The Intergenerational Transmission of Employers and the Earnings of Young Workers*

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Abstract

To what extent do connections in the labor market shape intergenerational mobility? I use employer-employee linked data to study one important type of connection: jobs obtained at a parent's employer. 29 percent of individuals work for a parent's employer at least once by age 30. Exploiting transitory and idiosyncratic variation in the availability of jobs at the parent's employer, I estimate that working for a parent's employer increases initial earnings by 19 percent. The results are attributable to parents using their connections to provide access to higher-paying firms. Individuals with higher-earning parents are more likely to work for a parent's employer and experience larger earnings gains when they do. Consequently, the elasticity of initial earnings with respect to parental earnings would be 7.2 percent lower if no one found a job through these connections. The findings raise the possibility that connections to firms through one's social network could be an important determinant of intergenerational mobility.

Keywords: intergenerational mobility, labor market networks, job ladders
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1 Introduction

To what extent do connections in the labor market shape intergenerational mobility? The answer depends on how often individuals find jobs through connections, the earnings consequences, and how these two objects vary with parental earnings. Despite the fact that a majority of jobs are found through a social contact (Ioannides and Datcher Loury, 2004), it is not well understood how connections shape the intergenerational persistence in earnings. This is largely because it is difficult to estimate the earnings consequences.[1]

I study how the intergenerational persistence in earnings is shaped by one important type of connection: jobs obtained at a parent's employer. Combing data from the Longitudinal Employer-Household Dynamics (LEHD) program and the 2000 Decennial Census allows me to construct a large dataset with information on parent-child and employer-employee linkages. I exploit these features of the data to estimate the causal effect of finding a job through parental connections and use the estimates to quantify how the *intergenerational transmission of employers*—i.e., working for the same employer as a parent—shapes the intergenerational persistence in earnings. My estimates of the magnitude and source of the earnings gains shed light on how and why connections, more broadly defined, might shape intergenerational mobility. Furthermore, connections at the parent's employer may play a nontrivial role on their own, as 5 percent of individuals work for a parent's employer at their first job and 29 percent do so by age 30.[2]

I begin by investigating why some individuals work for their parent's employer. Parental connections are one explanation, but there are other possibilities. For example, children and parents may have similar skills, making them well-suited to work for the same firms. To distinguish between the role of connections and other explanations (e.g., correlated skills) I use parents' future employers to assess how often children would work for their parents' employers if their parents did not work there. Relative to a firm that their parent

[1]Existing evidence of the earnings consequences of finding a job through a social contact is mixed, in part, because it is difficult to fully account for factors that affect earnings and method of job finding. But a number of recent papers establish that social contacts can lead to employment and earnings gains (Beaman, 2012; Cingano and Rosolia, 2012; Schmutte, 2015; Caldwell and Harmon, 2019).

[2]These estimates are consistent with other work from Sweden (Kramarz and Skans, 2014), Canada (Corak and Piraino, 2011), and the United States (Stinson et al., 2014).

will join in the near future, children are 5 times more likely to work for a firm that their parent recently joined (and currently works at). If the presence of parental connections is the only systematic difference between the current and future employers, then these estimates suggest that 80 percent of individuals who work for a parent's employer found their job via parental connections. If parental connections also provide access to the future employers (perhaps indirectly through other social contacts like extended family), then this overstates the likelihood that an individual finds a job at their parent's employer for reasons unrelated to parental connections.

The main empirical challenge is to estimate the earnings consequences: of individuals who work for their parent's employer, how much more do they earn at their parent's employer relative to their next best option? Estimating this causal parameter is difficult because those who work for their parent's employer may differ in unobserved ways. In an ideal experiment, I would prohibit some firms from hiring the children of current employees and use this random assignment as an instrument. If individuals earned less when not allowed to work for their parent's employer then these parental connections provide positive earnings benefits. To mimic this ideal design, I instrument for whether an individual works for their parent's employer with the hiring rate at that firm. Intuitively, a firm will be less likely to offer a job to an employee's child when they are not hiring. My empirical model includes two-way fixed effects for the parent's employer and the local labor market and thus I exploit variation in the hiring rate that is specific to both the parent's employer and the time at which the child is looking for their first job. To illustrate the source of the identifying variation, I show that the outcomes of the child are strongly related to the contemporaneous hiring rate at the parent's employer but are unrelated to the contemporaneous hiring rate at other similar firms and the historical hiring rate at the parent's employer measured just a few years earlier. I find that working for a parent's employer leads to a 19 percent increase in initial earnings at the first job.[3]

I use the parents' future employers to quantify and correct for potential bias. There

[3]My analysis focuses on the first stable job, which has important consequences for an individual's career (Von Wachter and Bender, 2006; Kahn, 2010; Arellano-Bover, 2020; Arora et al., 2021). Section 3 presents the definition of the first stable job.

are a number of ways that violations of the exclusion restriction could lead to bias. For example, hiring conditions at the parent's employer might be related to labor demand shocks that are not fully accounted for by the local labor market fixed effects. If true, then we would expect the outcomes of the child to also be strongly correlated with hiring conditions at the parent's future employer, since these firms likely hire similar workers. However, relative to the firms that the parents will join in the near future, the initial earnings of the children are 10 times more strongly correlated with the hiring conditions at firms that their parents recently joined. If working for a parent's future employer has no effect on earnings and the hiring conditions at these firm suffers from the same omitted variable bias, then 10 percent of the instrumental variables estimate is attributable to bias. In other words, working for a parent's employer increases initial earnings by 17 percent, not 19 percent. This likely overstates the bias since, as mentioned above, parental connections might also provide access to jobs at the future employers. These results rule out many sources of potential bias since they imply that any threats to identification must apply to the hiring conditions at the parent's current employer but not their future employer.

The credibility of the empirical strategy is further supported by a number of additional results. First, the association between the hiring rate and the outcomes of the child is strongest within industries in which the use of social contacts is most common, which argues against sources of bias not specific to these industries. Second, while firms might offer higher wages when hiring more intensively, the estimates are robust to controlling for proxies for time-varying offer wages, which include the employment growth rate and average earnings growth of incumbent workers at the parent's employer. Third, an event study design, which relies on distinct assumptions, yields similar results.

The earnings gains appear to be explained by parents providing access to higher-paying firms. Using the AKM decomposition of earnings (Abowd et al., 1999), I estimate firm-level pay premiums and find that working for a parent's employer leads individuals to work for firms that pay all workers 17 percent more, which is almost identical to the effect on individual earnings. A wide class of models illustrate how search frictions lead to job ladders, whereby more productive firms offer higher wages (Manning, 2013). Consistent with these models, I find that parents provide access to jobs on a higher rung of the firm job ladder as measured by productivity, average wages, and worker flows. Intuitively, some young workers use their parents' connections to find jobs at high-paying firms (e.g., manufacturing plant), but without help from their parents, they would have worked for low-paying firms (e.g., fast food restaurant). The gains fade with time but those who work for a parent's employer at their first job earn 7 percent more even three years later.

Lastly, I show that the intergenerational transmission of employers leads to a modest increase in the intergenerational persistence in earnings. Individuals with higher-earning parents are more likely to work for a parent's employer and experience larger earnings gains when they do. I use the descriptive and causal estimates to quantify the difference between observed measures of the *intergenerational elasticity of earnings* (IGE)—i.e., the elasticity of the initial earnings of an individual with respect to the earnings of their parents—and measures that correspond to a counterfactual world in which no one worked for a parent's employer.[4] I find that the IGE would be 10 percent lower if no one worked for a parent's employer. As mentioned above, absent parental connections some individuals might work for a parent's employer and there may be some bias in the causal estimates. I implement a conservative adjustment for these issues based on the analysis of the parents' future employers and find that the IGE would be 7.2 percent lower if no one found a job through these parental connections. Disaggregating the results by sex, race, and ethnicity reveals that non-Black males with high-earning parents are the largest beneficiaries of working for a parent's employer.

My main contribution is to show that the positive association between the earnings of an individual and the earnings of their parents is attributable, in part, to parents using their connections to provide access to higher-paying firms. For some individuals, a job at their parent's employer offers better pay relative to jobs they could find through alternative search methods. Individuals from higher-income backgrounds benefit more

[4]Corak and Piraino (2011) and Stinson et al. (2014) estimate an intergenerational earnings regression and compare the estimates to those from a modified specification that controls for whether an individual works for their parent's employer. Nonrandom selection into a parent's employer complicates the interpretation of these estimates and my empirical strategy directly addresses these selection issues.

from these connections because their parents are more likely to hold positions of authority at high-paying firms. Most research on intergenerational mobility focuses on the development of human capital during childhood (Mogstad and Torsvik, 2021). I show that parents also directly affect the labor market outcomes of their adult children by using their connections to provide access to jobs. My results raise the possibility that connections to firms through one's social network (beyond the connections at the parent's current employer) could be an important determinant of intergenerational mobility. Recent work by Eliason et al. (2022), San (2020), and Dobbin and Zohar (2021), also document patterns consistent with parents providing access to higher-paying firms. In contrast to these papers, I estimate the causal effect of finding a job through parental connections and quantify implications for the intergenerational persistence in earnings.[5]

I also provide novel evidence that firm-level pay policies are an important determinant of earnings. Prior research finds that earnings growth of job switchers is strongly related to the firms that the workers move to and from. However, this is not necessarily explained by firm pay premiums since worker mobility is endogenous. A number of recent papers study workers who separate for exogenous reasons and find that earnings changes are related to changes in firm pay premiums (Schmieder et al., 2022; Lachowska et al., 2022). I provide complementary evidence of the importance of firm pay premiums since my empirical strategy isolates exogenous variation in the firms that individuals join.

The paper is structured as follows. Section 2 presents the conceptual framework. Section 3 discusses the data. Section 4 investigates how often young workers find jobs through parental connections. Section 5 estimates the earnings consequences. Section 6 quantifies implications for the intergenerational persistence in earnings. Section 7 concludes.

[5]Eliason et al. (2022) and San (2020) study how parental connections affect overall earnings inequality and the earnings gap between ethnic groups, respectively. Dobbin and Zohar (2021) use an AKM decomposition of earnings to show that, conditional on worker effects, individuals with higher income parents tend to work for higher-paying firms. None of these papers estimate the causal effect of finding a job through a parental connection.

2 Conceptual Framework

This section presents a conceptual framework that relates the intergenerational transmission of employers to the intergenerational persistence in earnings. Let y_{ij} denote the log earnings of individual i at their first stable job, which is at firm j. And let y_p denote the log earnings of i's parents. My objective is to understand how the intergenerational persistence in earnings (i.e., the association between y_{ij} and y_p) would change if no one worked for their parent's employer. Estimates of the intergenerational persistence in earnings often use long-run measures of earnings for both parents and children. In contrast, I focus on initial labor market outcomes of the children.

Using the potential outcomes framework, let $y_{ij(1)}$ denote the individual's earnings if they work for their parent's employer and let $y_{ij(0)}$ denote their earnings if they work for the firm that is their next best option (i.e., where they would work if they did not work for their parent's employer). The treatment effect of working for a parent's employer is the difference between potential outcomes and is denoted $\beta_i = y_{ij(1)} - y_{ij(0)}$. Thus,

$$y_{ij} = D_i\beta_i + y_{ij(0)}, \tag{1}$$

where D_i is an indicator equal to one if the individual works for their parent's employer. It is possible that working for a parent's employer could affect when and even whether an individual finds their first stable job, which poses potential challenges to estimating the earnings benefits. Section 5.3 discusses this point in more detail.

I quantify how the intergenerational transmission of employers affects the IGE, which is a common measure of the intergenerational persistence in earnings. The IGE is the coefficient obtained from regressing y_{ij} on y_p and is denoted $\rho(y_{ij}, y_p)$. By combining equation 1 with the identity $\rho(y_{ij}, y_p) \equiv \frac{\text{cov}(y_{ij}, y_p)}{\text{var}(y_p)}$, it follows that the difference between the observed IGE and the IGE that corresponds to the counterfactual in which no one worked for their parent's employer can be written as

$$\rho(y_{ij}, y_p) - \rho(y_{ij(0)}, y_p) = \frac{\text{cov}(D_i\beta_i, y_p)}{\text{var}(y_p)}. \tag{2}$$

To estimate $\text{cov}(D_i\beta_i, y_p)$ I develop the following approximation:

$$\text{cov}(D_i\beta_i, y_p) \approx \mathbb{E}\bigg[\mathbb{E}\big[D_i|r_p\big]E\big[\beta_i|r_p, D_i = 1\big]\mathbb{E}\big[y_p|r_p\big]\bigg] - \mathbb{E}\big[D_i\big]\mathbb{E}\big[\beta_i|D_i = 1\big]\mathbb{E}\big[y_p\big], \qquad (3)$$

where r_p is the quantile rank of parental earnings. The approximation relies on two insights. First, by iterated expectations, the average benefit of working for a parent's employer can be written as $\mathbb{E}[D_i\beta_i] = \mathbb{E}[D_i]\mathbb{E}[\beta_i \mid D_i = 1]$. Second, the expected value of the product of two random variables is approximately equal to the product of their expected values if there is little variation in one of the variables: $\mathbb{E}[D_i\beta_i y_p|r_p] \approx \mathbb{E}[D_i\beta_i|r_p]\mathbb{E}[y_p|r_p]$. See Appendix D for details. To validate the approximation, I show that the IGE based on the micro data, 0.136, is similar to estimates derived from the approximation, 0.140. Section 6 explains why measuring the earnings of the child at their first job yields a smaller IGE compared to estimates of the IGE that use earnings measured later in life.

Equation 2 illustrates that the intergenerational transmission of employers will increase the intergenerational persistence in earnings if the average benefits, $\mathbb{E}[D_i\beta_i \mid y_p]$, are increasing in parental earnings. As noted above, the average benefit of working for a parent's employer is equal to the product of the proportion of individuals who work for their parent's employer and the average treatment effect on the treated (ATT). Thus, my goal is to estimate how these two objects vary with parental earnings.

To anticipate how the intergenerational transmission of employers might affect the intergenerational persistence in earnings, I develop a stylized model that is consistent with the main empirical findings from my paper. I summarize the key points here and refer the reader to Appendix E for the details. Following the literature, earnings depend on human capital, which is positively correlated with parental earnings. I depart from existing models of intergenerational mobility by allowing earnings to also depend on a firm-level pay premium. Individuals receive a job offer through formal job search, and those with higher human capital tend to receive offers from firms with higher pay premiums. The parent's employer may also make a job offer to the child and this offer decision depends on the human capital of the child and the parent. The child will accept the offer if the benefits—which are positive if the parent's firm has a higher pay premium relative to the child's outside option—are sufficiently large.[6]

There are two insights from the model. First, the effect of the intergenerational transmission of employers on the intergenerational persistence in earnings is theoretically ambiguous. On the one hand, higher-earning parents are better able to produce high-paying job offers. On the other hand, children of lower-earning parents have lower levels of human capital and are more reliant on their parents to find a decent-paying job. Second, decisions to invest in human capital may interact with the expectation of working for a parent's firm. On the one hand, the marginal returns to investment in human capital might be particularly high for those who work for a parent's employer (since these are high-paying firms). On the other hand, the marginal returns to human capital investment are lower because higher-ability individuals have better outside options and therefore benefit less from parental connections. Thus, human capital investment decisions could either amplify or dampen the direct effect of the intergenerational transmission of employers on the intergenerational persistence in earnings. My counterfactual exercise should be viewed as a partial equilibrium analysis, which does not account for the possibility that individuals might adjust investment in human capital if there was no option to work for their parent's employer.

3 Data

I rely on two main sources of data (1) the 2000 Decennial Census and (2) the LEHD program.[7] The Decennial Census is a household survey that allows me to measure the relationships between parents and children who live in the same household in 2000. In principle, these data include all individuals living in the United States. In practice, some individuals are not surveyed and non-respondents are more likely to be minorities and low-income households (Mulry, 2007). The LEHD is an employer-employee linked dataset produced by the U.S. Census Bureau and allows me to measure labor market outcomes

[6] Magruder (2010) and Corak and Piraino (2010) develop models of intergenerational mobility that incorporate parental contacts. In contrast to my model, neither paper considers the role of firm pay premiums nor the endogenous use of social contacts.

[7] I use the Hundred Percent Census Edited File (HCEF), which edits the raw data from the short-form survey to remove duplicates and to ensure consistency between the long- and short-form surveys.

of both parents and their children between 1990 and 2018. The LEHD is constructed from two core administrative datasets: (1) unemployment insurance (UI) records, which provide job-level earnings records; and (2) the Quarterly Census of Employment and Wages, which provides establishment-level characteristics. These data capture roughly 96 percent of private non-farm wage and salary employment in the United States but do not cover self-employment (Abowd et al., 2009). While previous work, such as Dunn and Holtz-Eakin (2000), documents strong patterns of intergenerational persistence in self-employment, I focus on more formal employer-employee relationships.

My sample frame includes individuals for whom I can measure parent-child relationships and early-career outcomes. Specifically, the sample frame includes children in the 2000 Decennial Census who (1) live with a parent, (2) are expected to graduate high school between 2000 and 2013, and (3) reside in a state that began reporting to the LEHD at least two years prior to the expected year of high school graduation.[8] 91 percent of individuals younger than 18 live with a parent in 2000 (see Figure A.1). By the end of 2018, the youngest and oldest individuals in the sample were 23 and 37 and years old, respectively. The third criteria accounts for the fact that coverage of the LEHD varies by state, with 8 states and Washington, D.C. starting to report after 2000 (see Figure A.2). There are approximately 48 million individuals in the sample frame.

I drop individuals from the sample if I am unable to link them across datasets or accurately measure parental earnings. Individuals are identified by a Protected Identification Key (PIK), which the Census Bureau generates using personally identifiable information. I drop 19 percent of the sample frame because the child is not assigned a PIK and therefore cannot be linked to the LEHD. I drop an additional 7 percent because a parent is not assigned a PIK or the household in the Decennial Census contains more than 15 individuals. Some individuals with very low earnings have earnings from other sources not covered by the LEHD. Thus, I drop an additional 7 percent of the sample frame if the combined annual earnings of the parents is less than $15,000 (I discuss the

[8] Expected year of high school graduation is based on month and year of birth and individuals born between September 1st and August 31st are assigned to the same cohort. The sample frame includes individuals born between September 1st of 1981 and August 31st of 1995. When measuring parent-child relationships, I include biological, adopted, and step children.

measurement of parental earnings in more detail below). Of the 48 million individuals in the sample frame approximately 32 million, or 67 percent of the sample frame, meet these restrictions (see Table B.1). The resulting sample is broadly representative of families for whom wages constitute the majority of earnings and income, a group that excludes the very poor (approximately the bottom 10 percent of households) and extremely rich (approximately the top 1 percent of households).[9]

First stable job. I define the first stable job as the first quarter in which an individual earns at least $3,300 per quarter—which approximately corresponds to working 35 hours per week at the federal minimum wage—in the current and two consecutive quarters, and receives positive earnings from the same employer for those three quarters.[10,11] Conceptually, this is the first period in which work becomes a primary activity. I refer to this employment spell as the *first stable job* and measure *initial earnings* during the first full-quarter of employment at this job.[12] 26 million individuals, or 82 percent of those that meet the sample restrictions, obtain a first stable job by the end of 2018. Individuals who never find a first stable job have persistently low earnings, with an average annual earnings of only $1,130 at age 30.

Three pieces of evidence suggest that my definition of a first stable job is reasonable. First, individuals experience a dramatic and persistent increase in earnings when they start their first job. Average annual earnings increase from $7,084 to $29,080 in the year when the first job begins (Figure A.3 plots the age-earnings profiles). Second, the age at first job agrees with common perceptions of when people start their careers. 86 percent of young workers in my data find their first job between the ages of 18 and 26. I calculate an analogous measure using the NLSY97 and find that 86 percent of respondents find their first stable job between these ages.[13] Furthermore, 83 percent of workers in the

[9]Using data from the the Current Population Survey, I find that wages tend to be the primary source of income for households above the 10th percentile of the income distribution. Smith et al. (2019) find that non-wage earnings become increasingly important in the top 1 percent of earners.

[10]Dollar values are converted to 2016 dollars using the Consumer Price Index for All Urban Consumers.

[11]Kramarz and Skans (2014) use a similar set of criteria to identify the first stable job.

[12]A full-quarter employment spell occurs when a worker receives strictly positive earnings from the same employer in the current, previous, and subsequent quarter. By construction, every worker experiences a full-quarter employment spell in the second quarter at their first stable job.

[13]Figure A.4 presents the distribution of age at first job for individuals in my sample and in the NLSY97. The analogous measure constructed from the NLSY97 is the first time an individual works at

NLSY97 data are not enrolled in school when they find their first job, which suggests that my measure is not primarily picking up jobs held by students. Third, 40 percent of young workers remain at their first employer for at least three years.

Parental earnings. Without data on the full labor market history, a common approach is to calculate parental earnings as the average earnings over a limited number of years. In addition to the measurement issues raised by Solon (1989) and Zimmerman (1992), the LEHD present unique challenges as there is no way to distinguish between zero earnings and earnings that are not covered by the LEHD frame. To account for these issues, I construct a long-run measure parental earnings by regressing quarterly earnings on an individual fixed effect and a third degree polynomial in age within samples defined by the interaction between state of residence in 2000, sex, and education.[14] Using these parent-specific age-earnings profiles, I calculate the average annual earnings between the ages of 35 and 55. Parental earnings is the sum of the individual earnings of both parents. I calculate percentile ranks based on parental earnings within cohorts defined by expected year of high school graduation. See Appendix C.1 for details.

Employers. Employers are identified by a state-level employer identification number (SEIN), which typically captures the activity of a firm within a state and industry.[15] I use the terms "firm" and "employer" to refer to the entity identified by the SEIN. About half of individuals work for a firm with multiple establishments and the LEHD imputes the link between workers and establishments. I primarily focus on the firm, but in some analyses I use the establishment impute to measure the location of the job within a state.

least 35 hours for 36 consecutive weeks (three quarters). An alternative approach is to focus on labor market outcomes after all schooling is completed and Figure A.4 also presents results for this measure.

[14] The data are a panel measured at a quarterly frequency that include all strictly positive earnings records between 1990 and 2018 for the parents in the sample. Quarters with zero earnings are not included in the sample. I further restrict the panel to individuals between the ages of 25 and 65 and drop individuals that have fewer than 12 quarters of strictly positive earnings over the entire time period. Parents not included in this sample are assumed to have zero earnings.

[15] A worker could have positive earnings at multiple employers in a given quarter. In such cases, I measure the characteristics of the employer providing the most earnings in that quarter.

4 Use of Parental Connections

I begin by documenting how common it is to work for a parent's employer. The first column of Table 1 presents summary statistics for the entire sample. The second and third columns present results for individuals who do not and do work for a parent's employer, respectively. 5 percent of individuals work for a parent's employer at their first stable job and these individuals tend to stay at their first jobs longer, are less (more) likely to be employed in the unskilled service (production) sector, and earn slightly less.[16] Of individuals who work for a parent's employer, only 19 percent have a parent who is in the top percentile of the within-firm earnings distribution, suggesting that the patterns are not driven by executives or owners hiring their own children. Individuals are more likely to work for a parent of the same sex: sons are 1.5 times more likely to work with their father and daughters are 2.3 times more likely to work with their mother. 29 percent of individuals work for the same firm as a parent at some point between the ages of 16 and 30, which is consistent with Stinson et al. (2014), who find that 22 percent of sons work with their father by the time they are 30 years old. While there are several explanations for why individuals might work for a parent's firm, the following paragraphs argue that connections are the primary reason.

I use parents' future employers to assess how often children would work for their parents' employers if their parents did not work there. I identify parents who begin a new job within three years of their child entering the labor market. Figure 1 plots the proportion of children who work for that employer against the quarter in which their parent started the job. The sample includes parents with a minimum tenure of three years, implying that the parents are employed at the firm when their child enters the labor market if they joined the firm before their child entered the labor market. Individuals are 5 times more likely to work for a firm if their parent started working there 2-3 years before compared to 2-3 years after the child finds their first job.[17] If the

[16] I group two-digit North American Industry Classification System (NAICS) industry codes into three sectors: unskilled services, skilled services, and production. See Appendix C.3 for details.

