</td>
<td>7.735</td>
<td>0.194</td>
<td>0.568</td>
<td>0.193</td>
</tr>
<tr>
<td>6</td>
<td>Natural Scientists</td>
<td>7.458</td>
<td>0.272</td>
<td>0.586</td>
<td>0.188</td>
</tr>
<tr>
<td>7</td>
<td>Health Diagnosing Occupations</td>
<td>7.408</td>
<td>0.303</td>
<td>0.608</td>
<td>0.183</td>
</tr>
<tr>
<td>8</td>
<td>Health Assessment and Treating Occupinations</td>
<td>7.728</td>
<td>0.244</td>
<td>0.548</td>
<td>0.184</td>
</tr>
<tr>
<td>9</td>
<td>Therapists</td>
<td>7.468</td>
<td>0.281</td>
<td>0.560</td>
<td>0.188</td>
</tr>
<tr>
<td>10</td>
<td>Teachers, Postsecondary</td>
<td>7.352</td>
<td>0.309</td>
<td>0.561</td>
<td>0.185</td>
</tr>
<tr>
<td>11</td>
<td>Teachers, Except Postsecondary</td>
<td>7.428</td>
<td>0.292</td>
<td>0.497</td>
<td>0.198</td>
</tr>
<tr>
<td>12</td>
<td>Librarians, Archivists, and Curators</td>
<td>7.358</td>
<td>0.267</td>
<td>0.488</td>
<td>0.189</td>
</tr>
<tr>
<td>13</td>
<td>Social Scientists and Urban Planners</td>
<td>7.451</td>
<td>0.276</td>
<td>0.597</td>
<td>0.186</td>
</tr>
<tr>
<td>14</td>
<td>Social, Recreation, and Religious Workers</td>
<td>7.428</td>
<td>0.266</td>
<td>0.473</td>
<td>0.199</td>
</tr>
<tr>
<td>15</td>
<td>Lawyers and Judges</td>
<td>7.470</td>
<td>0.283</td>
<td>0.599</td>
<td>0.184</td>
</tr>
<tr>
<td>16</td>
<td>Writers, Artists, Entertainers, and Athletes</td>
<td>7.534</td>
<td>0.233</td>
<td>0.528</td>
<td>0.202</td>
</tr>
<tr>
<td>17</td>
<td>Health Technologists and Technicians</td>
<td>7.806</td>
<td>0.178</td>
<td>0.486</td>
<td>0.198</td>
</tr>
<tr>
<td>18</td>
<td>Engineering and Related Technologists and Technicians</td>
<td>7.811</td>
<td>0.156</td>
<td>0.566</td>
<td>0.192</td>
</tr>
<tr>
<td>19</td>
<td>Science Technicians</td>
<td>7.710</td>
<td>0.157</td>
<td>0.554</td>
<td>0.193</td>
</tr>
<tr>
<td>20</td>
<td>Technicians, Except Health, Engineering, and Science</td>
<td>7.676</td>
<td>0.243</td>
<td>0.589</td>
<td>0.183</td>
</tr>
<tr>
<td>21</td>
<td>Sales Occupations</td>
<td>7.953</td>
<td>0.175</td>
<td>0.507</td>
<td>0.192</td>
</tr>
<tr>
<td>22</td>
<td>Miscellaneous Administrative Support Occupations</td>
<td>7.886</td>
<td>0.156</td>
<td>0.468</td>
<td>0.195</td>
</tr>
<tr>
<td>23</td>
<td>Computer and Communication Equipment Operators</td>
<td>7.863</td>
<td>0.066</td>
<td>0.489</td>
<td>0.202</td>
</tr>
<tr>
<td>24</td>
<td>Secretaries, Stenographers, and Typists</td>
<td>7.909</td>
<td>0.151</td>
<td>0.457</td>
<td>0.195</td>
</tr>
<tr>
<td>25</td>
<td>Information Clerks</td>
<td>7.789</td>
<td>0.147</td>
<td>0.458</td>
<td>0.201</td>
</tr>
<tr>
<td>26</td>
<td>Records Processing Occupations, Except Financial</td>
<td>7.741</td>
<td>0.179</td>
<td>0.538</td>
<td>0.193</td>
</tr>
<tr>
<td>27</td>
<td>Financial Records Processing Occupations</td>
<td>7.857</td>
<td>0.157</td>
<td>0.482</td>
<td>0.196</td>
</tr>
<tr>
<td>28</td>
<td>Mail Distribution Occupations</td>
<td>7.890</td>
<td>0.092</td>
<td>0.537</td>
<td>0.202</td>
</tr>
<tr>
<td>29</td>
<td>Material Recording, Scheduling, and Distributing Clerks</td>
<td>7.920</td>
<td>0.133</td>
<td>0.463</td>
<td>0.199</td>
</tr>
<tr>
<td>30</td>
<td>Adjusters and Investigators</td>
<td>7.883</td>
<td>0.143</td>
<td>0.495</td>
<td>0.196</td>
</tr>
<tr>
<td>31</td>
<td>Private Household Occupations</td>
<td>7.888</td>
<td>0.047</td>
<td>0.414</td>
<td>0.203</td>
</tr>
<tr>
<td>32</td>
<td>Guards</td>
<td>7.816</td>
<td>0.144</td>
<td>0.535</td>
<td>0.195</td>
</tr>
<tr>
<td>33</td>
<td>Firefighting and Fire Prevention Occupinations</td>
<td>7.550</td>
<td>0.143</td>
<td>0.599</td>
<td>0.205</td>
</tr>
</tbody>
</table>
C.4 Additional Estimation Results