[17] Figure A.7 plots analogous results for parents that separate from a firm just before or after their child enters the labor market. These results are more difficult to interpret because parents might retain useful connections at past employers. Nevertheless, I find similar patterns: individuals are 6 times more

presence of parental connections is the only systematic difference between the current and future employers, then these estimates suggest that 80 percent of individuals who work for a parent's employer found their job via parental connections. This likely overstates the likelihood that an individual finds a job at their parent's employer for reasons unrelated to parental connections since parents may provide access to the future employers indirectly through other social contacts like extended family or friends.

Working for a parent's firm is not explained by the fact that children and parents often work in the same local labor market. Table 1 indicates that individuals who work for a parent's employer are no more likely to work for large firms and 70 percent of these individuals are located in urban areas. This suggests that the tendency to work for a parent's employer is not driven by cases in which a single employer dominates a local labor market. For each employed parent, I identify ten other firms in the same commuting zone, two-digit industry, and size class (greater or less than 500 employees). In this sample, 6 percent of individuals work for their parent's employer at their first job. On average, only 0.03 percent of individuals work for the other firms.[18] In other words, individuals are about 200 times more likely to work for a parent's employer compared to other similar firms in the same local labor market.

The likelihood of working for a parent's firm is highest in industries where the use of labor market networks is most common. Using responses to the first wave of the NLSY97, I calculate the proportion of individuals who were hired by or recommended for their job by a parent. Figure 2 plots this statistic against the proportion of individuals who work for a parent's firm by industry. The correlation between these two measures is positive with regression coefficient of 2.5 and a p-value of 0.003. Both measures suggest that social connections are less commonly used in the unskilled service sector and more commonly used in the production sector.

Taken together, these results suggest that individuals who work for a parent's firm do so primarily because parental connections influence the hiring or job search process. The

likely to work for a firm if their parent stopped working there 2-3 years after compared to 2-3 years before the child finds their first job.

[18] Across the 10 draws of firms, the minimum and maximum percent of individuals who work for one of these other firms is 0.033 and 0.035 percent, respectively.

use of parental connections is consistent with Loury (2006), who finds that 10 percent of young men found their current job through a parent, as well as with research that finds that informal search methods are used frequently and affect where individuals work (Bayer et al., 2008; Hellerstein et al., 2011; Rajkumar et al., 2022).

Descriptive statistics provide some evidence that individuals with limited outside options use their parents' connections to find good jobs. I link educational attainment from the American Community Survey to a subset of the sample. Column 1 of Table B.2 shows that less educated individuals are more likely to work for a parent's employer. Column 2 shows that individuals are also more likely to work for a parent's employer when the county-level unemployment rate is high, and column 3 shows that this association is robust to controlling for county and year fixed effects. Figure A.8 illustrates that individuals who work in industries with higher wage premiums—which are estimated conditional on age, sex, and education—and higher rates of unionization, are more likely to work for a parent's employer. These results provide suggestive evidence that parents use their connections to help children with limited labor market options to find high-paying jobs.

5 Earnings Consequences

Of individuals who work for their parent's employer, how much more do they earn at their parent's employer relative to their next best option? There are two channels through which working for a parent's employer could affect wages. First, parents may provide access to firms that pay all workers higher wages, possibly by sharing information about job openings as in Mortensen and Vishwanath (1995) or through pure favoritism. Second, firms might offer different wages to children of current employees relative to otherwise similar workers. This could happen if parents reduce information asymmetries between workers and employers as in Montgomery (1991), or if working with a parent affects worker productivity as in Heath (2018). My objective is to estimate the effect of working for a parent's firm and investigate the mechanisms.

Estimating a causal parameter is difficult because individuals who work for their parent's employer may be different in unobserved ways. For example, the previous section finds that individuals are more likely to work for a parent's employer if they are less educated and searching for a job in labor markets with higher unemployment. This suggests that a naive comparison between individuals who do and do not work for their parent's employer would understate the earnings benefits.

If I were able to run an ideal experiment, I would prohibit some firms from hiring the children of current employees and use the random assignment across firms as an instrument. With perfect compliance, the estimates would identify the ATT, which is the parameter of interest. I mimic this ideal experiment and instrument for whether an individual works for their parent's employer with the hiring rate at the parent's employer measured at the time the individual enters the labor market. Intuitively, a firm will be less likely to make a job offer to the child of a current employee when they are not hiring.

My empirical strategy exploits transitory and idiosyncratic variation in the hiring rate at the parent's employer. I estimate the following two-stage least squares regression,

$$\begin{aligned} \text{Second stage: } & y_i = \pi^2 + \beta D_{ij(p)} + \delta^2_{j(p)} + \lambda^2_{l(j(p),t)} + v_i \\ \text{First stage: } & D_{ij(p)} = \pi^1 + \gamma Z_{j(p)t} + \delta^1_{j(p)} + \lambda^1_{l(j(p),t)} + u_i \end{aligned} \tag{4}$$

where t is the quarter in which individual i starts their first stable job; $D_{ij(p)}$ is equal to one if i works for parent p's employer, which is denoted by $j(p)$; $\delta_{j(p)}$ is a fixed effect for the parent's employer; $\lambda_{l(j(p),t)}$ is a fixed effect for the local labor market in which the parent's employer is located, which is defined by the interaction between the commuting zone, two-digit industry, and quarter; and u_i and v_i are regression residuals, which are clustered at the level of the parent's employer. I instrument for $D_{ij(p)}$ using $Z_{j(p)t}$, which is the quarterly hiring rate at the parent's employer in the quarter in which the child begins their fist stable job. I estimate equation 4 on a sample that includes employed parents who have at least one year of tenure and excludes singleton observations.[19] Unless otherwise stated, p denotes the parent who is the primary earner.

[19]I drop singleton observations—i.e., observations which have a unique value of a fixed effect—since they do not contribute to the identification of the model and retaining them would bias the estimates of the standard errors.

Three assumptions are needed to interpret estimates from equation 4 as causal. First, the hiring rate must affect the probability of working for a parent's employer. Second, the independence assumption requires that, conditional on the covariates in the model, the hiring rate only be related to the earnings of the individual through its effect on the propensity to work for the parent's employer. Third, the hiring rate must have a monotonic affect on the probability of working for a parent's employer.[20] If the three identifying assumptions are met, the two-stage least squares estimator identifies a *local average treatment effect* (LATE), which is the average effect for the *compliers*—the population whose treatment status depends on the instrument (Imbens and Angrist, 1994).

The identifying variation comes from the difference across firms in the variation in the hiring rate over time. The first stage compares individuals whose parents work for the same firm but who enter the labor market at different times. I ask if the individual is less likely to work with their parent if they enter the labor market when their parent's firm is hiring less, and whether this difference is larger relative to individuals whose parents' firm experiences a smaller decline in hiring. The following paragraphs present results to more clearly illustrate the source of the identifying variation.

There is a strong association between an individual's outcomes and the contemporaneous hiring conditions at their parent's firm, but the strength of this relationship decays sharply when the hiring rate is measured earlier in time. Figure 3(A) presents estimates from the first stage and illustrates that the contemporaneous hiring rate at the parent's firm is highly predictive of whether the child finds their first job there. In contrast, when the hiring rate is measured three years before, the first-stage coefficient is statistically indistinguishable from zero. Figure 3(B) shows a similar pattern of decay when the outcome variable is initial log earnings. Thus, I exploit transitory variation in the hiring rate specific to the period when the child finds their first job. Below I show that my results

[20]With the two sets of fixed effects in the model, this assumption implies that for any two employers and any two periods, the employer that experiences a larger increase in the hiring rate also experiences a larger increase in the propensity to hire a child of a current employee. The hiring rate may be correlated with the composition of new hires but this does necessarily lead to a violation of the identifying assumptions. To see why, consider the following example. The parent's employer only makes job offers to the high-ability individuals when hiring is relatively low and makes job offers to both high- and low-ability individuals when hiring is relatively high. While this affects the interpretation of the estimates (the estimates would identify the average effect for low-ability individuals), it does not affect the validity of the instrument.

are robust to using very recent lags of the hiring rate, which addresses the concern that the hiring rate could be affected by the child joining their parent's firm.

The outcomes of the child are strongly related to the parent's firm but unrelated to similar firms in the same local labor market. Figure 4 presents the first-stage and reduced-form estimates for specifications in which I replace all variables related to the parent's employer with variables related to a placebo firm drawn from the same commuting zone, two-digit industry, and size class (greater or less than 500 employees). The hiring rates of the placebo firms are unrelated to the outcomes of the child, which illustrates that my specification exploits variation specific to the parent's firm as opposed to conditions common to similar firms in the same local labor market.

5.1 Effect on Initial Earnings

Table 2 presents the two-stage least squares estimates from equation 4 and shows that working for a parent's employer leads to a substantial increase in initial earnings. Column 1 presents estimates from my preferred specification, which controls for a vector of demographic covariates in addition to the fixed effects for the parent's firm and the local labor market.[21] The results indicate that working for a parent's employer increases initial earnings by 17 log points, or 19 percent.[22] The first stage is highly significant with an associated F-statistic of 24,300. Column 2 presents estimates from a specification that excludes the demographic covariates and finds a slightly larger effect of 21 log points.

There are two potential issues with measuring the hiring rate in the quarter of entry. First, a firm might create a new job to hire the child of a current employee, which would produce a positive association between the hiring rate at the parent's employer and the probability that the child works there. Second, working for a parent's firm could affect when the child enters the labor market, which could potentially affect the association between the outcomes of the child and hiring conditions at the parent's employer. To

[21] The demographic covariates include log earnings of the parent, sex, race, and ethnicity.

[22] For comparison, the Ordinary Least Squares (OLS) estimator (i.e., regressing log initial earnings on an indicator for working for a parent's employer and the same fixed effects and covariates) yields a point estimate (standard error) of 0.004 (0.003). The OLS estimates could be negatively biased if children with limited labor market opportunities are more likely to work for their parent's employer. The OLS estimates might suffer severely from bias since my data lack meaningful measures of human capital.

assess these concerns, Table 2 presents estimates from two alternative specifications in which the instrument is the average quarterly hiring rate in the (column 3) four quarters prior to when the child began their first job and (column 4) year in which the child turns 18.[23] I continue to find large earnings gains from working for a parent's employer using these alternative instruments. In both cases, the first stage is weaker and the second stage estimates are less precise. Relative to column 1, the effect in column 3 is larger because either the estimators identify different LATEs or at least one of the estimators is biased. To the extent that the difference reflects negative bias in column 1, my main specification offers a conservative estimate of the gains from working for a parent's employer.

The results are robust to controlling for time-varying conditions of the parent's employer and local labor market. Beyond affecting the probability of working with their parent, the hiring rate could be correlated with the initial earnings through characteristics of the parent's employer or local labor market conditions. I provide evidence that my empirical specification exploits variation orthogonal to these channels. Column 5 of Table 2 shows that the results are robust to controlling for hiring conditions at all other firms in the same commuting zone, quarter, and industry; the employment growth rate at the parent's employer; and the average log earnings and average earnings growth of incumbent workers at the parent's employer. The robustness to controlling for the employment growth rate—which is distinct from the hiring rate—and the earnings growth of incumbent workers is particularly important and helps to address the concern that firms might offer higher wages when hiring more intensively.

The estimated earnings benefits of working for a parent's employer are large but not inconsistent with other evidence of the importance of place of work in determining earnings. For example, the estimated effect is about the same size as the union wage premium (Farber et al., 2021) and about one standard deviation of the inter-industry wage premium (Katz et al., 1989). Another way to assess the magnitude of my estimates is to compare them to the college premium—the relative wage of college versus high

[23]In column 4 the fixed effects for the local labor market are defined based on the parent's employer when the child is 18. Thus, none of the covariates are a function of when the child finds their first job. The sample includes individuals whose parent is employed at the same firm between the ages of 18 and 22, which is the five-year period in which the most children enter the labor market.

school educated workers—which is about 68 log points (Acemoglu and Autor, 2011). Using panel data from the United States, Stinson et al. (2014) estimate specifications with individual fixed effects and find that sons and daughters who work for the employer of their father experience an increase in earnings by 23 percent and 8 percent, respectively. My results differ more dramatically relative to Kramarz and Skans (2014), who study the school-to-work transition in Sweden and find small wage losses in the short run, which appear to be offset by stronger wage growth in the medium run; this finding is supported by Eliason et al. (2022), who use more recent data from Sweden.

I use the parents' future employers to quantify and correct for potential bias. I identify parents who begin a new job within three years of their child finding their first job and remain at this new employer for at least three years (the same sample is used to produce Figure 1). The odd columns of Table 3 present estimates from equation 4 on the sample of parents who started a new job 2-3 years before their child entered the labor market. These results are similar to the main estimates: working for a parent's employer leads to a 19 log point increase in earnings. The even columns present estimates from a placebo specification where all variables in equation 4 that correspond to the parent's current employer are replaced with variables that correspond to the parent's future employer and the sample includes parents who started a new job 2-3 years after their child entered the labor market. Both the first-stage and reduced form coefficients are 10 times larger when using the hiring conditions at the firm that their parent recently joined (and currently works at).[24] Under the assumption that working for a parent's future employer has no effect on earnings and the hiring conditions at these employers suffers from the same omitted variable bias, this suggests that 10 percent of my main estimates in Table 2 is attributable to bias.[25] In other words, working for a parent's employer increases initial earnings by 15.3 log points, not 17 log points. These estimates likely overstate the bias since parents might have other connections that provide access to the future employers.

[24]Table B.3 presents analogous results for the parent's past employer. Relative to the parent's past employer, the reduced form for the parent's current employer is twice as large. As previously discussed, the results for the parent's past employers are more difficult to interpret since the parent may retain some connection to these firms even after separating.

[25]Appendix F formalizes this argument.

These results rule out many sources of potential bias since any threats to identification must apply to the hiring conditions at the parent's current employer but not their future employer.

5.2 Mechanisms and Other Results

One possible channel through which working for a parent's employer could affect earnings is by matching individuals to firms that pay all workers more. I investigate this in column 1 of Table 4, where the outcome is the AKM firm fixed effect of the child's employer.[26] Working for the parent's employer leads individuals to work for firms that pay all workers 16 log points (or 17 percent) more, which is approximately half a standard deviation improvement in the firm effect. A comparison to the main results in column 1 of Table 2 reveals that the effect on individual earnings is virtually identical. Splitting the sample by the median pay premium of the parent's firm, I find working for the parent's firm leads to a 29 (12) and 5 (13) log point increase in initial earnings for individuals whose parents are employed by high- and low-paying firms, respectively (standard errors in parentheses). While there is some debate over how to interpret the AKM fixed effects, these results strongly suggest that the earnings gains are driven by parents providing access to higher paying firms.[27]

I provide additional evidence that parents provide access to higher paying firms by focusing on firm-level outcomes that are directly measurable and thought to be strongly correlated with firm pay premiums. A wide class of models illustrate how search and matching frictions lead to dispersion in firm-level pay policies.[28] In these models more productive firms poach workers from less productive firms by offering higher wages. Con-

[26] I estimate the AKM firm fixed effect using code adapted from Crane et al. (2022) and based on national data that excludes the young workers in my sample. See Appendix C.4 for details.

[27] Identification of the AKM empirical model places restrictions on the relationship between an unobserved error term and the individual- and employer-level components of earnings, whereas my empirical strategy makes no assumptions about the relationship between these variables. Importantly, the AKM model includes a firm fixed effect for the employer of the individual, whereas equation 4 includes a firm fixed effect for the parent's employer.

[28] Dispersion in firm-level pay policies also arise out of static models in which heterogeneous preferences over a firm's non-wage characteristics lead to imperfect competition (Card et al., 2018). While these models could also be used to interpret my results, dynamic models that emphasize the role of frictions (Burdett and Mortensen, 1998; Postel-Vinay and Robin, 2002) offer a more explicit explanation for the dynamic outcomes related to poaching hires and subsequent job mobility.

sistent with this class of models, columns 2-4 of Table 4 illustrate that working for the employer of a parent leads individuals to start their careers on a higher rung of the firm job ladder as defined by productivity, the proportion of hires made through poaching flows, and wages.[29] Column 5 shows that individuals who work for their parent's employer end up at smaller firms. While job ladder models typically predict that larger firms will occupy higher rungs of the job ladder, Haltiwanger et al. (2018) find that firm age complicates this prediction because there are productive young firms that have not had ample time to grow into large firms. Consistent with this explanation, column 6 indicates that working for a parent's employer leads individuals to work for younger firms.

Parents provide access to higher-paying firms, largely by providing access to higher-paying industries. Columns 7-9 of Table 4 present estimates in which the outcome is an indicator equal to one if the child works in one of three broad sectors. Working for a parent's employer reduces the probability of working in the unskilled service sector by 31 percentage points and increases the probability of working in the production sector by 33 percentage points. The outcome in column 10 is the industry-level pay premium, and the results suggest that working for a parent's employer leads individuals to work in industries that pay all workers 11 log points more. Thus, 69 percent of the effect on individual earnings is attributable to individuals working in higher paying industries. To the extent that young workers are aware of pay differences across industries, these results cast doubt on the possibility that parents simply provide general information to their children about where to look for high-paying jobs. Lastly, the outcome in column 11 is the child's earnings rank within their first employer. Here the effect is negative, suggesting that, while parents provide access to higher-paying firms, they do not provide access to relatively high-paying jobs within firms.

Working for a parent's employer leads individuals to stay at their first employer longer. Column 1 of Table 5 indicates that working for a parent's employer increases the probability of remaining at the first employer for at least three years by 17 percentage points.

[29]The outcomes in columns 2-4 correspond to the rank of time-invariant characteristics of the first employer relative to the national distribution of firms. See Appendix C.5 for details. For examples of papers that use similar measures to define job ladders, see Haltiwanger et al. (2021), Bagger and Lentz (2019), and Haltiwanger et al. (2018).

Columns 2 and 3 illustrate that this effect is driven by a reduction in the probability of making a job-to-job (j2j) transition as opposed to affecting the probability of making a job-to-nonemployment (j2n) transition. If the outcomes in columns 2 and 3 are viewed as proxies for quits and layoffs, respectively, then these results suggest that working for a parent's employer provides access to firms that are more desirable than the outside option, whereas the firms do not gain access to more desirable workers. While this seems to suggest that the children are the primary beneficiaries, the parent's employer may benefit from the lower quit rates if it is costly to hire and retain workers.

Columns 4-6 of Table 5 illustrate that the earnings benefits of working for a parent's employer are quite persistent. Working for the parent's employer increases annual earnings in the first year of the job by $3,380. The effects are persistent but by the third year the magnitude of the effect falls to $1,870. The effects on both job mobility and long-run earnings are consistent with parent's providing access to jobs on a higher rung of the firm job ladder, as individuals who do not work for their parent's employer are able to slowly climb the ladder and catch up.

There are larger earnings gains of working for the father's employer compared to the mother's employer. Table 6 presents estimates from the main specification on samples defined by the sex of the child and parent. For daughters and sons I find that working for the father's employer leads to a 20 and 23 log point increase in initial earnings, respectively. In contrast, working for the mother's employer only leads to a 6 log point increase for both sons and daughters. While sons and daughters experience similarly large earnings gains from working for their father's employer, sons are twice as likely to work for their father's employer.

5.3 Additional Robustness Checks

The results are stronger for parents employed in industries where it is more common to hire workers through social contacts, which argues against sources of bias that are not specific to these industries. Motivated by the industry-level correlation in Figure 2, I calculate the share of individuals whose first job is at a parent's employer for each threedigit industry and group industries into deciles.[30] Figure 5(A) presents estimates from a first-stage specification that interacts the hiring rate with these deciles and shows that the first-stage coefficient is stronger if the parent is employed in an industry where the use of social contacts is more common.[31] For all industries, the coefficient on the hiring rate is positive, which provides some support for the monotonicity assumption. Figure 5(B) presents analogous results for the second stage. The earnings gains of working for a parent's employer are positively related to the share of young workers in that industry who work with a parent. These results help to rule out violations of the independence assumption that apply equally to all industries. For example, local labor market conditions are an unlikely source of bias since there is no clear reason why the bias would be more severe for parents employed in an industry where the use of social contacts is more common.

The hiring rate at the parent's employer has no effect on whether an individual finds a job and a small effect on the timing of entry. I find that working for a parent's employer leads individuals to find their first job just one quarter earlier. Consistent with the evidence discussed in Table 2, this suggests that the timing of entry is unlikely to bias the results. Furthermore, the earnings gains are unlikely to be explained by improvements in educational attainment or job quality through extended search, as both mechanisms would delay entry into the labor market.[32] Column 4 of Table 2 shows that the main results are robust to measuring the hiring rate in the year the child turns 18. While this helps to address concerns related to the timing of entry, I assess the concern that the hiring conditions could affect the extensive margin by regressing an indicator for whether the child ever finds a first job on the hiring rate at their parent's employer at age 18.[33] The hiring rate is unrelated to whether the child ever finds a first job with a

[30]I use decile groupings to increase power, but find similar results using two-digit industry instead.

[31]Figure A.10 presents estimates from the reduced form.

[32]The option to work for the parent's employer might raise an individual's reservation wage, leading them to match with better employers even if they do not end up working with their parent. Alternatively, the hiring rate might be correlated with other measures of parental financial well-being, which could improve educational outcomes. Both mechanisms ought to delay entry into the labor market. The fact that these mechanisms do not appear to explain my results is consistent with Hilger (2016) and Fradkin et al. (2019), who find that parental job loss during adolescence does not meaningfully impact educational attainment or job quality through extended search.

[33]The specification includes the same covariates as in column 4 of Table 2 and is estimated on a sample

point estimate (standard error) of .0002 (.003). See Table B.5. Thus, my results do not appear to be biased by the hiring rate affecting when or whether an individual finds their first stable job.

I use comparisons between siblings to investigate potential issues that could arise from parents sorting into employers. I estimate one specification that includes a fixed effect for the parent's employer and another that includes a fixed effect for the parent's employer by parent, which limits the identifying variation to comparisons between siblings. Both regressions are estimated on the same subsample, which retains cases in which at least two siblings enter the labor market when the primary earner was at the same employer. The estimates (standard errors) from the specification with the employer fixed effect and the parent by employer fixed effect are 0.15 (0.01) and 0.13 (0.02), respectively. See Table B.4. The similarity of the estimates suggests that the results are not driven by unobserved differences across households.

5.4 Alternative Empirical Strategy

I assess the robustness of my findings using an event study design that relies on an entirely distinct set of assumptions. I identify a set of individuals who work for their parent's employer at some point between their second and fourth years of labor market experience, but not before. For each of these workers, I find a similar worker who does not work for their parent's employer in their first six years of experience. Similar workers are selected using nearest-neighbor matching, which is implemented within subgroups defined by quarter, sex, and the quintile of parental earnings, and using pre-treatment earnings, the AKM premium of the prior employer, tenure, and experience. I then estimate

$$y_{it} = \alpha_i + \phi_{m(i)t} + \gamma X_{it} + \sum_{k \neq -1} D_{it}^k \beta^k + u_{it}, \tag{5}$$

where i is the individual, t is the quarter, $m(i)$ is the matched pair, X_{it} is a quadratic in experience, D_{it}^k is an indicator equal to one if the individual joined their parent's employer

of all children (including those who never find a first stable job) who have a parent that is employed at the same firm between the ages of 18 and 22.

k quarters ago as of quarter t, and u_{it} is a regression residual clustered at the match pair. The estimation sample is a balanced panel that includes the eight quarters with strictly positive earnings before and after the event.

The event study design leads to similar conclusions: working for a parent's employer leads to a large increase in earnings that is driven by the firm pay premium. Figure 6 presents the estimates from equation 5 and shows that, relative to the control group, earnings increase by 27 log points in the quarter in which the child joins their parent's firm and the AKM firm premium increases by 20 log points.[34] The magnitude of the effect declines over time but is still substantial eight quarters later.

6 Intergenerational Persistence in Earnings

The previous sections show that children use the connections of their parents to gain access to higher-paying jobs. The implications for intergenerational mobility depend on whether children from high- or low-income backgrounds benefit more. This section documents how the benefits vary across the parental earnings distribution and uses the methodology from Section 2 to quantify how the intergenerational persistence in earnings would change if no one worked for their parent's employer.

Individuals with higher-earning parents are more likely to work for their parent's employer. Figure 7 presents the proportion of individuals who work for a parent's employer for each percentile of the parental earnings distribution. Only 2 percent of children with parents at the bottom percentile of the earnings distribution work for a parent's employer. In contrast, 7 percent of children with parents at the top percentile of the earnings distribution work for a parent's employer. I find similar disparities looking at longer run measures. Figure A.12 shows that 31 percent of individuals parents in the top decile of the earnings distribution work for a parent's employer at some point between the ages of 16 and 30, compared to 25 percent for the bottom decile.

A plausible explanation for why children with higher-earning parents are more likely to work for their parent's employer is that their parents are more likely to be employed

[34] Figure A.11 presents the average values of log earnings and the AKM firm premium by event time.

and hold a position of authority within the firm. The percent of individuals who have an employed parent when they find their first job rises steeply from 42 percent to 63 percent between the 1st and 20th percentiles of the parental earnings distribution and eventually plateaus at 85 percent. The percent of individuals who have a parents that is a top earner at their firm rises gradually from 3 to 14 percent between the 1st and 90th percentiles of the parental earnings distribution and then rises steeply to 33 percent in the top percentile. Thus, the nonlinear relationship between the probability of working for a parent's employer and parental earnings closely tracks the probability that the parent is employed or is a top earner within their firm.[35]

Individuals with higher-earning parents experience larger earnings gains from working for a parent's employer. Figure 8 presents estimates from the main two-stage least squares specification estimated on five distinct samples defined by the quintile of the parental earnings distribution. Working with a parent in the bottom quintile of the earnings distribution leads to a statistically insignificant 5 log point increase in initial earnings. In contrast, working with a parent in the fourth and fifth quintile of the earnings distribution leads to a 25 and 18 log point increase in earnings, respectively.

The IGE in my sample is lower than other estimates in the literature because I focus on the initial earnings at the first job. I regress the log earnings of the child at their first job on the log earnings of their parents and find an IGE of 0.136. To facilitate a more direct comparison to the existing literature, which often focuses on long-run measures of earnings for both the children and parents, I limit my sample to the older cohorts and measure the earnings of the children between the ages of 29 and 31 (I add one to earnings to include zeros). I find an IGE of 0.482 for this long-run measure of earnings, which is more similar to estimates from the literature (Black and Devereux, 2010). However, when limiting the sample to individuals whose average quarterly earnings between ages 29 and 31 exceeds $3,300 (the same restriction used to define the first stable job), I find an IGE of 0.162.[36] This pattern highlights a well-documented problem, which is

[35]Figure A.13 presents these results in detail by plotting the proportion of parents that are employed and that are top earners within their employer against the percentile of parental earnings.

[36]The estimates of the IGE are presented in Table B.6. Column 4 shows that I find a similar IGE if I measure parental earnings as the average earnings in the years when the child was between the ages of

that the IGE is sensitive to how very low earnings are dealt with. Figure 9 presents a visual representation of the IGE by plotting the average log earnings at the first job against the average log earnings of the parents for each percentile of the parental earnings distribution. The flatter slope at the bottom of the parental earnings distribution is likely attributable to the fact that, by construction, everyone in my sample has a stable job.

Individuals with higher-earning parents are more likely to work for a parent's employer and experience larger earnings gains when they do, and thus the intergenerational transmission of employers leads to a modest increase in the intergenerational persistence in earnings. The red dashed line in Figure 9 represents the counterfactual earnings of the children if no one worked for a parent's employer. As described in Section 2, the difference between the observed and counterfactual earnings is the product of the proportion of individuals who work for a parent's employer, $\mathbb{E}[D_i]$, and the earnings consequences of doing so, $\mathbb{E}[\beta_i \mid D_i = 1]$. I estimate $\mathbb{E}[D_i]$ separately by parent type (i.e., primary and secondary earner) and percentile of parental earnings (estimates presented in Figure 7). I estimate $\mathbb{E}[\beta_i \mid D_i = 1]$ using the two-stage least squares estimator for samples defined by the parent type and the quintile of parental earnings (estimates from the primary and secondary earner presented in Figures 8 and A.14, respectively).[37] Since the earnings gains are positive, all groups earn less in the counterfactual but the difference is larger for children with higher-earning parents. Using the methodology described in equation 3, I find that the IGE would be 10 percent lower (with a standard error of 1.9) if no one worked for a parent's employer.[38]

My conclusions are robust to making conservative adjustments for potential bias in the descriptive and causal estimates. My previous analysis of the future employers suggests that 20 percent of people who work for their parent's employer do so for reasons unrelated to parental connections (Figure 1) and 10 percent of the estimated effect on initial earnings is attributable to bias (Table 3). I adjust for this potential bias by multiplying the

16 and 18.

[37]There are relatively few low-income individuals with two employed parents. To increase power, I pool the bottom three quintiles together to estimate the effect of working with the secondary earner.

[38]Standard errors for the counterfactual exercise are calculated using the Delta method and take into account the uncertainty in the estimates of the earnings consequences.

proportion of individuals who work for a parent's employer by 0.8 and the estimated effects on earnings by 0.9. Using these adjusted estimates, I find that the IGE would be 7.2 percent lower if no one found a job at their parent's employer through the use of parental connections. As argued before, this is a conservative adjustment since individuals might have useful connections at their parents' future employers. Indeed, I also find that individuals are about 200 times more likely to work for a parent's employer relative to a different firm in the same commuting zone, industry, and size class and the initial earnings of the child are unrelated to the hiring conditions at these other firms (Figure 4). This suggests that virtually everyone who works for a parent's employer does so because of labor market networks and the bias in the causal estimates is negligible.

Estimating the counterfactual requires an estimate of the ATT but the two-stage least squares estimator identifies a LATE. To investigate treatment effect heterogeneity, I residualize the hiring rate at the parent's employer on the standard set of covariates and create three binary variables that are equal to one if the residualized hiring rate is larger than the 25th, 50th, and 75th percentiles. Table B.7 illustrates that the estimated earnings gain is 17 log points regardless of which binary instrument is used and the first-stage estimates imply that the proportion of the treated sample that are also compliers is 0.32, 0.17, and 0.10 for the three binary instruments. Figure 10 plots the average residualized values of initial log earnings against the indicator for works for parent's employer for each ventile of the residualized hiring rate.[39] A linear relationship implies that a marginal increase in the probability of treatment induced by an increase in the hiring rate leads to a constant increase in initial earnings, which suggests that compliers at different parts of the hiring rate distribution have similar average treatment effects.[40] The lack of heterogeneity in treatment effects across the hiring rate distribution and the relatively large size of the complier population provides suggestive evidence that the LATE is a reasonable estimate of the ATT. Appendix G presents a theoretical argument for why this might be the case. The key insight is that working for the parent's employer

[39] Figure A.9 plots the average residuals for the treatment indicator and log earnings against the ventile of the residualized hiring rate and shows that, conditional on the covariates, the propensity to work for a parent's employer and the initial log earnings are increasing in the hiring rate.

[40] The slope in Figure 10 is 0.17, which matches the main estimates in column 1 of Table 2.

depends on decisions made by both the child and the firm. The multi-agent nature of the selection process potentially breaks the link between the instruments and the treatment effects. I identify conditions under which both the compliers and the treated are a random sample of individuals who would accept an offer from their parent's employer and show that these conditions imply that the LATE is equal to the ATT.

I assess the robustness of the counterfactual exercise using alternative estimates of the earnings consequences. Figure A.15 presents estimates from the event study specification in equation 5 for five distinct samples defined by the quintile of parental earnings. The estimated earnings gains rise monotonically in parental earnings; I find a 14 and 37 log point increase in quarterly earnings for children whose parents are in the bottom and top quintile of the earnings distribution, respectively. Using these alternative estimates of the earnings consequences, I find that the IGE would be 15 percent lower if no one worked for a parent's employer. The conclusions are more sensitive to allowing for treatment effect heterogeneity by parental earnings. I calculate the counterfactual using the two-stage least squares estimates in Table 2 and the event study estimates in Figure 6—both of which estimate a single earnings effect for the full sample—and find that the IGE would be 2 and 3 percent lower if no one worked for a parent's employer, respectively. Thus, the quantitative implications for the IGE depend on whether the effects on earnings are larger for individuals with higher-earning parents.

My earlier findings of the importance of networks in the production sector do not conflict with the finding that individuals with higher-earnings parents benefit more. Figure A.16 shows that the probability of finding a job that is both at a parent's employer and in the production sector is increasing in parental earnings, and earnings gains tend to be largest for high-earning parents in the production sector.

I further disaggregate results by sex, race, and ethnicity. Figure 11 plots the proportion of individuals who work for a parent's employer by sex, race, ethnicity, and the percentile of parental earnings. For daughters, there are not large differences in the propensity to work for a parent's employer conditional on parental earnings. In contrast, Black sons are significantly less like to work for a parent's employer relative to White sons whose parents are in the same percentile of the earnings distribution. This is interesting in light of recent work from Chetty et al. (2020), who find that conditional on parental income, Black males have lower expected income compared to White males. Figure A.17 replicates this finding, and shows a conditional Black-White earnings gap of 8 log points in my sample. I calculate the counterfactual earnings for both groups and find that this conditional Black-White earnings gap would be 4 percent smaller if no one worked for their parent's employer.[41] The patterns also have implications for the gender wage gap. On average, sons earn 7 log points more than daughters at their first job. The estimates by sex in Table 6 imply that the initial gender wage gap would be 8 percent smaller if no one worked for a parent's employer.[42]

7 Conclusion

My papers shows that parents influence the earnings of their children by using their connections to provide access to higher-paying firms. Existing research documents the ubiquitous use of social contacts in the labor market but has less to say about the earnings consequences. I exploit transitory and idiosyncratic variation in the availability of jobs at the parent's employer and estimate substantial earnings gains from finding a job through parental connections. Individuals with higher-earning parents are more likely to work for a parent's employer, and experience larger earnings gains when they do, and thus the intergenerational transmission of employers leads to a modest increase in the intergenerational persistence in earnings.

While connections within the parent's employer are clearly not the main determinant of the intergenerational persistence in earnings, individuals may find jobs through a wider set of social contacts such as friends or extended family. Understanding how these broader connections shape intergenerational mobility should be a priority for future research.

[41] The estimated earnings effects for sons are presented in Figure A.18. Note that I do not have sufficient power to estimate heterogeneous effects by both parental earnings and race and thus assume that average treatment effects do not differ by race within parental earnings quintiles.

[42] Using the estimates by sex in Table 6, I find that the average benefits, $\mathbb{E}[D_i\beta_i] = \mathbb{E}[D_i]\mathbb{E}[\beta_i \mid D_i = 1]$, of working for the mother or father are 0.5 and 1.1 log points for daughters and sons, respectively. The difference between the two is 8 percent of the 7 log point gender pay gap in initial earnings.

My results relate to the normative assessment of whether rates of intergenerational mobility are too low in the United States, an assessment that depends on whether the economic system that produces the intergenerational persistence in earnings is equitable and efficient.[43] While equity depends on subjective moral values, a core ideal in the United State is that of equality of opportunity, which requires that an individual's success be a function of their hard work and ability rather than the circumstances into which they were born.[44] Thus, from an equity standpoint, my findings raise concerns about the relatively low levels of intergenerational mobility in the United States. My results do not speak directly to the implications for efficiency and future research should aim to understand whether family connections lead to gains or losses in productivity.

My results also inform the positive assessment of what would be required to achieve equality of opportunity. One view is that economic rewards are determined by hard work and ability, which suggests that efforts to expand economic opportunity should aim to equip everyone with the skills they need to succeed in the labor market. My results challenge this purely meritocratic view of the labor market, as individuals from high-income families earn more not only because they are more skilled, but also because their parent's connections provide access to high-paying firms. If the labor market plays a direct role in propagating intergenerational disadvantage, then achieving equality of opportunity in terms of education will not necessarily produce equality of opportunity in the labor market. Rather, individuals from disadvantaged backgrounds may require additional support throughout their early careers. Gaining a better understanding of the mechanisms through which parents help their children find high-paying jobs may offer ideas for how to help young workers who cannot rely on the connections of their parents to more successfully navigate the labor market.

[43]Intergenerational mobility in the United States is low both relative to the past (Chetty et al., 2017) and relative to other developed countries (Solon, 2002).

[44]Roemer (1998) argues that a society provides equality of opportunity if the outcomes of individuals are not systematically determined by factors for which they are not responsible. Determining what to hold someone responsible for is a subjective judgment. But most people would likely agree that individuals should not be responsible for their parents' lack of connections in the labor market.

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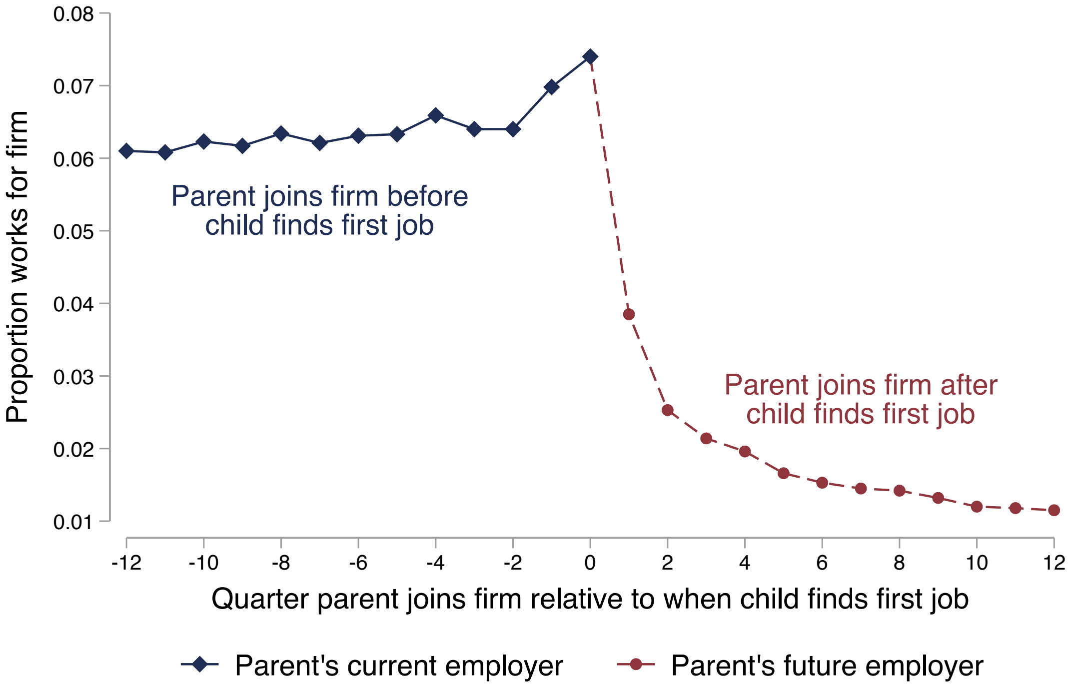
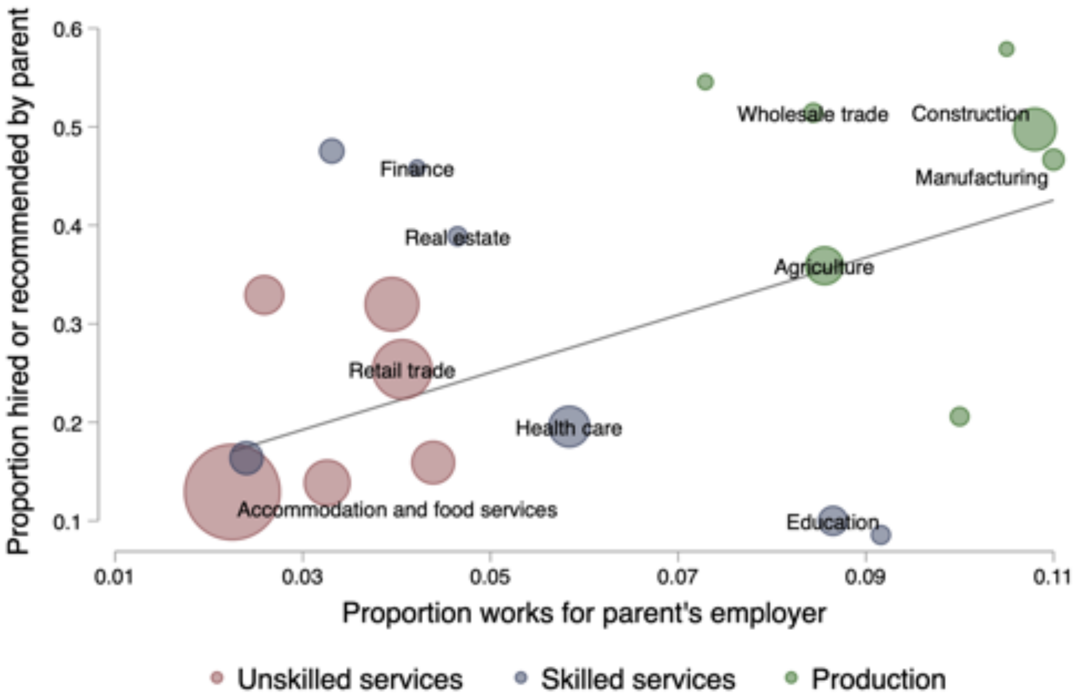
8 Figures

Figure 1: Likelihood of Working for Parent's Current and Future Employer



Notes: The horizontal axis defines a sample of individuals based on when their parent started working for a new firm. The sample is limited to parents who remain at these new jobs for at least 12 quarters. Thus, the blue diamond markers represent cases in which the parent recently joined and currently works for the firm when their child starts their first stable job. The red circle markers represent cases in which the parent will join the firm in the near future but is not currently working there when their child starts their first stable job. Each point plots the proportion of individuals who work for their parent's current or future employer.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.

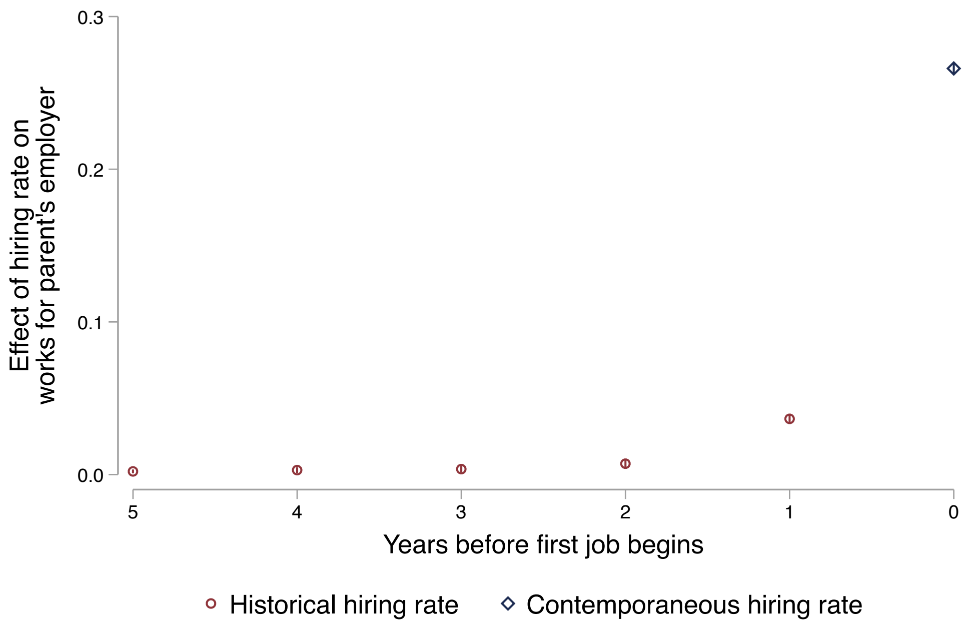
Figure 2: Industry-Level Association with Use of Social Contacts



Notes: Each point represents a statistic for an industry and is proportional to sample size. The horizontal axis is the proportion of first stable jobs that are at a parent's employer. The vertical axis is the proportion of jobs where the individual was hired or recommended by a parent, which is estimated from the NLSY97. Source: Author's calculations based on data from the NLSY97, LEHD, and 2000 Decennial Census.

Figure 3: Association with Hiring Rate at Parent's Employer in Earlier Years

(A) First Stage

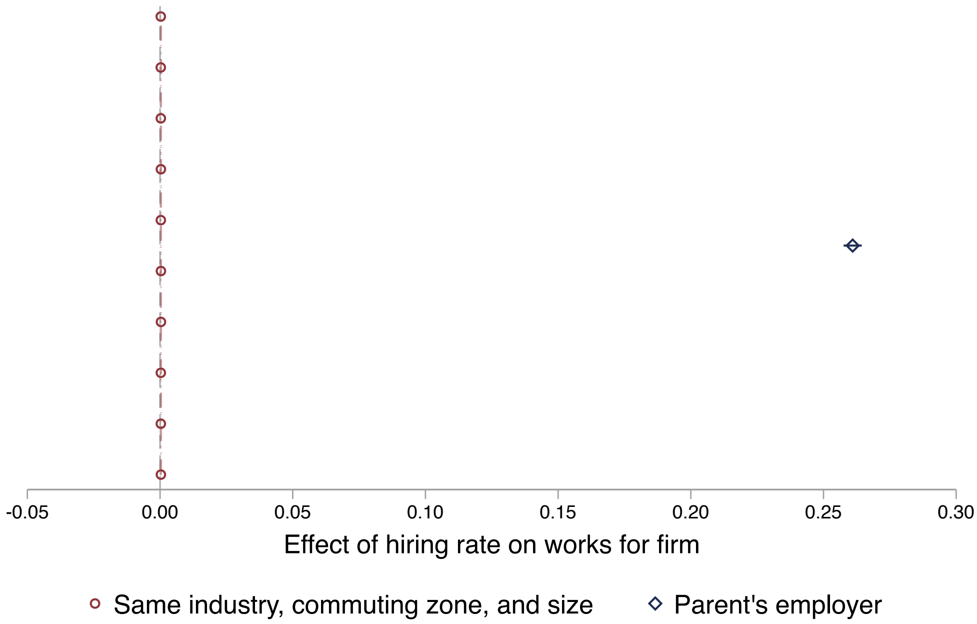


(B) Reduced Form

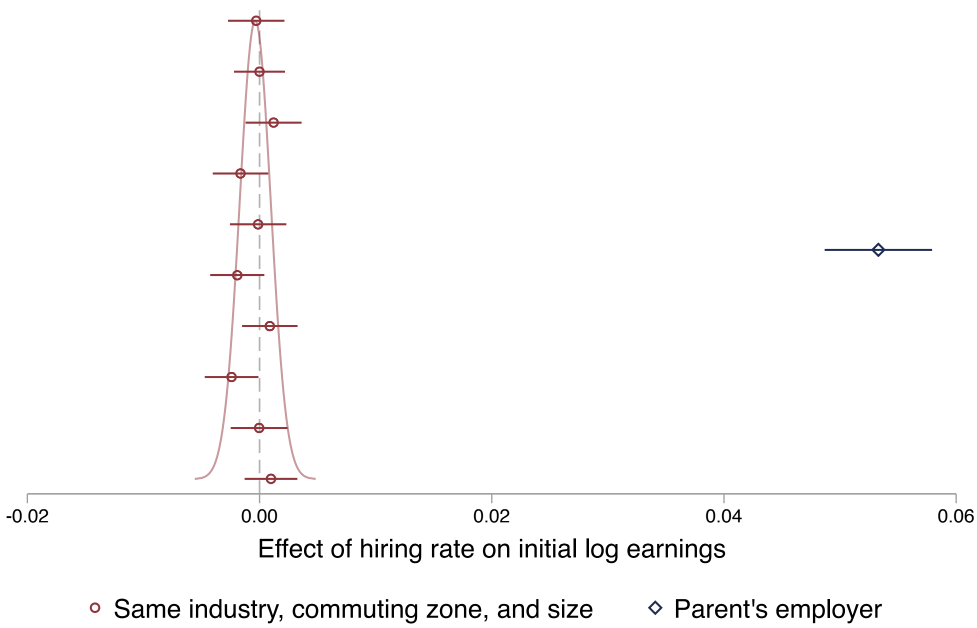
Notes: Each point represents an estimate from a regression of an outcome variable on the hiring rate at the parent's firm and fixed effects for the parent's employer and the local labor market in which the employer is located. The outcome variable in panels A and B is an indicator for whether the individual works for their parent's employer and initial log earnings, respectively. The horizontal axis defines the time at which the hiring rate at the primary earner's employer is measured. All specifications are estimated on the same sample, which is limited to cases in which the parent's employer exists five years prior to the start of the first stable job. The vertical bars denote the 95 percent confidence intervals.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.