C.4.1 Untargeted Moments

Table 8 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 9 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
Table 8: Schooling Attainment Conditional on Parental Endowment

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Poor parent</td>
<td>Rich parent</td>
<td>Poor parent</td>
</tr>
<tr>
<td>No high-school</td>
<td>0.05</td>
<td>0.01</td>
<td>0.21</td>
</tr>
<tr>
<td>High-school</td>
<td>0.42</td>
<td>0.18</td>
<td>0.24</td>
</tr>
<tr>
<td>Some college</td>
<td>0.27</td>
<td>0.23</td>
<td>0.23</td>
</tr>
<tr>
<td>College degree</td>
<td>0.16</td>
<td>0.33</td>
<td>0.19</td>
</tr>
<tr>
<td>Graduate degree</td>
<td>0.10</td>
<td>0.25</td>
<td>0.13</td>
</tr>
</tbody>
</table>

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

Table 9: Occupational Choice Conditional on Parental Endowment and Schooling

<table>
<thead>
<tr>
<th></th>
<th>Corr(data,model)</th>
<th>Poor parent</th>
<th>Rich parent</th>
</tr>
</thead>
<tbody>
<tr>
<td>No high-school</td>
<td>0.68</td>
<td>0.27</td>
<td></td>
</tr>
<tr>
<td>High-school</td>
<td>0.85</td>
<td>0.76</td>
<td></td>
</tr>
<tr>
<td>Some college</td>
<td>0.64</td>
<td>0.14</td>
<td></td>
</tr>
<tr>
<td>College degree</td>
<td>0.64</td>
<td>0.57</td>
<td></td>
</tr>
<tr>
<td>Graduate degree</td>
<td>0.81</td>
<td>0.76</td>
<td></td>
</tr>
</tbody>
</table>

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 endowment below the median. Rich parents are those with log parental endowment above the median.

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.4.2 Policy Functions

Figure 16 displays the policy functions for education investment $h^*(y)$ and direct transfers $b^*(y)$. As Panel (a) of the figure shows, both direct transfers and education investment are increasing in parental endowment. Panel (b) shows that poor parents transfer resources to their children mainly by investing in their human capital. In contrast, rich parents devote a larger share of their endowment to direct transfers. We note that the apparent non-monotonicity in the policy function for the share of endowment spent on children’s
education simply reflects the discrete nature of our education groups. That this share is decreasing in parental endowment at high levels of parental endowment is a consequence of the fact that in the PSID data we only observe the number of years of schooling and cannot distinguish more refined aspects of schooling attainment such as the major or the quality of college education. In summary, the policy function under the estimated model broadly satisfies the main condition of the theory.