Figure 4: Association with Hiring Rate at Firms Similar to Parent's Employer

(A) First Stage



(B) Reduced Form

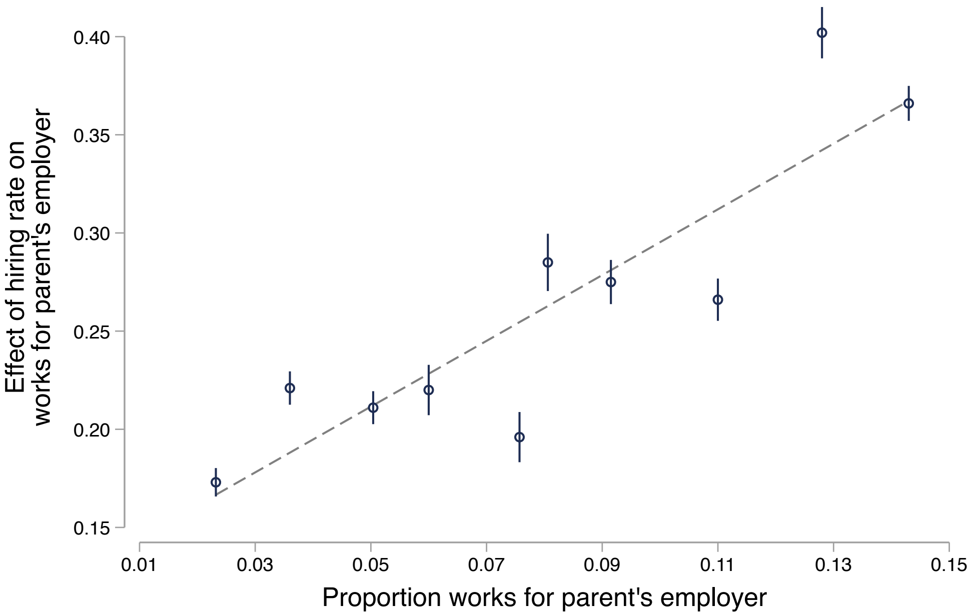


Notes: Each point represents an estimate from a regression of an outcome variable on the hiring rate of the parent's employer (blue diamond) or a similar firm (red circle) and fixed effects for the parent's employer and the local labor market in which the employer is located. The outcome variable in panels A and B is an indicator for whether the individual works for the firm and initial log earnings, respectively. All specifications are estimated on the same sample, which is limited to cases in which there are at least 10 unique firms in the same commuting zone, industry, and firm size class. The vertical bars denote the 95 percent confidence intervals. A normal distribution is fitted to the point estimates from the placebo regression.

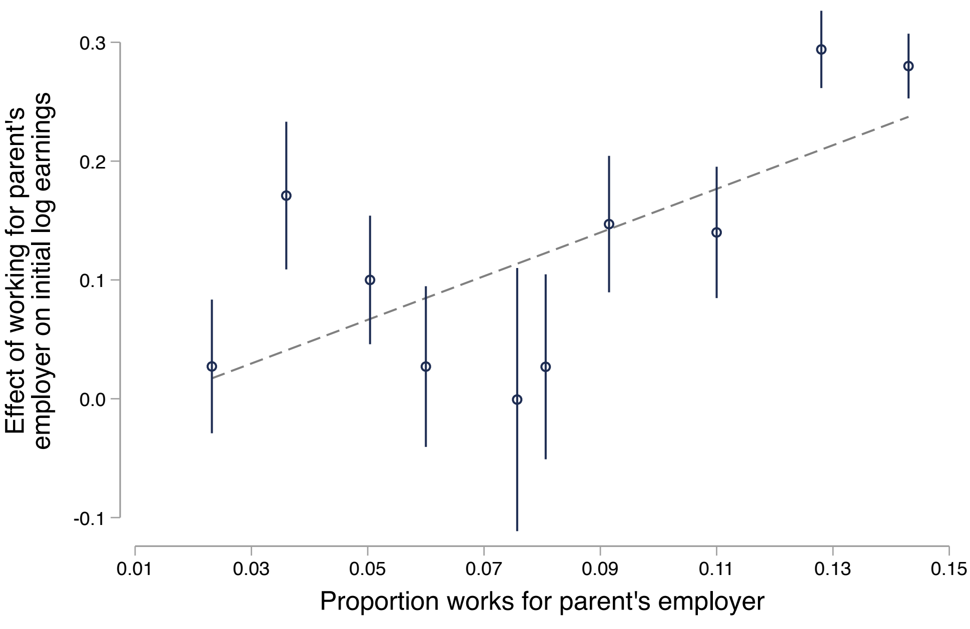
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.

Figure 5: Heterogeneous Effects by Parent's Industry

(A) First Stage

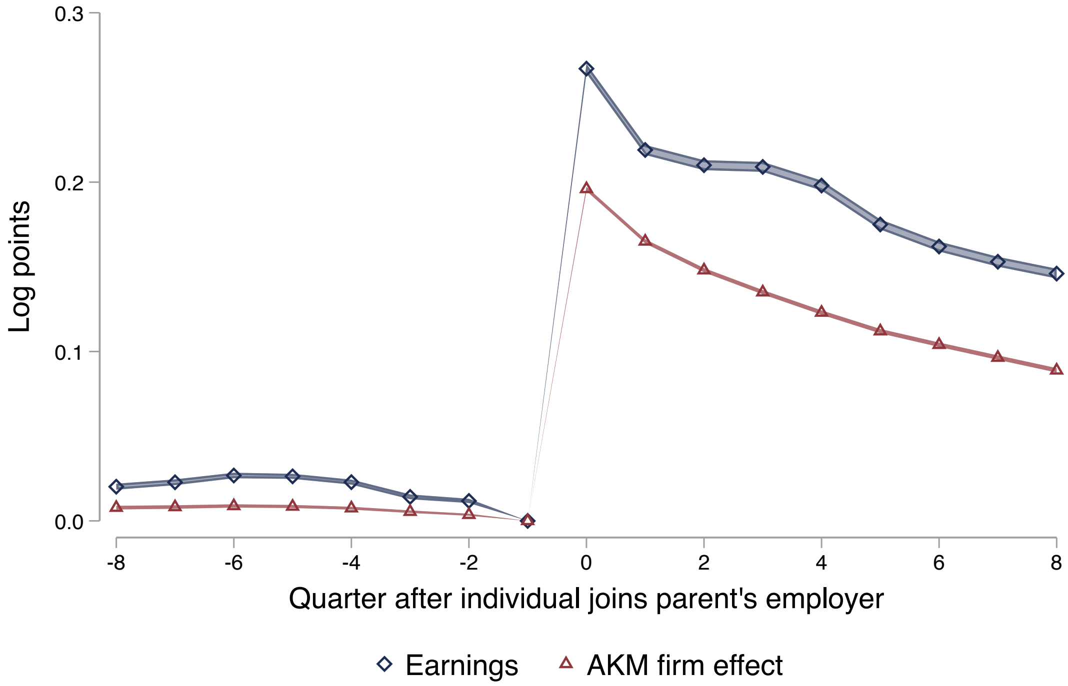


(B) Second Stage



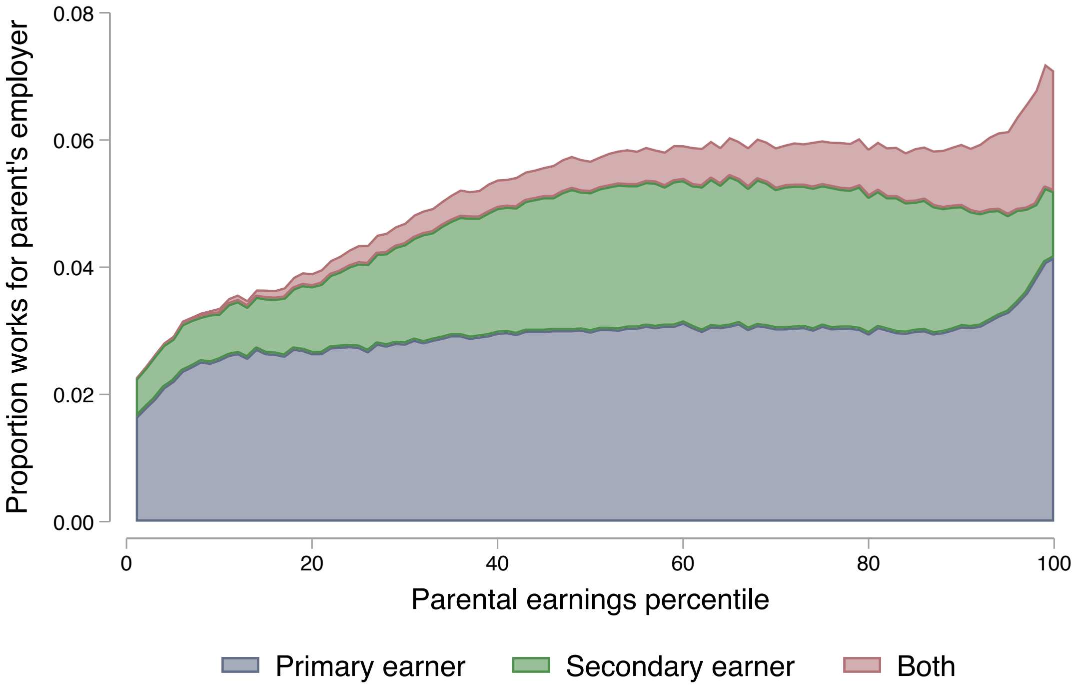
Notes: Industries are grouped into deciles based on the share of individuals in that industry who work for a parent's employer. Panels A and B present estimates from the first- and second-stage specifications, respectively. All specifications interact the hiring rate with deciles corresponding to the industry of the parent's employer and include the standard vector of demographic covariates as well as fixed effects for the parent's firm and the local labor market in which the employer is located. The vertical bars denote the 95 percent confidence intervals.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.

Figure 6: Estimates from Event Study Specification



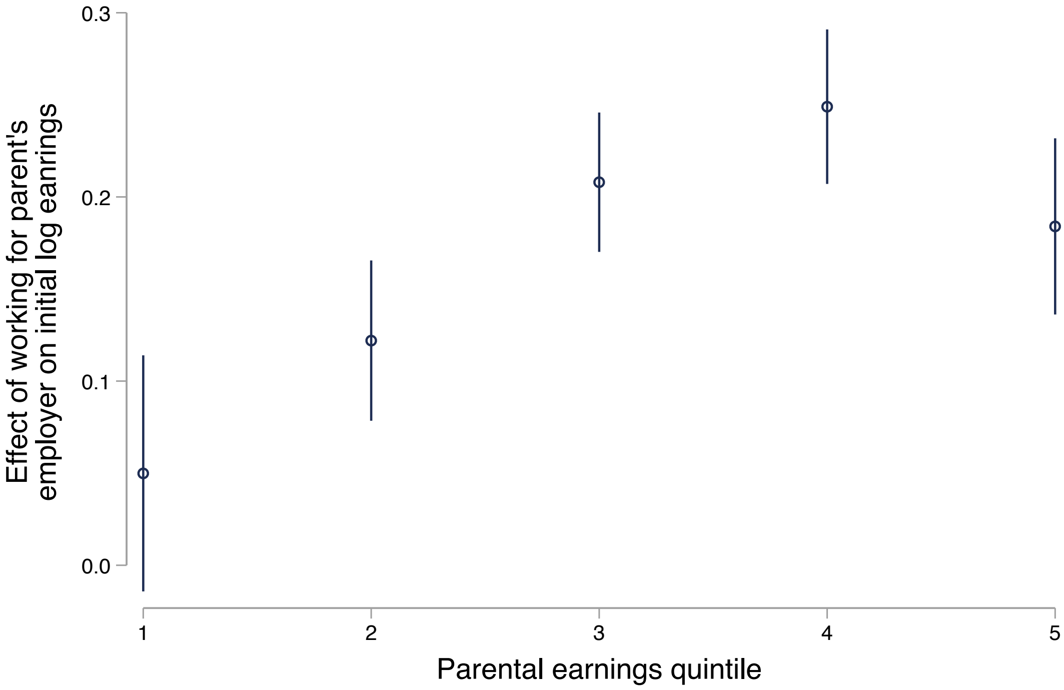
Notes: The series represent estimates from separate event study regressions described in equation 5 where the outcome is individual log earnings or the firm fixed effect. The shaded regions denote denote the 95 percent confidence interval.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Figure 7: Works for Parent's Employer by Parental Earnings



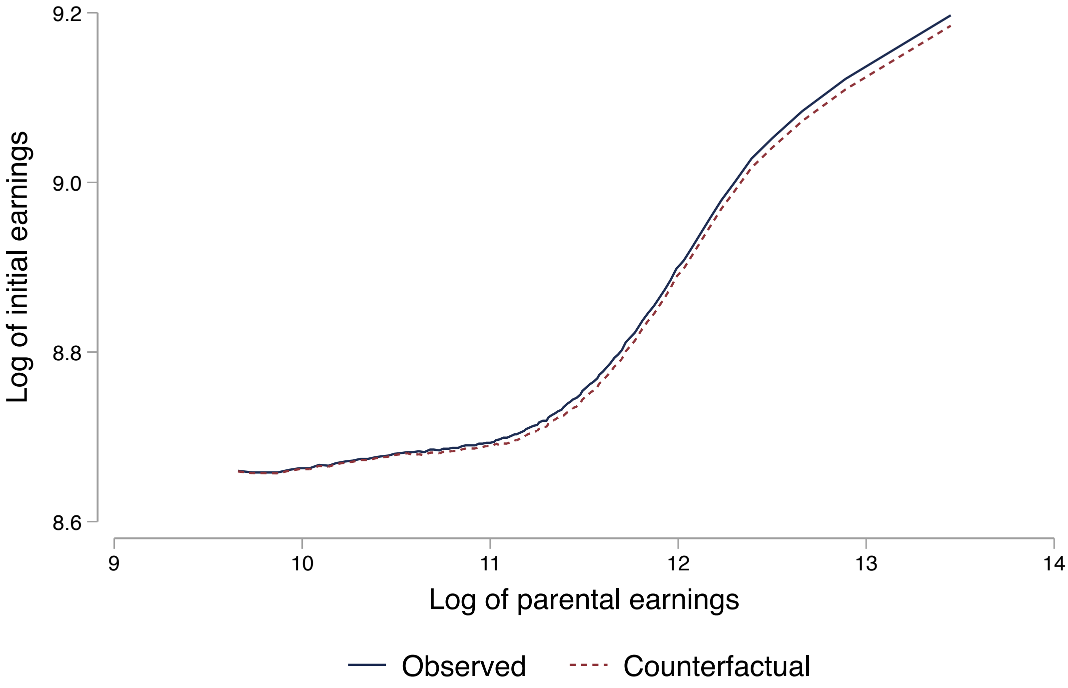
Notes: The figure plots the proportion of individuals who work for their parent's employer for each percentile of the parental earnings distribution. The shaded regions represent the proportion that work for the employer of the primary earner, secondary earner, and both parents.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.

Figure 8: Effect on Initial Earnings by Parental Earnings



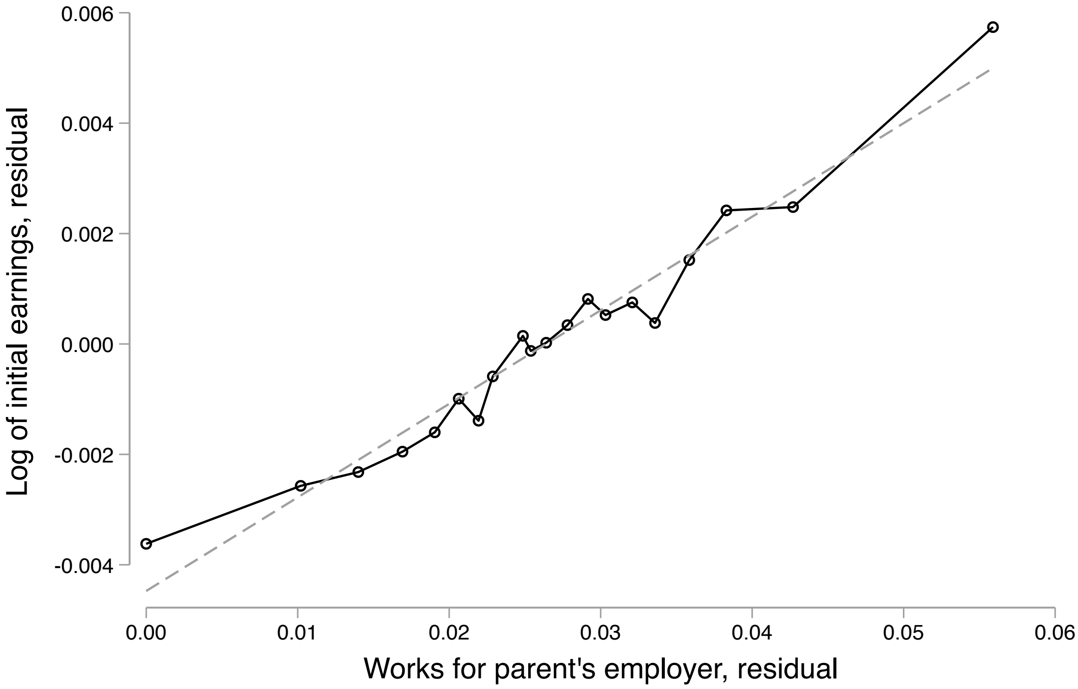
Notes: Each point represents an estimate from the main two-stage least squares specification, which is estimated on five distinct samples defined by the quintile of parental earnings. All specifications control for the standard vector of demographic characteristics as well as fixed effects for the parent's employer and the local labor market in which the employer is located. The vertical bars denote the 95 percent confidence intervals.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.

Figure 9: Intergenerational Elasticity of Earnings



Notes: The figure plots the average initial log earnings of the child against the average log earnings of their parent for each percentile of the parental earnings distribution. The blue solid line represents the observed earnings of the child. The red dashed line represents the counterfactual earnings of the child if no one were to work for a parent's employer.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.

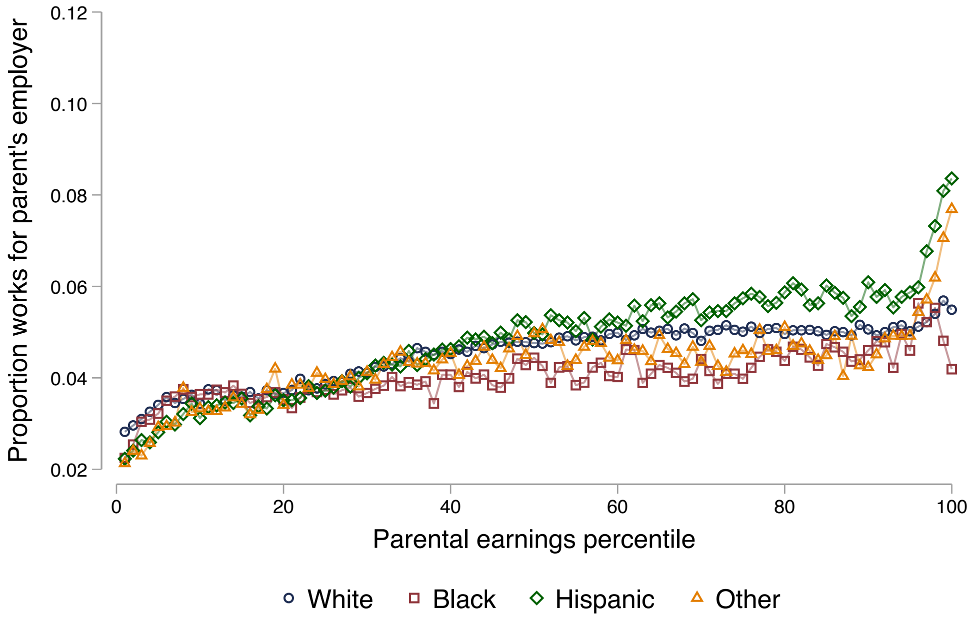
Figure 10: Visualization of Treatment Effect Heterogeneity



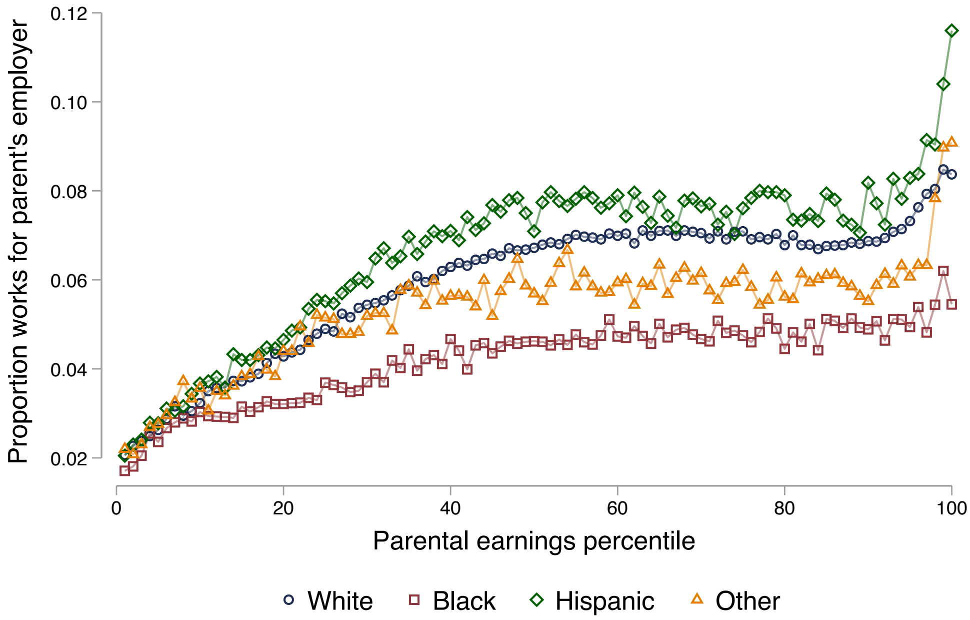
Notes: I regress the hiring rate on the vector of demographic characteristics and fixed effects for the parent's employer and the local labor market in which the employer is located and group the residuals from this regression into ventiles. I then residualize the indicator for works for the parent's employer and log of initial earnings on the same covariates and plot the average value of these residuals for each ventile of the residualized hiring rate. The solid line connects ventiles one rank apart and the dashed line is the linear fit.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.

Figure 11: Works for Parent's Employer by Parental Earnings, Sex, Race, and Ethnicity

(A) Daughters



(B) Sons



Notes: Each point represents the proportion of individuals who work for their parent's employer for a sample defined by the interaction between sex, race, ethnicity, and the percentile of the parental earnings distribution.

Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.

9 Tables

Table 1: Summary Statistics

		Works for parent's employer	
	Full sample	No	Yes
	(1)	(2)	(3)
Demographic			
Age	21.5	21.6	20.6
Male	0.51	0.50	0.57
White, non-Hispanic	0.71	0.71	0.74
Black, non-Hispanic	0.10	0.10	0.07
Asian, non-Hispanic	0.03	0.03	0.03
Hispanic	0.13	0.13	0.13
Single parent	0.16	0.16	0.10
Parent is top earner in firm	0.08	0.07	0.19
Parental earnings (thousands)	54.7	54.2	63.0
First Stable Job			
Annual earnings (thousands)	27.0	27.1	25.4
Stay for three years	0.40	0.39	0.56
Skilled services	0.36	0.35	0.38
Unskilled services	0.47	0.48	0.30
Production	0.17	0.17	0.32
Large firm (employees>500)	0.41	0.41	0.41
Urban	0.73	0.73	0.70
Observations (millions)	25.86	24.51	1.35

Notes: The table presents the average value of the variable defined in the row. Column 1 presents results for the full sample. Columns 2 and 3 present results for the sample of children who do not and do work for a parent's employer at their first stable job, respectively.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.

Table 2: Effect on Initial Earnings

	Log of initial earnings				
	(1)	(2)	(3)	(4)	(5)
Works for parent's employer	0.17***	0.21***	0.24***	0.17*	0.19***
	(0.01)	(0.01)	(0.02)	(0.07)	(0.01)
First-stage F-statistic	24,300	24,500	6,180	533	22,100
Time of hiring rate	first job	first job	year before	age 18	first job
Covariates	demographic	none	demographic	demographic	additional
Observations (millions)	17.81	17.81	17.81	11.80	17.55

Notes: Each column presents estimates from a separate regression. All specifications include fixed effects for the parent's employer and the local labor market in which the employer is located. Across columns the specifications include different covariates or measure the hiring rate at different times. Standard errors are presented in parentheses.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.
*** p≤0.001, ** p≤0.01, * p≤0.05

Table 3: Placebo Test Using Parent's Future Employer

	First stage		Reduced form		Second stage	
	(1)	(2)	(3)	(4)	(5)	(6)
Hiring rate at current employer	0.146***		0.028***			
	(0.004)		(0.005)			
Hiring rate at future employer		0.014***		0.0027		
		(0.001)		(0.004)		
Works for current employer					0.192***	
					(0.035)	
Works for future employer						0.194
						(0.277)
First-stage F-statistic					1,390	126
Estimator	OLS	OLS	OLS	OLS	2sls	2sls
Observations (millions)	2.165	1.031	2.165	1.031	2.165	1.031

Notes: The samples in the odd and even columns include parents who started a new job 2-3 years before and after their child started their first job, respectively. The outcome variable in columns 1 and 2 is an indicator equal to one if the individual worked for their parent's current and future employer, respectively. The outcome variable in columns 3-6 is initial log earnings. All specifications control for the standard vector of demographic characteristics as well as fixed effects for the parent's current or future employer and the local labor market in which the employer is located. Standard errors are presented in parentheses.

Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.

*** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$

Table 4: Effect on Employer Characteristics

		Firm ranking					Sector				
	AKM pay premium (1)	log revenue per worker (2)	poaching hires (3)	average earnings (4)	log firm size (5)	firm age (6)	skilled services (7)	unskilled services (8)	production (9)	industry premium (10)	within-firm earnings rank (11)
Works for parent's employer	0.16***	2.25**	1.94***	16.70***	-1.26***	-1.37***	-0.02*	-0.31***	0.33***	0.11***	-7.97***
	(0.01)	(0.84)	(0.47)	(0.51)	(0.05)	(0.25)	(0.01)	(0.01)	(0.01)	(0.00)	(0.50)
First-stage F-statistic	23,900	11,800	24,300	24,300	24,300	24,300	24,300	24,300	24,300	24,300	23,900
Mean	-0.12	57.10	54.50	43.80	5.66	23.62	0.37	0.47	0.16	-0.13	39.30
Standard deviation	0.34	28.30	23.30	27.00	2.47	12.78	0.48	0.50	0.37	0.16	24.70
Observations (millions)	17.69	10.54	17.81	17.81	17.81	17.81	17.81	17.81	17.81	17.81	17.35

Notes: The table presents estimates from the two-stage least squares specifcation. Each column presents estimates from a separate regression for a different outcome. All specifications control for the standard vector of demographic characteristics as well as fixed effects for the parent's employer and the local labor market in which the employer is located. Standard errors are presented in parentheses.

Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.

*** p≤0.001, ** p≤0.01, * p≤0.05

Table 5: Effect on Earnings and Job Mobility Three Years After Entry

	Job transition			Annual earnings year after		
	stay	j2j	j2n	one	two	three
	(1)	(2)	(3)	(4)	(5)	(6)
Works for parent's employer	0.17***	-0.14***	-0.04***	3,380***	2,960***	1,870***
	(0.01)	(0.01)	(0.01)	(306)	(397)	(446)
First-stage F-statistic	21,300	21,300	21,300	21,300	21,300	21,300
Mean	0.36	0.41	0.23	26,700	26,800	28,100
Standard deviation	0.48	0.49	0.42	15,900	20,300	22,700
Observations (millions)	15.17	15.17	15.17	15.17	15.17	15.17

Notes: The table presents estimates from the two-stage least squares specifcation. Each column presents estimates from a separate regression for a different outcome. All specifications control for the standard vector of demographic characteristics as well as fixed effects for the parent's employer and the local labor market in which the employer is located. The sample is restricted to individuals who find their first stable job at least three years before the coverage of the LEHD ends. Standard errors are presented in parentheses.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.
*** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$

Table 6: Effect on Initial Earnings by Sex

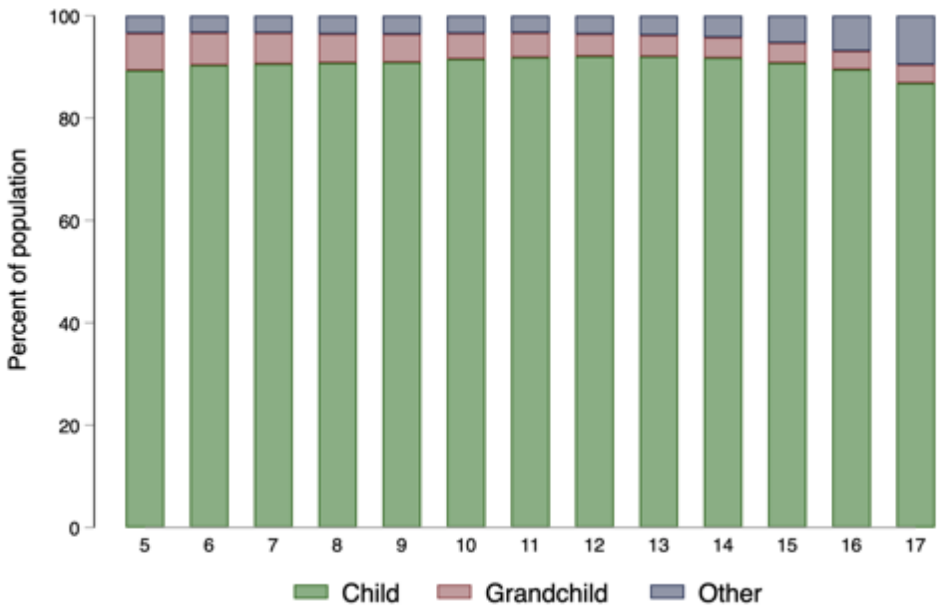
	Father		Mother	
	(1)	(2)	(3)	(4)
Works for parent's employer	0.20***	0.23***	0.06**	0.06*
	(0.04)	(0.01)	(0.02)	(0.03)
Sex of child	daughters	sons	daughters	sons
First-stage F-statistic	3,320	11,500	5,110	4,210
Proportion works for parent's employer	0.02	0.04	0.03	0.03
Observations (millions)	5.02	5.28	5.75	5.79

Notes: The table presents estimates from the two-stage least squares specifcation. Each column presents estimates from a separate regression where the outcome variable is the log of initial earnings and the sample is defined by the sex of the child and parent. All specifications control for the standard vector of demographic characteristics as well as fixed effects for the parent's employer and the local labor market in which the employer is located. Standard errors are presented in parentheses.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.
*** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$

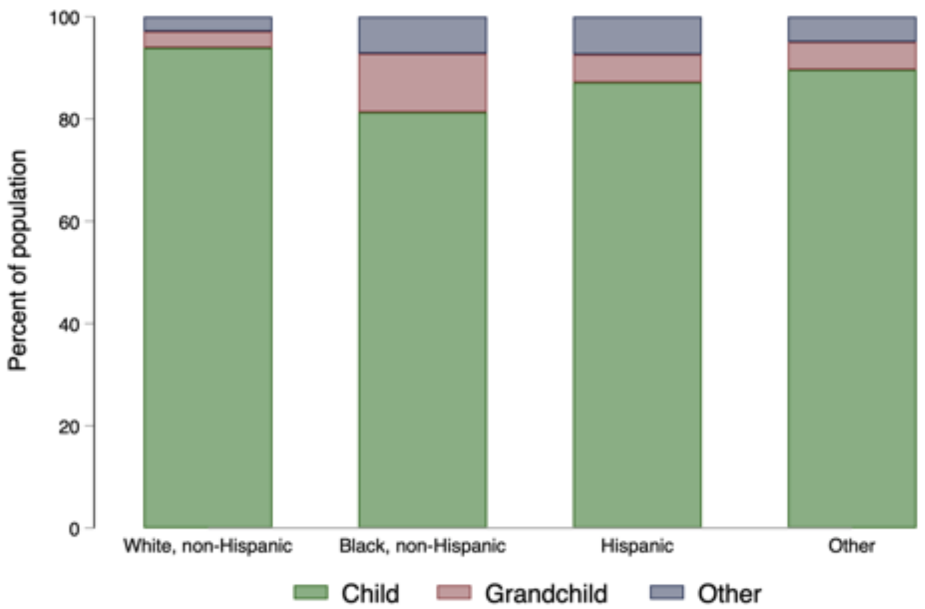
Appendix A Additional Figures

Figure A.1: Relationship to Head of Household

(A) By Age in 2000

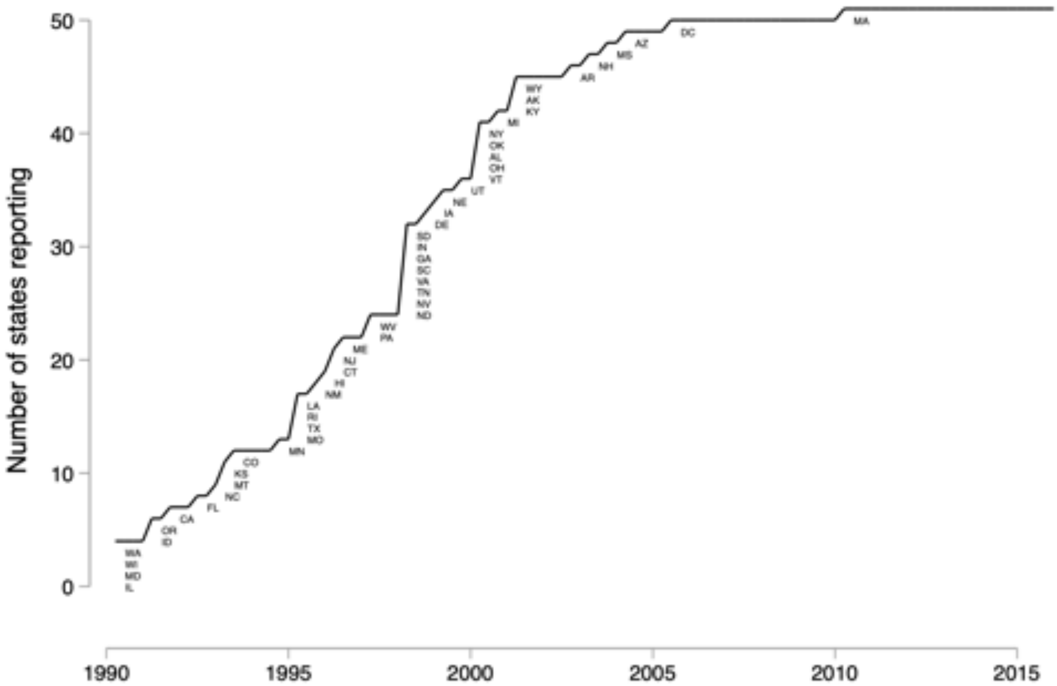


(B) By Race and Ethnicity



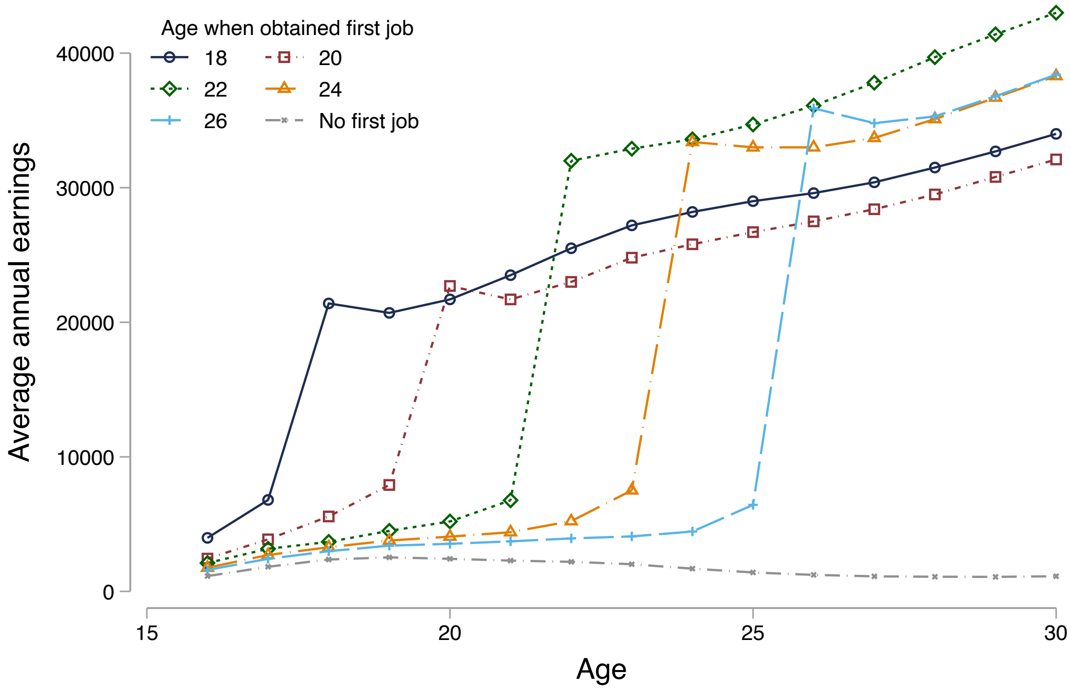
Notes: The figures present the proportion of children ages 5 through 17 whose relationship to the head of household in the 2000 Decennial Census was defined as: child, grandchild, or other. Panel A breaks out the results by the age of the child at the time of the Decennial Census and Panel B breaks out the results by the race and ethnicity of the child.
Source: Author's calculations based on a 1 percent sample from the 2000 Decennial Census obtained from IPUMS (Ruggles et al., 2019).

Figure A.2: States Participating in the LEHD Program



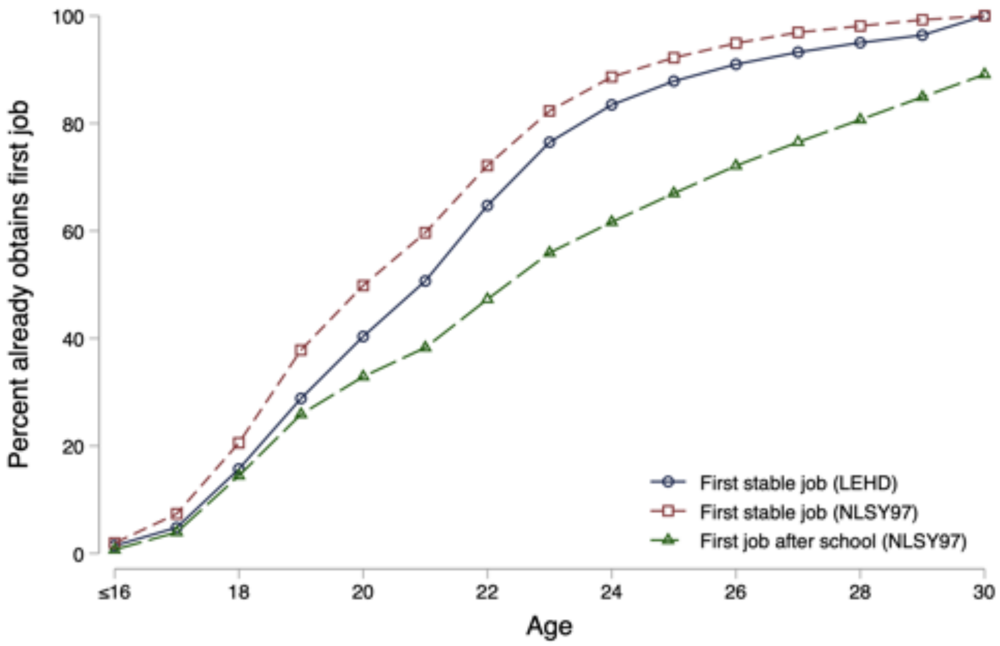
Notes: The figure plots the number of states that are reporting to the Longitudinal Household-Employer Dynamics (LEHD) program in a given year. The abbreviations below the solid line represent the states that begin reporting in that year.

Figure A.3: Age-Earnings Profile



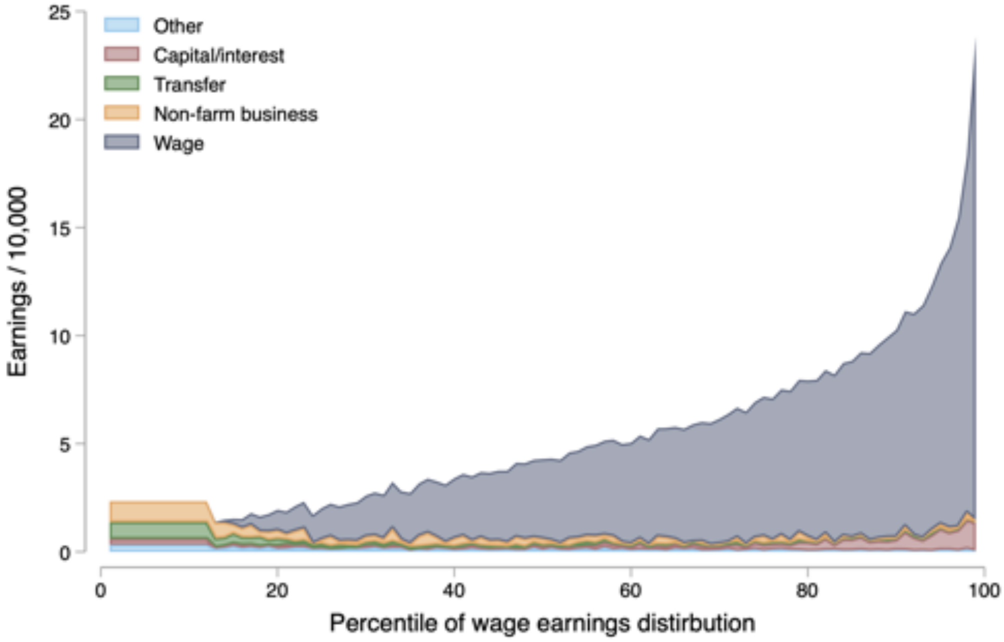
Notes: The figure plots the average annual earnings by age for different groups of workers defined by the age they were when they found their first stable job. The sample includes individuals who turned 30 by 2018.
Source: Author's calculations based on matched data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Figure A.4: Age of Entry



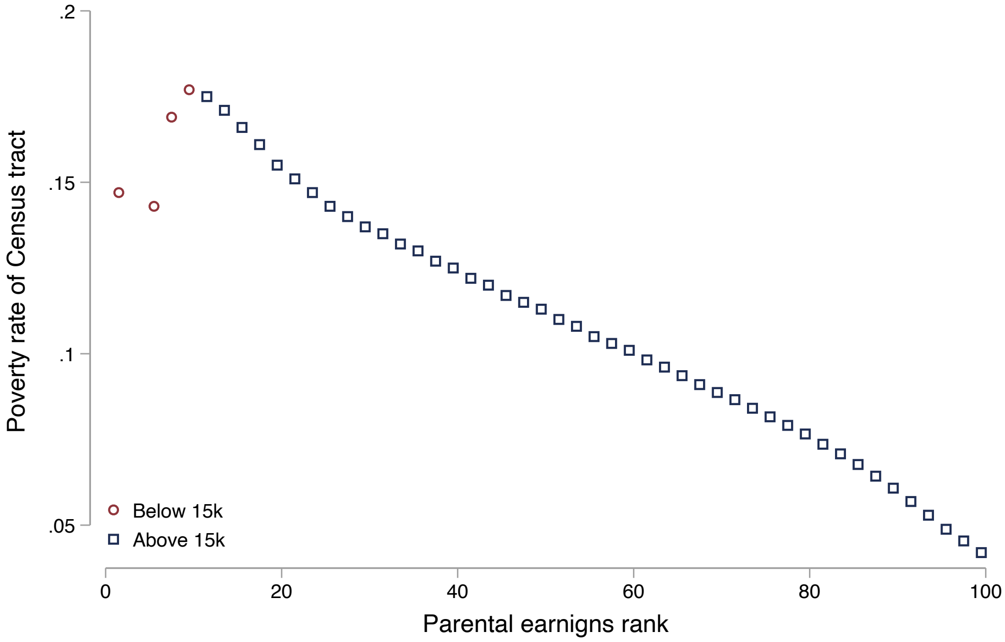
Notes: The figure plots the cumulative proportion of children that have entered the labor market by the age indicated on horizontal axis. For comparison, I also plot results using alternative measures of entry constructed from the NLSY97. These measures include the first stable job (working at least 35 hours for 36 consecutive weeks) and the first stable job after all schooling is completed.
Source: Author's calculations based on matched data from the Longitudinal Employer-Household Dynamics (LEHD) and 2000 Decennial Census files and data from the National Longitudinal Survey of Youth 1997 cohort (NLSY97).

Figure A.5: Source of Income Across the Wage Earnings Distribution



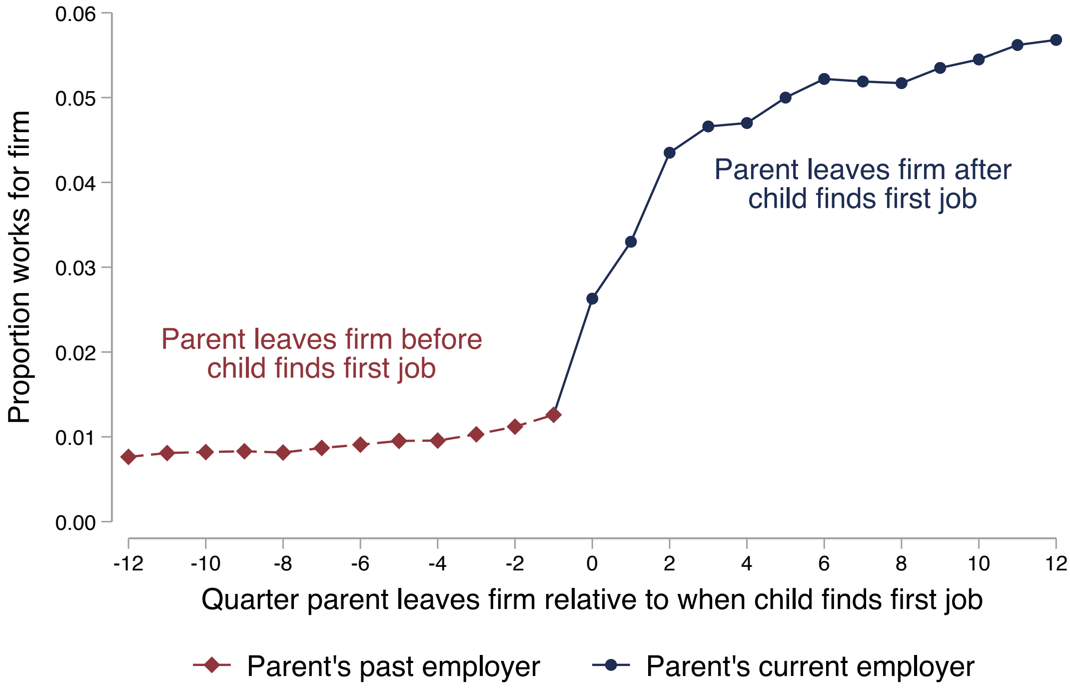
Notes: The figure presents the average household income by the percentile of total household wage earnings. Income is broken out into five sources that include: capital/interest, transfer, non-farm business, other, and wages. The sample includes all households that have at least one child present and excludes the households in the top percentile of the wage earnings distribution due to outlier values.
Source: Author's calculations based on data from the the 2000 March supplement to the Current Population Survey (CPS) and were obtained from IPUMS (Ruggles et al., 2019).