### C.5 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 $C_{ey}(\log e, \log y)$ denote the covariance between log earnings and log parental endowment:

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

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

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

\[ P(j, s, u|y) \equiv \mu_j(s, u, y) \mathbb{P}_u(u) \mathbb{P}_{s|h}(s|h^*(y)), \tag{35} \]

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

\[ P(j|y) \equiv \int \sum s P(j, s, u|y) du \]

and the conditional distribution of schooling given parental endowment is

\[ P(s|y) \equiv \int \sum_j P(j, s, u|y) du = \mathbb{P}_{s|h}(s|h^*(y)). \]

Based on the definitions above, Equation (13) implies that we can write the expected value of child earnings conditional on parental endowment as

\[ \mathbb{E}[\log e|y] = \bar{\alpha}(y) + \bar{\kappa}(y) \bar{s}(y) + \bar{\delta}(y) \log y + C_{js}(\kappa_j, s|y) + C_{ju}(\theta_j, u|y), \tag{36} \]

where we have defined the expected values of the parameters of the earnings function conditional on parental income \( y \), e.g., \( \bar{\alpha}(y) \equiv \mathbb{E}_j[\alpha_j|y] \equiv \sum_j \alpha_j \mathbb{P}(j|y) \), and similarly for \( \bar{\kappa}(y) \) and \( \bar{\pi}(y) \). Similarly, we have defined the expected level of schooling conditional on parental income as \( \bar{s}(y) \equiv \mathbb{E}_s[s|y] = \sum_s s \mathbb{P}_s(s|h^*(y)) \), as well as the following two conditional covariances given parental endowment \( y \):

\[ C_{js}(\kappa_j, s|y) \equiv \mathbb{E}_{j,s}[\kappa_j(s - \bar{s}(y))|y], \tag{37} \]

\[ C_{ju}(\theta_j, u|y) \equiv \mathbb{E}_{j,u}[\theta_j u|y]. \tag{38} \]

The first term in Equation (36) 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 (36) 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.
Figure 17: Child Earning vs. Parental Endowment

(a) Data vs. Model

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 $E_e[\log e|y]$ implied by the model. Panel (b) decomposes the conditional expected log earnings of the children given parental endowment to different components based on Equation (36).

The last two terms in Equation (36) 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 (37) and (38) 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 17a compares the conditional expected earnings of children $E_e[\log e|y]$ 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 17b decomposes the expected log earnings in the model into different components following Equation (36). 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 $\bar{\alpha}(y)$ 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 $\bar{\kappa}(y)\bar{s}(y)$ increases in parental endowment, due to both the rise in the expected

73
returns to schooling and the expected schooling attainment. 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 $\delta(y)\gamma$. Despite sizable variations in the patterns of sorting across occupations conditional on parental endowment, Figure 17b shows that these variations make quantitatively negligible contributions to the overall dependence of expected log earnings on parental endowment.

Figure 18b 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 value of occupations and thus do not respond as strongly to the earnings incentives in their occupational choice.

---

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., $\sigma_{\alpha} \equiv \sqrt{V_\alpha}$ 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.

---

37 Figure 18a 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 $\kappa(y)$ and to talent $\theta(y)$ rise in parental endowment, while the returns to parental endowment $\delta(y)$ fall in parental endowment.
Persistence of Earnings without Intrinsic Values  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 values. Several forces together help shape this change in persistence. First, the most pronounced effect of removing intrinsic values 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 value occupations, chosen mostly by the children of the poorest parents under the benchmark, and rise in high-intrinsic value occupations, chosen by the children of the richest. To the extent that the children of poor children switch to occupations with higher intrinsic values, this further lowers the fixed component of their earnings due to the negative correlation between the intrinsic values and the fixed components of income $\alpha$ 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 values, which happen to also have higher returns to schooling $\kappa$ (see Table 2b). Their expected earnings rise due to higher schooling investment and attainment.

Figure 19a compares the conditional expected log earnings as a function of parental endowment under the benchmark with that under the model with removed variations in intrinsic values. Therein, Figure 19b decomposes the changes between the two conditional expectations to the different components based on Equation (36). We can see that the conditional expectation of the fixed component of log earnings $\bar{\alpha}(y)$ explains most of the differences between the children of the poorest and the richest parents, while the term involving the expected returns to schooling $\bar{\kappa}(y)\bar{\varepsilon}(y)$ explains the change for the children of the middle class.

Decomposition with Shifts in Labor Demand  Figure 20a 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 19b further decomposes the changes between the two conditional expectations to the different components based on Equation (36). The term involving the expected returns to schooling $\bar{\kappa}(y)\bar{\varepsilon}(y)$ constitutes the main source of changes in expected log earnings.