Figure A.6: Parental Earnings and Neighborhood Poverty



Notes: The figure plots the average poverty rate of the Census tract in which the parents lived in 2000. Parents are grouped into 50 equal-sized bins based on their earnings and each point represents a statistic for one of these distinct samples.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Figure A.7: Likelihood of Working for Parent's Past and Current Employer

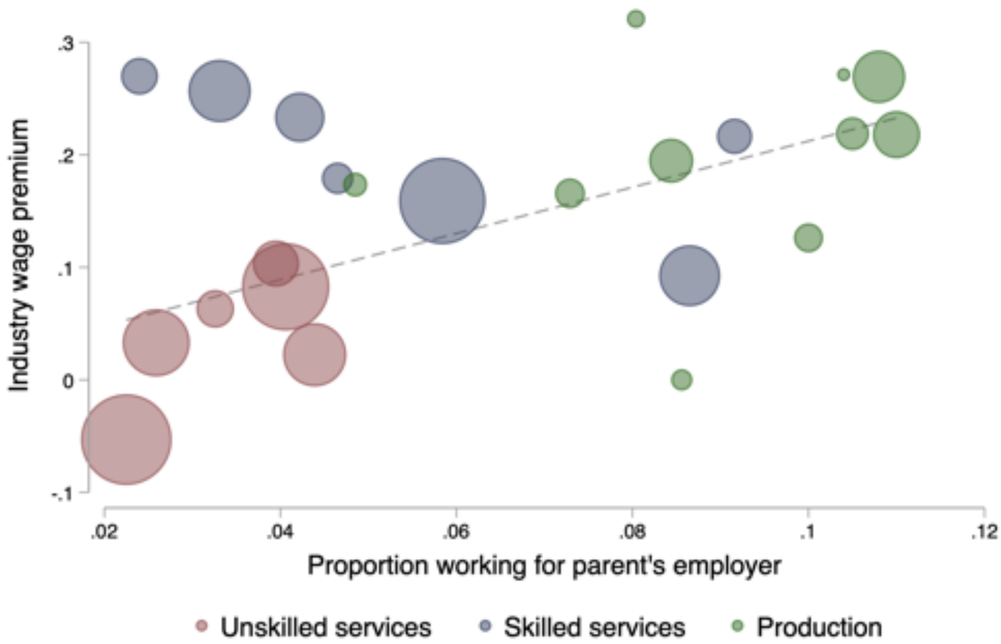


Notes: The horizontal axis defines a sample of individuals based on when their parent separated from a firm. The sample is limited to parents who had at least 12 quarters of tenure prior to the separation. Thus, the red diamond markers represent cases in which the parent recently left and no longer works for the firm when their child starts their first stable job. The blue circle markers represent cases in which the parent will leave the firm in the near future but is currently working there when their child starts their first stable job. Each point plots the proportion of individuals who work for their parent's past or current employer.

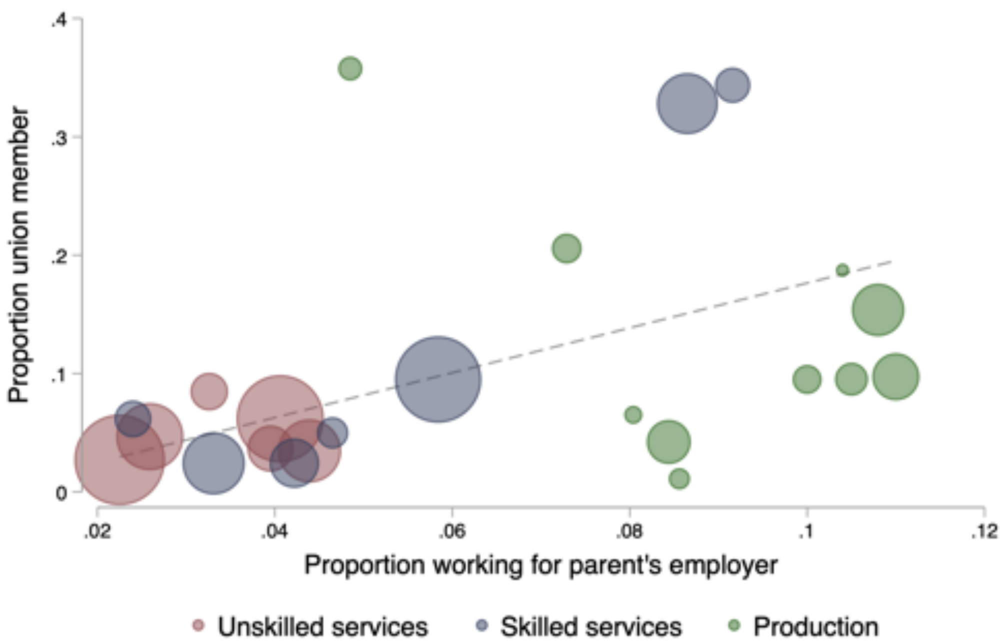
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.

Figure A.8: Industry-Level Association with Pay Premiums

(A) Industry Wage Premium



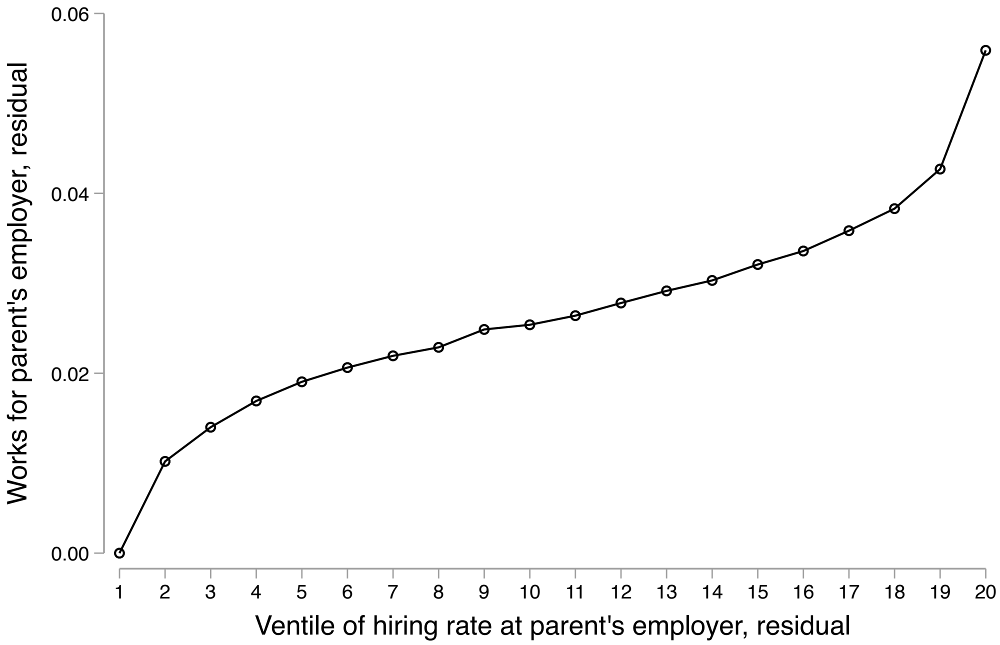
(B) Unionization



Notes: Each point represents an industry and the size is proportional to sample size. The horizontal axis is the proportion of first jobs at a parent's employer. In panel A the vertical axis is the industry-level pay premium, which is estimated by regressing log earnings on industry fixed effects, controlling for experience, sex, and education. In panel B the vertical axis is the share of works in a union. For both panel A and B, the variable on the vertical axis is measured using the Current Population Survey. Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics, 2000 Decennial Census files, and the Current Population Survey.

Figure A.9: Visualization of First Stage and Reduced Form

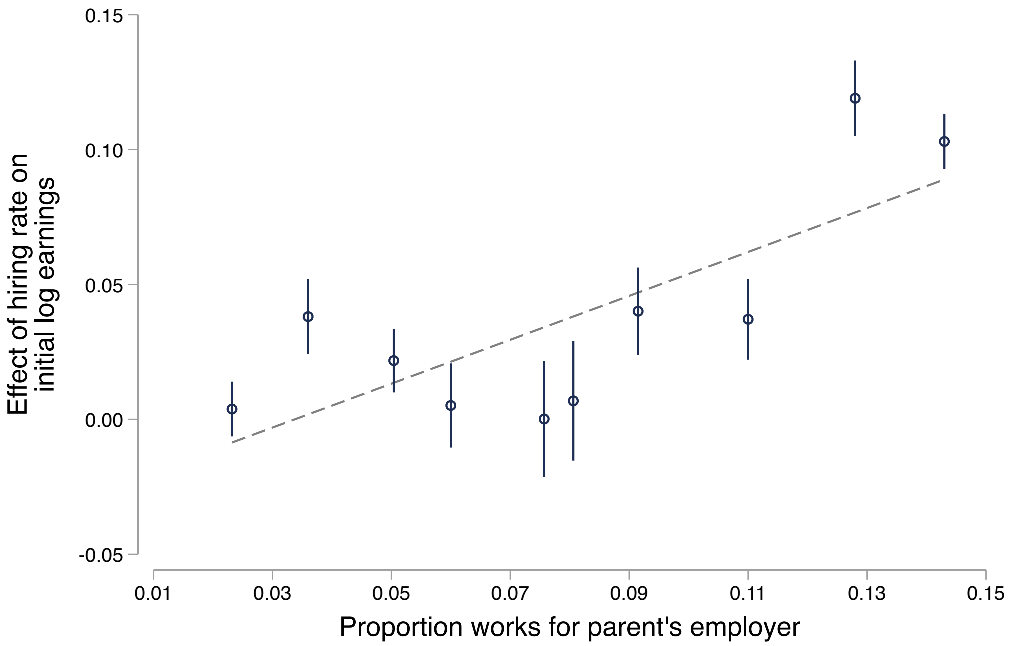
(A) First Stage



(B) Reduced Form

Notes: I regress the hiring rate on the vector of demographic characteristics and fixed effects for the parent's employer and the local labor market and group the residuals from this regression into ventiles. I then residualize the indicator for works for the parent's employer and initial log earnings and plot the average value of these residuals against the ventile of the residualized hiring rate.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics, 2000 Decennial Census files, and the Current Population Survey.

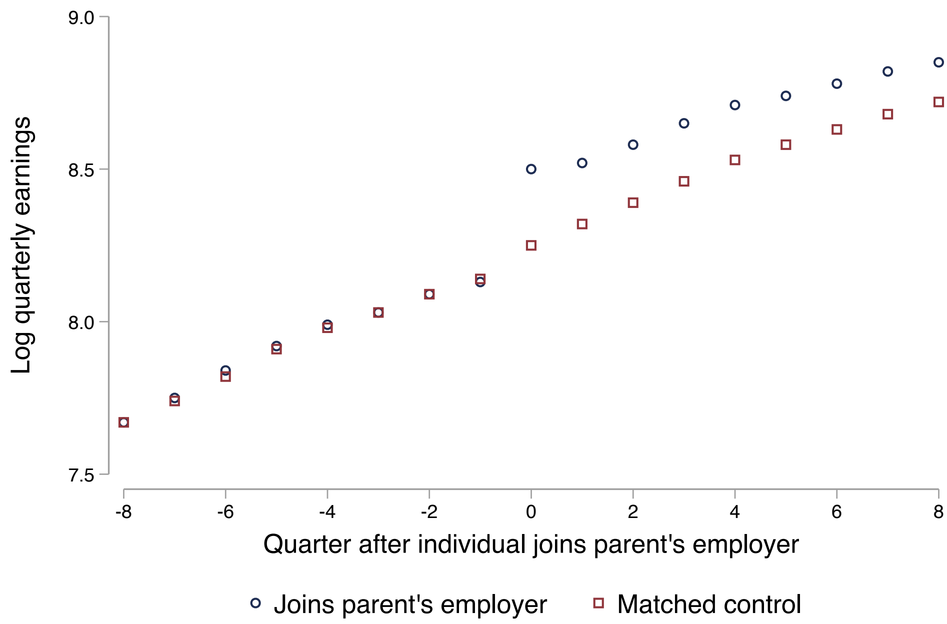
Figure A.10: Heterogeneous Effects by Parent's Industry, Reduced From



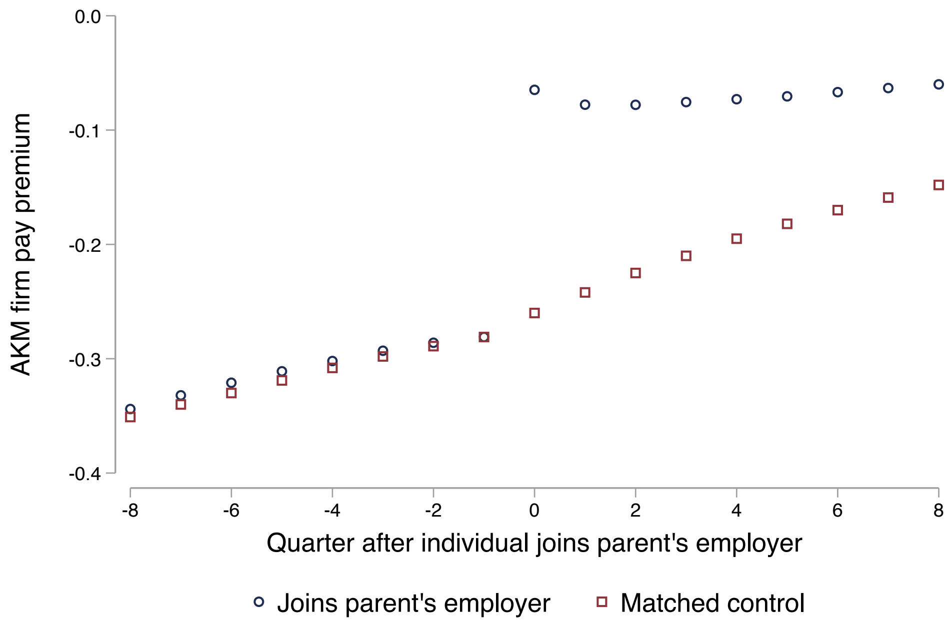
Notes: Industries are grouped into deciles based on the share of individuals in that industry who work for a parent's employer. The figure presents estimates from reduced-form specification that include interactions with these deciles. The vertical bars denote the 95 percent confidence intervals.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Figure A.11: Average Outcomes Before and After Joining Parent's Employer

(A) Log Earnings

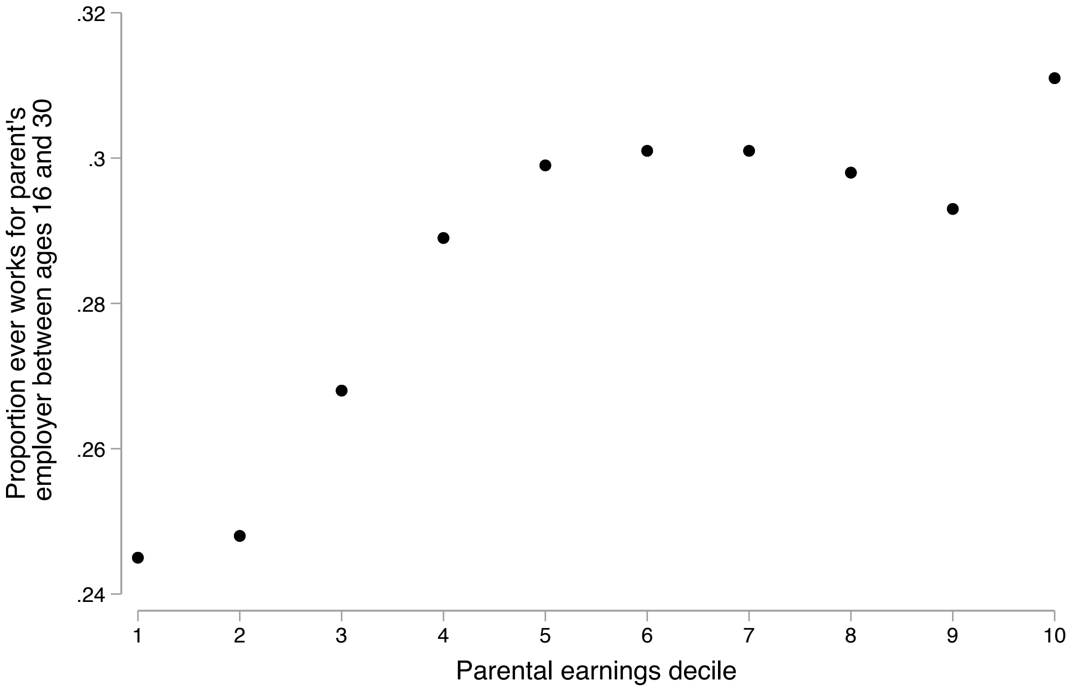


(B) AKM Firm Premium



Notes: Panel A presents the average log quarterly earnings before and after an individual joins their parent's employer. The blue circles denote the sample that joins their parent's employer and the red squares denote the matched control group. Panel B presents analogous results for the average AKM firm pay premium.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.

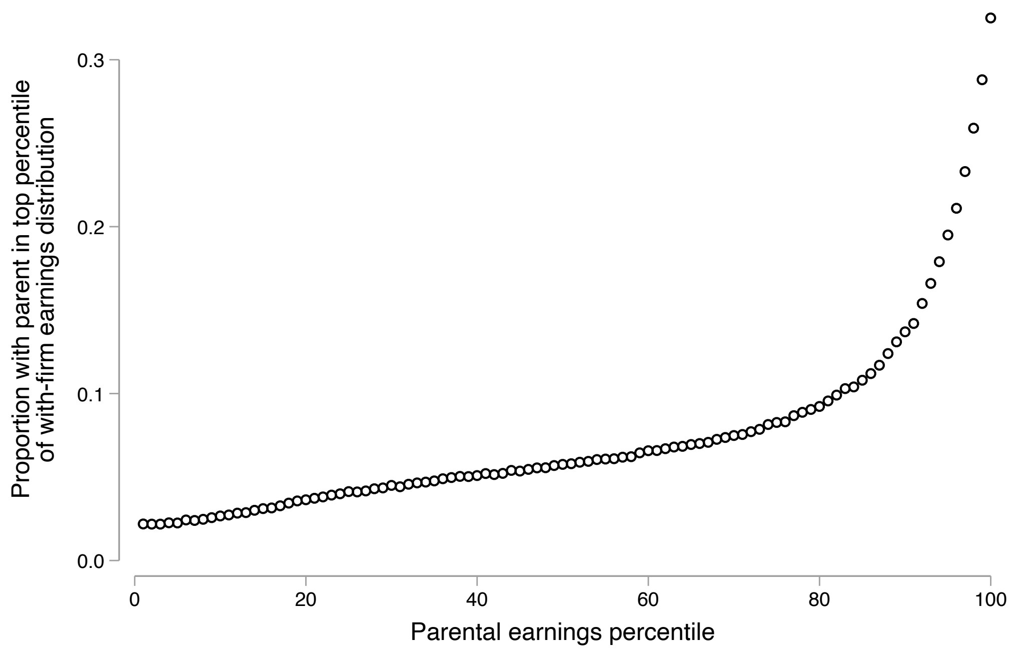
Figure A.12: Works for Parent's Employer Between Ages 16 and 30 by Parental Earnings



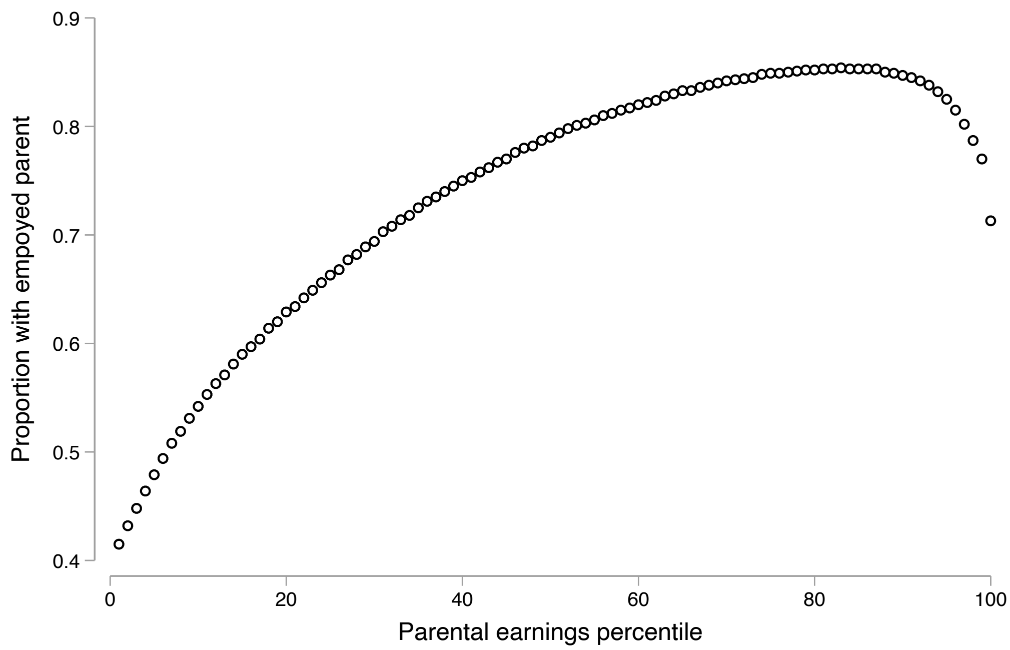
Notes: The figure plots the proportion of individuals who ever work for their parent's employer between the ages of 16 and 30 for each decile of the parental earnings distribution.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Figure A.13: Parent Characteristics by Parental Earnings

(A) Top Earner at Firm

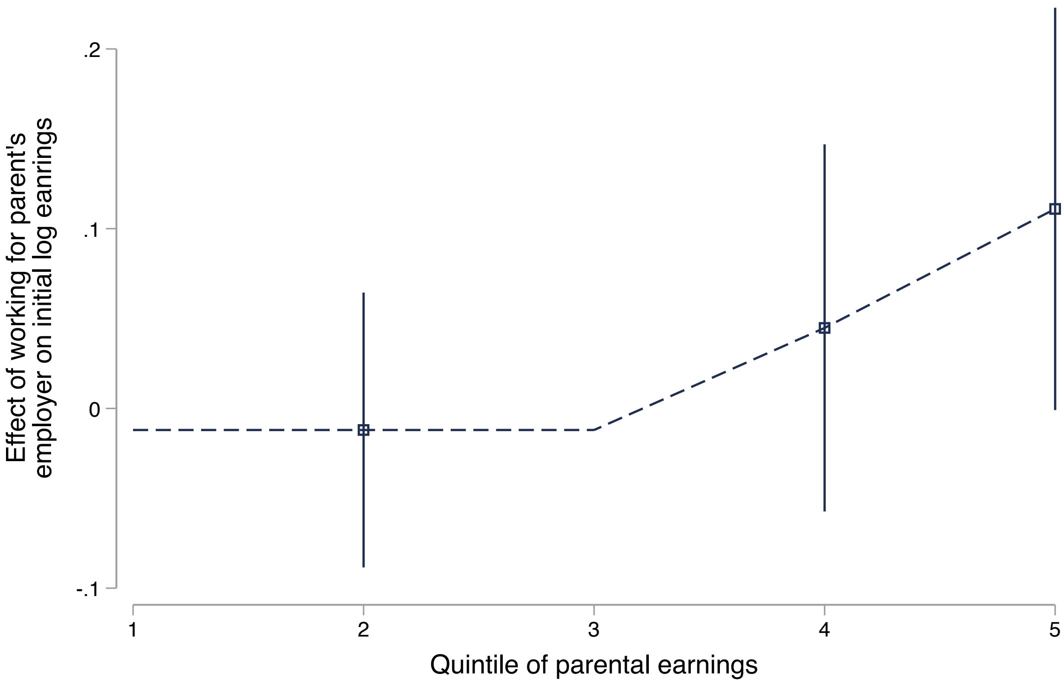


(B) Employed



Notes: Panel A plots the proportion of individuals with a parent in the top percentile of the within-firm earnings distribution for each percentile of parental earnings. Panel B plots the proportion of individuals with a parent that is employed for each percentile of parental earning.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics, 2000 Decennial Census files, and the Current Population Survey.

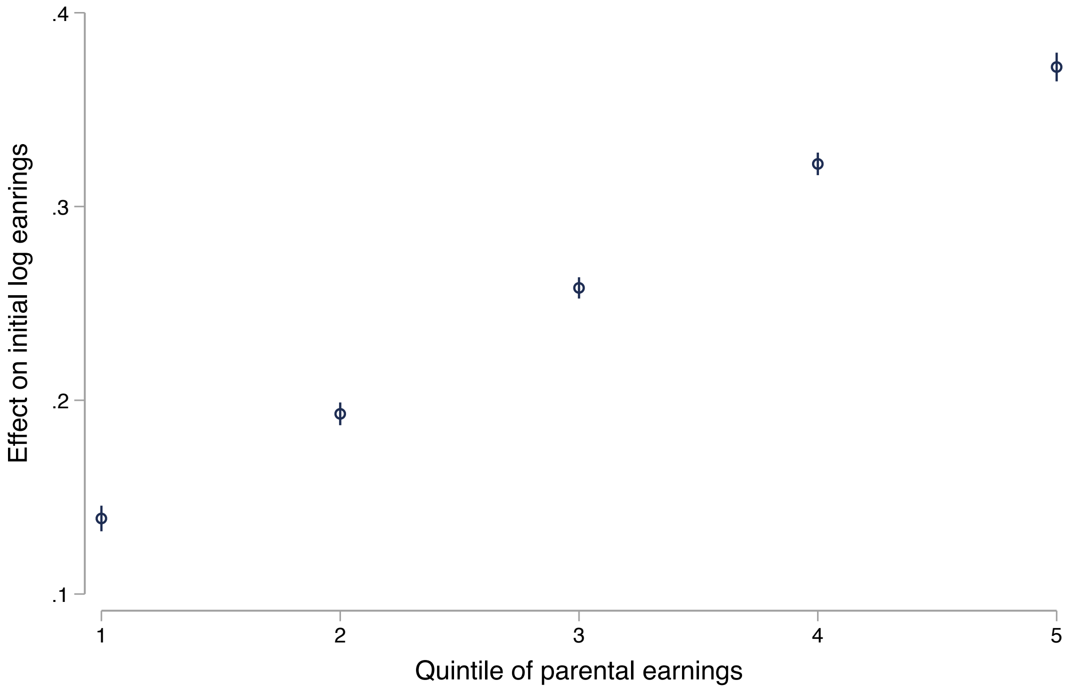
Figure A.14: Effect on Initial Earnings by Parental Earnings, Secondary Earner



Notes: Each point represents the estimated effect of working for the employer of the parent who is the secondary earner for three distinct samples defined by the parental earnings quintile (I pool the samples for the three lowest earnings quintiles). The estimates are from the main two-stage least squares specification, which is estimated on the three distinct subsamples. The vertical bars denote the 95 percent confidence intervals.

Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

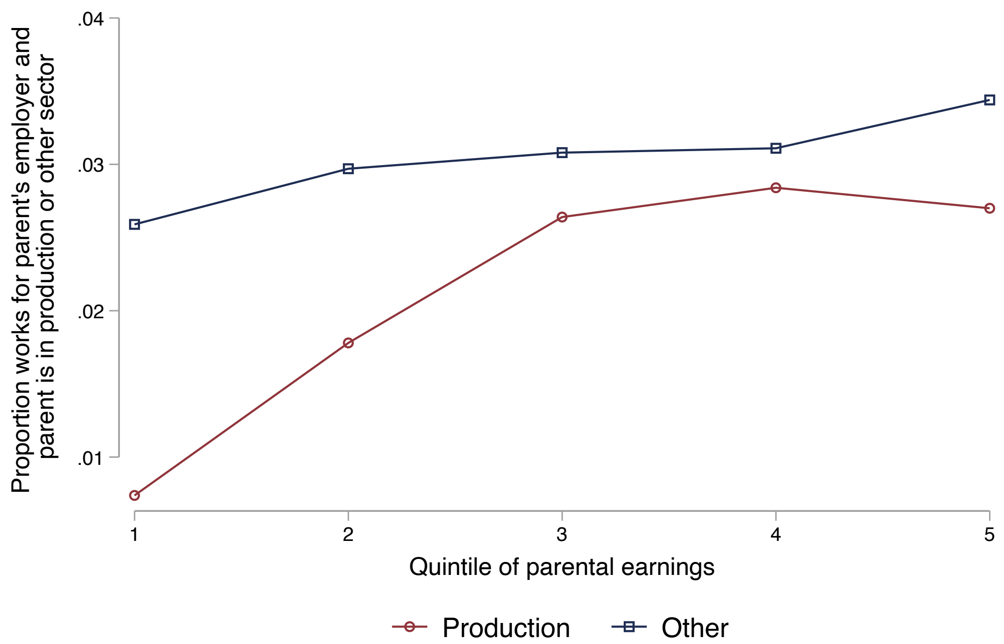
Figure A.15: Effect on Earnings by Parental Earnings, Event Study Estimator



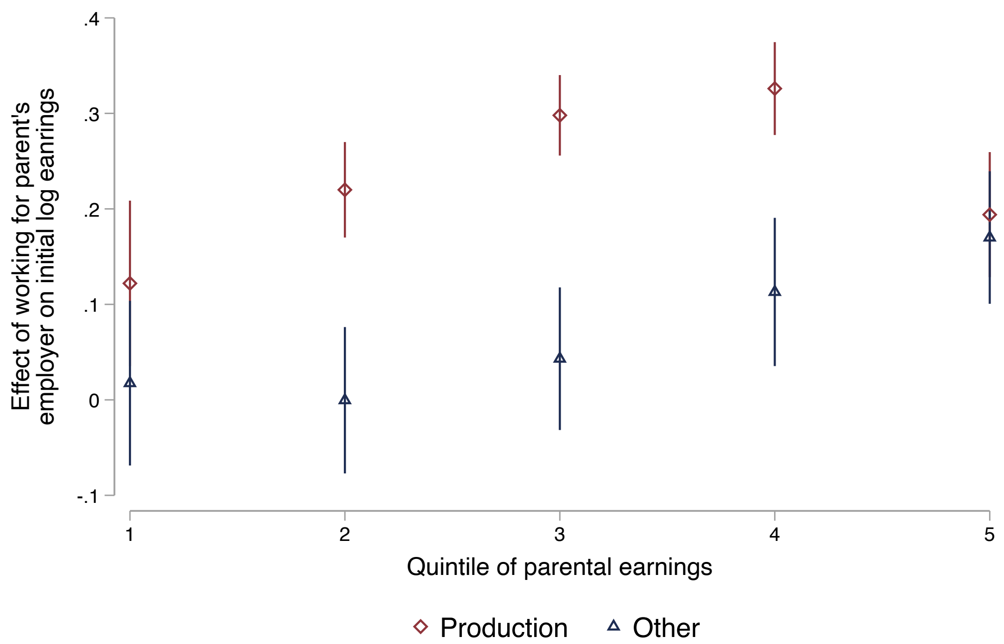
Notes: Each point represents an estimate from the event study regressions described in equation 5 where the outcome is individual log earnings. Each regression is estimated on a sample defined by the quintile of parental earnings and the points depicts the effect on log quarterly earnings in the quarter the child joins their parents firm. The vertical bars denote the 95 percent confidence intervals.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Figure A.16: Heterogeneity by Parental Earnings and Sector

(A) Likelihood of Working for Parent's Employer

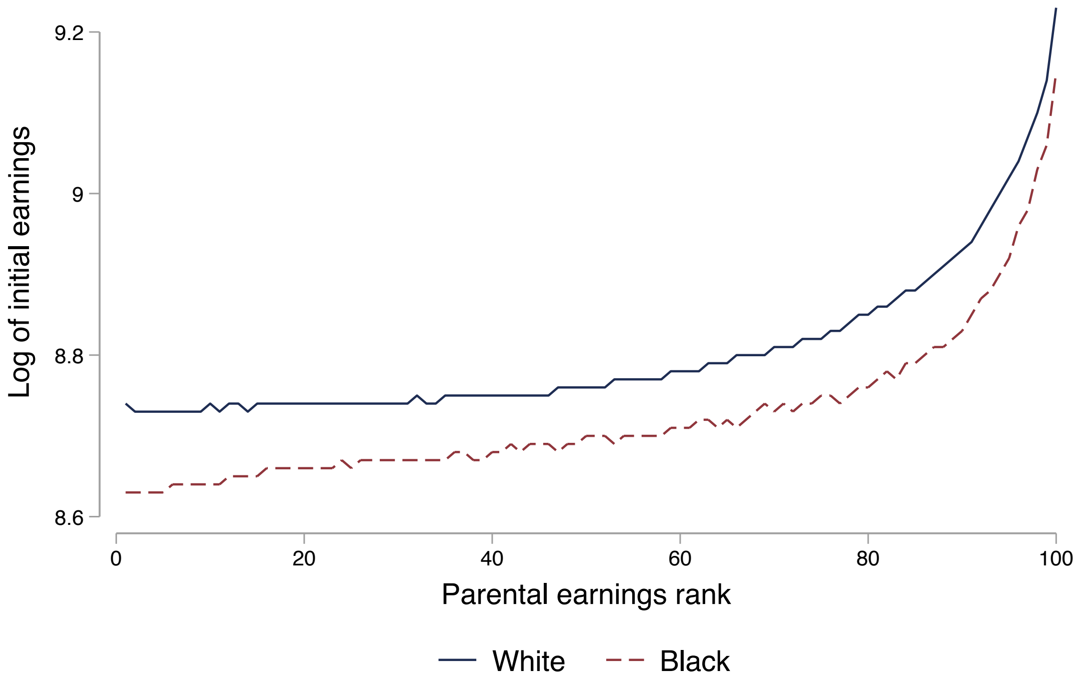


(B) Effect on Earnings



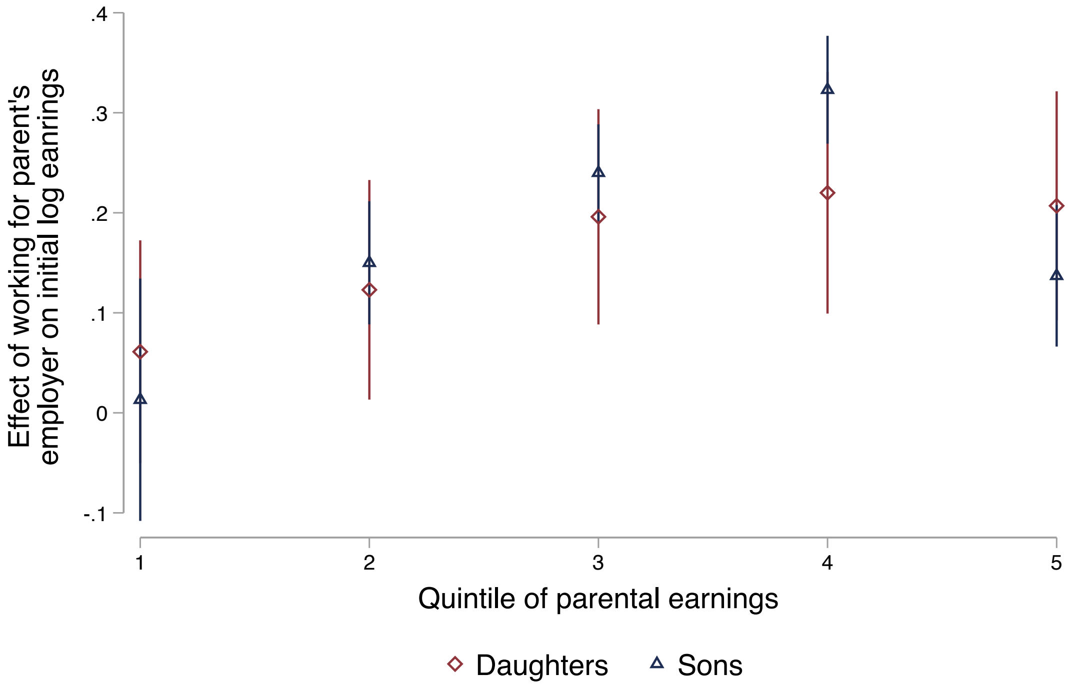
Notes: Panel A plots the proportion of individuals who work for a parent's employer and whose parent is employed in the production (red circles) or an other (blue squares) sector. Panel B presents estimates from the main two-stage least squares specification, which is estimated on ten distinct subsamples defined by the quintile of parental earnings and the sector (production or other) of the parent's employer. The vertical bars denote the 95 percent confidence intervals.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Figure A.17: Black-White Earnings Gap for Sons



Notes: The figure plots that average initial log earnings of the child against the average log earnings of their parent for each percentile of the parental earnings distribution. The blue solid line and the red dashed line represents the earnings of White and Black sons, respectively.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Figure A.18: Effect on Initial Earnings by Parental Earnings and Sex



Notes: Each point represents the estimated effect of working for a parent's employer on initial earnings for distinct samples defined by the parental earnings quintile and sex of the child. The estimates are from the main two-stage least squares specification, which is estimated on the distinct subsamples. The vertical bars denote the 95 percent confidence intervals.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Appendix B Additional Tables

Table B.1: Sample Restriction Criteria

Exclusion Criteria	Observations Remaining number	percent
None (sample frame with no restrictions)	47,556,000	100
Child not assigned a unique PIK	38,701,000	81
Unable to link child to parents because either parent is not assigned a unique PIK or the households contains more than 15 people	35,375,000	74
Combined earnings of the parents does not exceed $15,000	31,693,000	67
The child does not find a stable job by 2018	25,860,000	54

Notes: This table describes the sample restrictions applied to the sample frame. The first column describes the criteria and the second column presents the rounded number of observations that remain after dropping the observations that meet the criteria. These numbers represent a cumulative count after the all sample restrictions described in preceding rows are applied. The third column presents this infomration as a percent of the total sample frame.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Table B.2: Association with Education and Unemployment Rate

	Works for parent's employer		
	(1)	(2)	(3)
Some college	-0.013***		
	(0.001)		
Bachelor's plus	-0.025***		
	(0.001)		
Unemployment rate		0.092***	0.109***
		(0.016)	(0.027)
County and year fixed effects			yes
Observations (millions)	1.10	25.42	25.42

Notes: Each row presents estimates from a separate regression where the outcome variable is an indicator equal to one if the individual works for their parent's employer at their first stable job. In column 1 the independent variables include indicators for whether the individual has some college or at least a Bachelor's degree, with no college being the omitted category. Education data are measured for those who respond to the American Community Survey after age 25. In columns 2 and 3 the independent variable is the county-level unemployment rate. Column 3 also includes county and year fixed effects.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics, 2000 Decennial Census files, and the American Community Survey files.
*** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$

Table B.3: Placebo Test Using Parent's Past Employer

	First stage		Reduced form		Second stage	
	(1)	(2)	(3)	(4)	(5)	(6)
Hiring rate at current employer	0.135***		0.024***			
	(0.004)		(0.005)			
Hiring rate at past employer		0.019***		0.012*		
		(0.002)		(0.005)		
Works for current employer					0.175***	
					(0.037)	
Works for past employer						0.631*
						(0.281)
First-stage F-statistic					1,460	152
Estimator	OLS	OLS	OLS	OLS	2sls	2sls
Observations (millions)	2.551	1.588	2.551	1.588	2.551	1.588

Notes: The samples in the even and odd columns include parents who left a job 2-3 years before and after their child started their first job, respectively. The outcome variable in columns 1 and 2 is an indicator equal to one if the individual worked for their parent's current and past employer, respectively. The outcome variable in columns 3-6 is initial log earnings. All specifications control for the standard vector of demographic characteristics as well as fixed effects for the parent's current or past employer and the local labor market in which the employer is located. Standard errors are presented in parentheses.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.
*** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$

Table B.4: Robustness to Sibling Comparison

	Log initial earnings	
	(1)	(2)
Works for parent's employer	0.153***	0.129***
	(0.012)	(0.015)
Sibling comparison	no	yes
First-stage F-statistic	12,300	12,300
Observations (millions)	8.29	8.29

Notes: Each column presents estimates from a separate regression. Column 1 presents estimates from the main regression specification and column 2 presents estimates from a modified specification that includes fixed effects for the interaction between the parent and the parent's employer. Both regressions are estimated on the same sample, which retains cases in which at least two siblings enter the labor market when the primary earner was at the same employer. Standard errors are presented in parentheses.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.
*** p≤0.001, ** p≤0.01, * p≤0.05

Table B.5: Effect on When and Whether Individual Finds First Job

	Quarter finds first job	Ever finds first job
	(1)	(2)
Works for parent's employer	-1.040***	
	(0.178)	
Hiring rate at parent's employer		0.0002
		(0.0032)
First-stage F-statistic	24,300	
Observations (millions)	17.81	14.28

Notes: Each column presents estimates from a separate regression. Column 1 estimates the main two-stage least squares specification, where the outcome variable is the time at which the individual their first job, measured as the number of quarters after they turn 18. Column 2 regresses an indicator on whether the individual ever finds a first stable job on the hiring rate at their parent's emlpoyer when they are 18. Both specifications control for the standard vector of demographic variables and also include fixed effects for the parent's employer and the local labor market. Standard errors are presented in parentheses.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.
*** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$

Table B.6: Intergenerational Elasticity of Earnings

	Log initial earnings	Log average earnings ages 29-31		
	(1)	(2)	(3)	(4)
Log parental earnings	0.136	0.482	0.162	0.491
	(0.000)	(0.002)	(0.000)	(0.002)
Sample excludes low earners	yes	no	yes	no
Measure of parental earnings	long-run	long-run	long-run	age 16-20
Observations (millions)	25.860	7.619	5.150	7.073

Notes: Each column presents estimates from a separate regression of the log earnings of the child on the log earnings of the parent. In column 1 the earnings of the child are measured at the first job. In columns 2-4 the earnings of the child are measured as the average annual earnings between the ages of 29 and 31. In columns 1-3 parental earnings corresponds to the long-run measure described in the text. In column 4 parental earnings corresponds to the average earnings of the parents in the years when their child was between the ages of 16 and 20 and the sample excludes observations if the combined earnings of the parents is less than $15,000. Columns 1 and 3 exclude children with sufficiently low earnings, while columns 2 and 4 add one to earnings in order to retain zeros.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.

Table B.7: Effect on Initial Earnings with Binary Instrument

	(1)	(2)	(3)
A. Second Stage			
Works for parent's employer	0.168***	0.170***	0.169***
	(0.010)	(0.011)	(0.011)
B. First Stage			
Hiring rate at parent's employer	0.025***	0.020***	0.023***
	(0.0002)	(0.0001)	(0.0002)
First stage F-statistic	24,600	20,100	21,100
Hiring rate above	p25	p50	p75
Observations (millions)	17.81	17.81	17.81

Notes: The table presents estimates from the two-stage least squares specifcation. Panels A and B present estimates from the second and first stage, respeectively. Each column presents estimates from a separate regression where the outcome variable is the log of initial earnings and the instrument is an indicator equal to one if the residualized hiring rate is greater than the 25th, 50th, or 75th percentile of the distribution. Standard errors are presented in parentheses.
Source: Author's calculations based on data from the LEHD and 2000 Decennial Census.
*** p$\leq$0.001, ** p$\leq$0.01, * p$\leq$0.05

Appendix C Description of Data

C.1 Measuring Parental Earnings

The ideal dataset would contain earnings data for each worker over their entire working life, and lifetime earnings would simply be calculated as the sum of all observed earnings. However, the LEHD fall short of the ideal data because some sources of earnings are not included in the data and because they do not cover the full working life of all parents in the sample. Thus, I require an alternative method to estimate lifetime earnings.

A common approach in the literature is to calculate parental earnings as the average earnings over a limited number of years. For example, recent work by Chetty et al. (2014) measure parental earnings as the average earnings measured across five years. However, there are potential issues with this approach (see Mazumder 2016 for a detailed discussion). The first is related to the number of years over which the earnings are averaged. A large literature inspired by Solon (1992) and Zimmerman (1992) finds that measuring parental earnings over a short time periods introduces measurement error and leads to artificially low estimates of the intergenerational relationship in economic outcomes. Mazumder (2005) suggest that even fifteen years of data may not be enough to accurately measure lifetime earnings. The second issue, is that parental earnings measured at different points in the life cycle may not be comparable (see Jenkins 1987; Solon 1992; Grawe 2006; Bohlmark and Lindquist 2006; Haider and Solon 2006). For example, two individuals aged 35 and 55 might have similar earnings in a given year but very different levels of lifetime earnings.

Another complication is that, while most earnings (96 percent of salary employment) are covered by the LEHD frame, the data systematically miss some sources of income. Measurement issues at the bottom of the wage earnings distribution are of particular concern. Figure A.5 illustrates this point by using data from the CPS to plot average total household income by source against percentiles of parental wage earnings distribution. For most of the distribution, wage earnings (which are accurately measured in the LEHD) are the primary source of both income and earnings. However, this is not true at the bottom of the distribution. For example, households with zero reported wage earnings actually have higher average total income relative to households who have positive, but little, wage earnings. Most importantly, since my focus is on earnings, self-employment (not captured in the LEHD) is a main source of earnings for parents at the bottom of the wage earnings distribution. Wage earnings is the primary source of income for households with total income (as opposed to total wage earnings) that is above the 10th percentile. The same is not true for households with income below the 10th percentile, for whom transfer income is relatively more important. Smith et al. (2019) find that non-wage earnings become increasingly important in the top 1 percent of earners. In this way, my results do not speak to the experiences of the poorest (bottom 10 percent) and richest (top 1 percent) of households.

In order to address the measurement issues in the LEHD, I use an estimation procedure that leverages all of the available data. In particular, I estimate the following regression:

$$y_{it} = \alpha_i + \beta^g X_{it} + u_{it} \tag{C.1}$$

where is is the individual, t is the quarter, y is total quarterly earnings, α is an individual fixed effect and X is vector that consists of a third order polynomial in age. To allow for a flexible age earnings profile, I estimate this specification separately for groups, g, defined by the interaction between sex, education (less than high school, high school, some college, Bachelor's degree or advanced degree), and state of residence in 2000. The education data are either measured using the 2000 Decennial Census long-form and the American Community Surveys, or are imputed (based on earnings) for workers that do not respond to these surveys. The data are a panel that include all strictly positive earnings records between 2000 and 2016 for the parents in the sample. I further restrict the panel to individuals between the ages of 25 and 65 and drop individuals that have fewer than 12 quarters of strictly positive earnings over the entire time period.