D Additional Figures and Tables

Figure 21a displays the mean child earnings rank for 20 parent earnings bins. Figure 21b displays the evolution of the fraction of children who move to a higher earnings decile than their parents for five birth cohorts of children: pre-1950, 1951-1960, 1961-1970, 1971-1980,
Figure 19: Expected Log Earning vs. Parental Endowment, Removed Intrinsic Values

(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 values. Panel (b) decomposes the change in the conditional expected log earnings of the children given parental endowment to different components based on Equation (36), in going from the benchmark model to the one with removed variations in intrinsic values.

Figure 20: 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 change in the conditional expected log earnings of the children given parental endowment to different components based on Equation (36), in going from the benchmark model to the one with shifts to occupational labor demand.
Figure 21: Intergenerational Mobility of Earnings in PSID Data

(a) Rank-Rank Correlations

![Graph showing rank-rank correlations.]

(b) Probability of Move to Higher Decile

![Graph showing probability of move to higher decile.]

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


Figure 22 displays the correlation between endowment elasticities estimated with the PSID and NLSY data.

Figure 23 displays the relationship between occupational choice elasticities estimated with the PSID data and the intrinsic value of occupations under two alternative specifications. In the left panel, occupational choice elasticities and the intrinsic value of occupations are estimated for the 80 occupation groups in Table 6. In the right panel, we maintain the occupation classification with 54 groups in Table 5, but define the intrinsic value of occupations to be the first principal component of 5 job characteristics only: treated with respect, little hand movement, little heavy lifting, keep learning new things, do numerous different things. In both cases, the correlation remains positive, high (0.52 and 0.58, respectively) and statistically significant.

Figure 24 displays the relationship between occupational choice elasticities estimated with the NLSY data and the intrinsic value of occupations.

Table 10 examines whether controlling for the risk of occupations alters the relationship between occupational choice elasticities and intrinsic values. Column (1) reports results from projecting occupational choice elasticities on the intrinsic values of occupations. Columns (2) and (3) add to this projection a control for the coefficient of variation of log earnings by occupation, measured as the ratio between the standard deviation and the average log earnings by occupation. In column (2) the coefficient of variation of log earnings by occupation is calculated based on the pooled sample of the ASEC waves from 1976 to
Figure 22: 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 coefficient in the left panel is 0.111 and that of the correlation coefficient in the right panel is 0.131.

Table 10: Occupational Choice Elasticities, Risk and the Intrinsic Value of Occupations

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intrinsic value, ν</td>
<td>0.197</td>
<td>0.183</td>
<td>0.188</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.038)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Coeff. of variation log earnings</td>
<td>-3.101</td>
<td>-2.570</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.383)</td>
<td>(3.396)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.043</td>
<td>0.183</td>
<td>0.319</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td>(0.307)</td>
<td>(0.286)</td>
</tr>
<tr>
<td>Controls</td>
<td>-</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.352</td>
<td>0.372</td>
<td>0.359</td>
</tr>
</tbody>
</table>

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

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.

Figure 25 compares the occupational choice elasticities estimated that control for potential earnings against those without such controls, using the PSID data.
Figure 23: Occupational Choice Elasticities and The Intrinsic Value of Occupations, Robustness

Notes: The left panel is based on an occupation classification with 80 occupation groups. In the right panel the intrinsic value 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.

Figure 24: Occupational Choice Elasticities and the Intrinsic Value of Occupations, NLSY

Notes: Panel (a) shows the relationship between occupational choice elasticities (vertical axis) and the intrinsic value of occupations (horizontal axis). Panel (b) shows the relationship between occupational choice elasticities estimated controlling for potential earnings and the intrinsic value 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 25: Occupational Choice Elasticities Controlling for Potential Earnings

Notes: The y-axis shows occupational choice elasticities from the multinomial logit estimation of the random utility model of occupational choice, and the x-axis shows elasticities from the conditional logit estimation of the model.

Figure 26: Comparison Between the Two Welfare Measures $V^+$ and $\tilde{V}^+$

Notes: The figure displays a scatter plot of our two proxies for welfare of each child in our sample.
Figure 27: Growth Across Occupations

(a) Growth in Occupational Labor Demand

(b) Growth in Mean Earnings

Notes: Panel (a) shows the growth in occupational labor demand from the 1980–1985 average to the 2010–2015 average, as a function of the mean uncompensated earnings of the occupations under the benchmark model. Panel (b) plots the growth in mean uncompensated and compensated earnings across occupations in response to the growth in occupational labor demand over the period, as a function of the mean uncompensated earnings of the occupations under the benchmark model.