I use the estimates from this model to construct a measure of long-run earnings for each parent. I predict the value of earnings for each quarter and define long-run earnings as the average annual earnings between the ages of 35 and 55. Individuals with either missing or negative values are assigned a long-run earnings of zero. For single-headed households parental earnings is simply the earnings of the parent. For two-parent households, parental earnings is the sum of the earnings of both parents.

I validate my measure of parental earnings by showing that it strongly correlates with neighborhood poverty rates. Using the Decennial Census, I identify the neighborhood, or Census tract, in which each household lives. Figure A.6 plots the average poverty rate of the neighborhood of residence against the percentile rank of parental earnings. For households with income above $15,000, there is a negative monotonic relationship between earnings and neighborhood poverty rates: parents with higher earnings live in lower poverty neighborhoods. However, this strong relationship breaks down for parents with earnings below $15,000. Based on this finding, I drop individuals whose parents' combined earnings is less than $15,000.

C.2 Edits to Individual Earnings Records

Earnings data in the LEHD come from Unemployment Insurance (UI) records, which report total amount paid to each worker per employer per quarter. In measuring quarterly earnings, I sum earnings records across employers within a quarter for each individual to construct a measure of total individual earnings per quarter. While the administrative data are not subject to various types of measurement error that plague survey data, they are not error free. A key issue is that data errors can produce very large outlier observations. Researchers typically deal with these by editing or dropping earnings records above some percentile of the distribution. A drawback of this methodology is that it incorrectly impacts the earnings of workers who truly have earnings in the top percentiles.

In order to retain top earners in my sample, I use an alternative methodology to deal with outliers. The methodology, which I have also employed in Fallick et al. (2019), is based on the fact that outliers often appear in the form of a large spike for a single quarter for an individual. Let $z_i = max\{median(y_{it}), 10000\}$ be the greater of the median of earnings observed for individual i over the entire sample and 10,000.[45] Then define earnings growth as:

$$\Delta_{it} = \frac{y_{it} - z_i}{\frac{1}{2}(y_{it} + z_i)} \tag{C.2}$$

where t is the quarter and y is the earnings. The growth rate, Δ_{it}, captures the extent to which earnings in a given quarter exceeds the typical earnings of that individual. The choice to set a minimum value of z is motivated by the desire to avoid editing the earnings

[45] The median is calculated from a sample that contains strictly positive earnings.

of low earners, since the outliers are driven by very large levels of earnings.

I define outliers as earnings records that produce growth rates that exceed the 95th percentile of the distribution. Let $\Delta(p95)$ denote the 95th percentile, then the earnings variable used in this paper is defined as:

$$\tilde{y}_{it} = \begin{cases} y_{it} & \text{if } \Delta_{it} < \Delta(p95) \\ z_i * \frac{1+\frac{1}{2}\Delta(p95)}{1-\frac{1}{2}\Delta(p95)} & \text{if } \Delta_{it} > \Delta(p95) \end{cases} \tag{C.3}$$

This methodology edits outlier observations so that if the growth rate were calculated on the edited value it would be equal to the 95th percentile. The advantage of this methodology is that it retains the earnings records of individuals who consistently have high levels of earnings.

C.3 Grouping Industries into Sectors

I group two-digit North American Industry Classification System (NAICS) industry codes into three distinct sectors, which are defined below. The unskilled service sector includes: retail trade (44,45); administrative and support and waste management and remediation services (56); arts, entertainment and recreation (71); accommodation and food services (72); and other services (81). The skilled service sector includes: information (51); finance and insurance (52); real estate and rental and leasing (53); profession, scientific and technical services (54); management of companies and enterprises (55); educational services (61); health care and social assistance (62); and public administration (92). The production sector includes: agriculture, forestry, fishing and hunting (11); mining, quarrying, and oil and gas extraction (21); utilities (22); construction (23); manufacturing (31,32,33); wholesale trade (42); and transportation and warehousing (48,49).

C.4 Firm and Industry Pay Premiums

In order to estimate the earnings-premium associated with specific firms, I use the methodology developed by Abowd et al. (1999), or commonly referred to as the AKM model. Specifically, I estimate the following specification,

$$y_{it} = \alpha_i + \Psi_{j(i,t)} + X_{it}\beta + \epsilon_{it} \tag{C.4}$$

where i is the individual; t is the year; y is the log of average quarterly earnings; X_{it} is a vector of time varying controls that include a fixed effect for the year and a third order polynomial in age interacted with sex and education; α_i is an individual fixed effect; $\Psi_{j(i,t)}$ is a fixed effect for the employer of i in time t; and ϵ_{it} is a regression residual.[46] The estimate, $\hat{\Psi}_{j(i,t)}$, is a time-invariant measure of the firm pay premium.

I estimate equation C.4 using a national sample of quarterly earnings records from the LEHD measured between the years 2000 and 2016. The sample includes full quarter jobs

[46] Identification of the age and time effects in the presence of individual fixed effects is achieved by following Card et al. (2013) and omitting the linear age term in for each sex by education group and using a cubic polynomial in age minus 40. This normalization assumes that the age-earnings profile is flat at age 40. While the normalization affects the estimates of the individual fixed effects and the covariate index $X_{it}\beta$, the employer fixed effects are invariant to the normalization used. Data on education comes from the individual characteristics file and is sourced from various surveys and is imputed for many observations.

for workers between the ages of 15 and 65.[47] I drop children from my intergenerational sample. As is standard in the literature, I restrict the sample to the largest connected set. I estimate the model by implementing the iterative method proposed by Guimaraes and Portugal (2010). I am unable to compute the firm pay premium for firms that lie outside of the largest connected set.

I estimate the industry-level premium using the similar data and methodology. Because all industries are connected through worker mobility, I estimate the industry premiums on a 10 percent sample of workers and collapse the quarterly data to an annual frequency. In the empirical model I replace the employer fixed effect with a fixed effect for the industry code. I am able to estimate an industry-level pay premium for all industries, and thus there are no missing data for this variable.

C.5 Firm-Level Variables

C.5.1 Hiring Rate

To measure the hiring rate, I follow the methodology used to produce the Quarterly Workforce Indicators and calculate the End-of-Quarter Hiring Rate, which is the number of new hires that remain with the employer for at least one additional quarter divided by the average of the total employment at the employer at the beginning and end of the quarter.

C.5.2 Poaching Hires

For each employer I calculate the share of new stable hires that are acquired through poaching flows as opposed to nonemployment flows. In order to explain how poaching rates are constructed, it is useful to establish the following terminology. Each worker with positive earnings in quarter t can have one of four types of employment spells defined in Table C.1, where "+" denotes positive earnings and "0" denotes zero earnings at the employer at quarter t.

Table C.1: Classification of Employment Spells

	earnings at employer		
	t-1	t	t+1
beginning of quarter	+	+	0
end of quarter	0	+	+
middle of quarter	0	+	0
full quarter	+	+	+

A worker with a beginning of quarter employment spell is relatively attached to the employer at the start of quarter t but separates from the employer at some point during quarter t. Similarly, a work with an end of quarter employment spell joins the employer at some point during quarter t and experiences a stable spell of employment that continues into the following quarter. Middle of quarter employment spells represent spells that

[47]If the worker has multiple jobs in a quarter, I retain the highest-paying job. To limit the influence of outliers, I drop observations if the quarterly earnings exceed one million dollars.

begin and end within the quarter and, following the conventions used to construct the Job-to-Job Flows statistics, I do not use them when constructing poaching rates.

Workers who experience an end of quarter employment spell in quarter t are defined as stable new hires. These workers begin their employment spell at some point during quarter t, and I define the hire as a poaching hire if the worker also left their previous employer in quarter t. In other words, a poaching hire is an individual who switches employers and begins their new job no later than one quarter after leaving their old job. In practice, I identify poaching hires as individuals who experience an end of quarter employment spell in quarter t and experience either a full quarter or end of quarter employment spell (at a different employer) in quarter t-1. All stable new hires that do not meet these criteria are defined as hires from nonemployment.

For each employer, I calculate the total number of stable hires made through poaching and nonemployment flows between 2000 and 2016. I then calculate an employer-level poaching rate as the proportion of stable new hires made through poaching flows over the entire period. Lastly, I rank employers from 0 to 100 based on their poaching hire rate, where the ranks are calculated using average employer size as weights.

C.5.3 Average Earnings

I calculate average earnings at the employer using full quarter employment spells. Specifically, using data between 2000 and 2016, I retain all workers who experience a full quarter employment spell and take the log of their earnings (I top code earnings at $1,000,000 to mitigate the impact of outliers). The employer-level average of log earnings is simply the average of the quarterly earnings records. I rank employers from 0 to 100 based on their average log earnings, where the ranks are calculated using average employer size as weights. There are no missing data for any of the employers in the sample.

C.5.4 Productivity

The firm-level measure of productivity is based on data from the Revenue Enhanced Longitudinal Business Database (RE-LBD). The RE-LBD supplements the LBD with revenue data from the Census Business Registrar (BR). The BR contains annual measures of revenue measured at the tax reporting or employer identification number (EIN) level. Haltwanger et al. (2016) describe how the revenue data and the employment data from the LBD are combined to construct firm level measures of log revenue per worker, which represent the measure of productivity.

There are two limitations of this particular measure of productivity. First, the coverage is not universal since the employment and revenue data for some firms cannot be linked and since the coverage excludes non-profit firms and firms in the Agriculture, Forestry, Fishing and Hunting (NAICS=11) and Public Administration (NAICS=92) industries. Haltwanger et al. (2016) show that the revenue data cover about 80 percent of firms in the LBD and patterns of missing productivity data are only weakly related to observable firm characteristics. Second, the revenue per worker measure fails to account for differences in intermediate inputs across industries, which imply that this measure cannot be used to compare productivity of firms that are located in different industries.

In order to overcome the latter limitation, I follow Haltiwanger et al. (2017) and construct a time invariant measure of productivity. Specifically, after attaching firm productivity to the employer-level dataset, I calculate average productivity for each employer as the employment-weighted average of log revenue per worker observed across all periods. From each employer I then subtract the employment-weighted average of productivity at the level of the four-digit NAICS industry code. Thus, this measure of productivity is a time invariant measure that captures the productivity of an employer relative to other employers in the same industry. Productivity ranks that range from 0 to 100 are calculated within four-digit industry codes and are employment weighted, where employment refers to the average number of employees at the employer observed over the sample period.

C.5.5 Firm Age and Size

Measures of firm age and firm size are derived from the Longitudinal Business Database (LBD).[48] The LBD is an annual dataset that covers the universe of establishments and firms in the U.S. non-farm business sector with at least one paid employee. Establishment-level employment is measured as the number of workers on payroll in the pay-period that covers the 12th day of March in the previous year. Firm size is simply the sum of employment at all establishments within the firm. Firm age measures the number of years since the firms formation and accounts for changes in firm identifiers as well as mergers and acquisitions.[49]

C.6 References

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[48] See Jarmin and Miranda (2002) for a detailed description of the LBD and Haltiwanger et al. (2014) for a description of how firm-level outcomes from the LBD are linked to the employers int he LEHD.

[49] See Davis et al. (2007) for a detailed description of how the firm age variable is constructed.

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Appendix D Approximation Methodology

By definition, $\text{cov}(D_i\beta_i, y_p) = \mathbb{E}[D_i\beta_i y_p] - \mathbb{E}[D_i\beta_i]\mathbb{E}[y_p]$. By iterated expectations,

$$\mathbb{E}[D_i\beta_i] = \mathbb{E}\big[\mathbb{E}[D_i\beta_i|D_i]\big] = \mathbb{E}[D_i]\mathbb{E}[\beta_i|D_i = 1] \tag{D.1}$$

and

$$\mathbb{E}[D_i\beta_i y_p] = \mathbb{E}\big[\mathbb{E}[D_i\beta_i y_p|r_p]\big] \tag{D.2}$$

where r_p is the percentile rank of parental earnings. Because the Pearson correlation coefficient is bounded between -1 and 1, it follows that,

$$cov(D_i\beta_i, y_p|r_p)^2 \leq var(D_i\beta_i|r_p) \times var(y_p|r_p) \tag{D.3}$$

In practice, I condition on r_p, but one could think to condition on more detailed ranks. As the number of ranks approaches the sample size, $var(y_p|r_p)$ approaches zero and the covariance term therefore approaches zero. Thus,

$$\begin{aligned} \mathbb{E}[y_p D_i\beta_i|r_p] &= \mathbb{E}[y_p|r_p] \times \mathbb{E}[D_i\beta_i|r_p] + cov(D_i\beta_i, y_p|r_p) \\ &\approx \mathbb{E}[y_p|r_p] \times \mathbb{E}[D_i\beta_i|r_p] \end{aligned} \tag{D.4}$$

where equation D.3 suggests that $cov(D_i\beta_i, y_p|r_p)$ will be close to zero when conditioned on parental earnings ranks that are defined at a sufficiently high level of detail. Combing these pieces yields the approximation in equation 3.

I assess the performance of the approximation methodology by using the same methodology to approximate the observed IGE. By definition, $\rho(y_{ij}, y_p) = \frac{\text{cov}(y_{ij}, y_p)}{\text{var}(y_p)}$. The variance term, $\text{var}(y_p)$, is directly observed and I use the following approximation for the covariance term,

$$\text{cov}(y_{ij}, y_p) \approx \mathbb{E}\Bigg[\mathbb{E}[y_p|r_p] \times \mathbb{E}[y_{ij}|r_p]\Bigg] - E[y_p] \times E[y_{ij}] \tag{D.5}$$

Where this approximation relies on the same assumption used to derive equation 3.

Appendix E Stylized Model

E.1 Baseline Model

Let y_{ij} denote the log earnings of individual i employed at firm j. Assume that log earnings are additive in the log of the human capital (h_i), the firm pay premium (f_j), and an idiosyncratic error terms (u_i). Thus,

$$y_{ij} = h_i + f_j + u_i \tag{E.1}$$

Using the notation of the potential outcomes framework, let $j(1)$ denote the parent's employer and let $j(0)$ denote the employer that represents the outside option. The firm pay premium of the child's employer can be written as,

$$f_j = f_{j(0)} + D_i\beta_i \tag{E.2}$$

where D_i is an indicator equal to one if the individual works for their parent's employer and zero otherwise and $\beta_i = f_{j(1)} - f_{j(0)}$ is the effect of working for a parent's employer.

An individual's outside option is related to their human capital. Specifically, the labor market exhibits sorting between workers and firms, characterized by:

$$f_{j(0)} = \lambda h_i + \nu_i \tag{E.3}$$

where ν_i is an idiosyncratic error term and $\lambda > 0$ indicates that individuals with higher levels of human capital tend to match to employers that offer higher pay premiums. The same matching process applies to parents, but I abstract from the possibility that parents might work for the employers of their parents.[50] Furthermore, the relationship between the human capital of the child and earnings of the parent is characterized by,

$$h_i = x + \theta y_p + \eta_i \tag{E.4}$$

where $y_p \equiv y_{pj(1)} = h_p + f_{j(1)} + u_p$ denotes the parent of i, η_i is an idiosyncratic error term and $\theta > 0$ implies that human capital is increasing in parental earnings.

Whether a child works for the employer of their parent depends on choices made by both the employer and the child. Let O_i be equal to one if the parent's employer makes a job offer to the child and zero otherwise. The offer decision depends on a hiring cost, $z_i \in \{z', z''\}$ with $z' > 0 > z''$, and the human capital of the parent and the child. Specifically, $O_i = \mathbb{1}\{\phi h_p + \gamma h_i > z_i\}$, where ϕ and γ could be positive or negative.[51] Let A_i be equal to one if the child would accept a job offer from the parent's firm. The child will choose to accept the offer if the earnings gains, β_i, exceed any costs, c, such that $A_i = \mathbb{1}\{\beta_i > c\}$. The child will work with their parent only if they receive a job offer and

[50] Formally, I assume that $D_p = 0$, where p denotes the parent of i. This assumption simplifies the analysis and allows me to write the earnings benefits associated with working for the parent's employer as function of parental earnings and unobserved error terms $\beta_i = (\frac{\lambda}{1+\lambda} - \lambda\theta)y_p + [\lambda/(1+\lambda)](\lambda\nu_p - u_p) - [\lambda x + \lambda\eta_i + \nu_i]$.

[51] ϕ might be positive if higher-ability parents have more control over the hiring process because they hold leadership positions, or negative if lower-ability parents work at firms that rely more heavily on networks in the hiring process. γ may be positive if firms are more likely to make a job offer to high ability workers, or negative if parents exert more effort to procure job opportunities for low ability children.

it is optimal for them to accept,

$$D_i = \mathbb{1}\{\phi h_p + \gamma h_i > z_i\} \times \mathbb{1}\{\beta_i > c\} \tag{E.5}$$

Unlike the standard selection models, equation E.5 illustrates that selection into treatment depends on the choices of multiple agents.

Combining equations E.1, E.2, E.3, and E.4 yields the following relationship between the earnings of the child and the earnings of their parents,

$$y_{ij} = \alpha_1 + \alpha_2 y_p + D_i\beta_i + \epsilon_i \tag{E.6}$$

where $\epsilon_i = \nu_i + (1+\lambda)\eta_i + u_i$ is an unobserved error term, $\alpha_1 = (1+\lambda)x$, and $\alpha_2 = (1+\lambda)\theta$.

Regressing y_{ij} on y_p yields an estimate of the intergenerational elasticity of earnings (IGE). My goal is to understand how the IGE would change if no one worked for the same employer as a parent; i.e., if $D_i = 0$ of all i. Because of the presence of heterogeneous treatment effects and the potential correlation between D_i and ϵ_i, simply adding a control for D_i will not provide an answer to this question.[52] For this reason, I rely on the approximation methodology derived in Appendix D.

The counterfactual analysis requires an estimate of the average treatment effect on the treated (ATT), and the stylized model highlights why an instrumental variables estimator might recover that parameter. Under the assumption that the instrument is orthogonal to the unobserved components of the individual's earnings ($z_i \perp\!\!\!\perp \eta_i, \nu_i, u_i$) and parent's earnings ($z_i \perp\!\!\!\perp \nu_p, u_p$), an instrumental variables estimator that uses z_i as an instrument identifies a local average treatment effect (LATE), which is defined as $\mathbb{E}[\beta_i|D_i(z') < D_i(z'')]$. In the standard one-agent selection framework the LATE will depend on the value of the instruments since the decision-making process directly links the benefits and instruments. In my context, in which selection into treatment is determined by two agents, this link is potentially broken. The implication is stated in the following proposition,

Proposition 1 *If $\phi = 0$ and $\gamma = 0$, then $O_i \perp\!\!\!\perp \beta_i$ and*

$$\underbrace{E[\beta_i|D_i = 1]}_{ATT} = \underbrace{E[\beta_i|D_i(z') < D_i(z'')]}_{LATE} \tag{E.7}$$

Proof 1 *If $\gamma = 0$ and $\phi = 0$ then $O_i = \mathbb{1}\{0 > z_i\}$ and it follows that $O_i \perp\!\!\!\perp \beta_i$. For any two values of the instrument, $z' > 0 > z''$, it follows that,*

$$\begin{aligned}
\underbrace{E[\beta_i|D_i = 1]}_{ATT} &= E[E[\beta_i|A_i = 1]|O_i = 1] \\
&= E[E[\beta_i|A_i = 1]|O_i(z') < O_i(z'')] \\
&= \underbrace{E[\beta_i|D_i(z') < D_i(z'')]}_{LATE}
\end{aligned} \tag{E.8}$$

where the first and third inequalities hold by the law of iterated expectations and the second inequality holds as a result of $O_i \perp\!\!\!\perp \beta_i$.[53]

[52] To see the relationship between D_i and ϵ_i note that $\epsilon_i = \nu_i + (1+\lambda)\eta_i + u_i$, $O_i = \mathbb{1}\{(\frac{\phi}{1+\lambda} + \gamma\theta)y_{pj(1)} + \gamma x - \frac{\phi}{1+\lambda}(\nu_p + u_p) + \gamma(x + \eta_i) > z_i\}$, and $A_i = \mathbb{1}\{(\frac{\lambda}{1+\lambda} - \lambda\theta)y_{pj(1)} + (\frac{\lambda}{(1+\lambda)})(\nu_p/\lambda - u_p) > c + \lambda x + \lambda\eta_i + \nu_i\}$.

[53] It also exploits the fact that $O_i \perp\!\!\!\perp A_i$, which follows directly from $O_i \perp\!\!\!\perp \beta_i$.

If the offer decision is unrelated to the human capital of the parent ($\phi = 0$) and the human capital of the child ($\gamma = 0$), then the offer decision and the earnings gains will be independent ($O_i \perp\!\!\!\perp \beta_i$). Under these conditions, the instrument affects the treatment status of a random sample of individuals who would accept job offers at their parent's employer and the LATE is equivalent to the ATT. This equivalence, which may hold even in the presence of selection bias and selection on gains, is possible because treatment status is determined by the choices of multiple agents.

While the empirical evidence suggests that the intergenerational transmission of employers reduces mobility, the relationship is theoretically ambiguous. This is formalized in the following proposition, which states that the counterfactual IGE corresponding to a wold in which no one worked for a parent's employer could be greater or small than the observed IGE.

Proposition 2 *Consider a deterministic case of the model by letting z_i, η_i, ν_i and u_i be equal to zero and let $c \geq 0$. Then the following statements are true:*

- *if $\frac{1}{1+\lambda} > \theta$ and $\phi > -\theta\gamma(1+\lambda)$ then $\rho(y_{ij}, y_{pj(1)}) > \rho(y_{ij(0)}, y_{pj(1)})$*
- *if $\frac{1}{1+\lambda} < \theta$ and $\phi < -\theta\gamma(1+\lambda)$ then $\rho(y_{ij}, y_{pj(1)}) < \rho(y_{ij(0)}, y_{pj(1)})$*

Proof 2 *To prove the results it is useful to start by noting the implications of the deterministic setting (η_i, ν_i, u_i and z_i are set to zero) for the following expressions,*

$$
\begin{aligned}
O_i &= \mathbb{1}\{(\frac{\phi}{1+\lambda} - \theta\gamma)y_{pj(1)} > 0\} \\
A_i &= \mathbb{1}\{(\frac{\lambda}{1+\lambda} - \lambda\theta)y_{pj(1)} - \lambda x > c\} \\
\beta_i &= (\frac{\lambda}{1+\lambda} - \lambda\theta)y_{pj(1)} - \lambda x
\end{aligned}
\tag{E.9}
$$

It is straightforward to show that $cov(\beta_i, y_{pj(1)}) = (\frac{\lambda}{1+\lambda} - \lambda\theta)var(y_{pj(1)})$. In the first case, when $\frac{1}{1+\lambda} > \theta$ and $\phi > -\theta\gamma(1+\lambda)$, it immediately follows that $\frac{\partial \beta_i}{\partial y_{pj(1)}} > 0$, $\frac{\partial O_i}{\partial y_{pj(1)}} > 0$, $\frac{\partial A_i}{\partial y_{pj(1)}} > 0$ and $\frac{\partial D_i}{\partial y_{pj(1)}} > 0$. Under the assumption that $c \geq 0$, D_i and β_i are both increasing in $y_{pj(1)}$, and it follows that $D_i\beta_i$ is a monotonic transformation of β_i. Thus, $cov(\beta_i, y_{pj(1)})$ and $cov(D_i\beta_i, y_{pj(1)})$ have the same sign, which implies that, $cov(D_i\beta_i, y_{pj(1)}) > 0$. The proof for the second case uses the same logic.

Proposition 2 highlights two competing forces. On the one hand, high-income parents are best able to procure high-paying job offers for their children. On the other hand, children from low income households have lower levels of human capital and are more reliant on their parents to find a descent paying job. Thus, while my empirical evidence suggests that the intergenerational transmission of employers increases the intergenerational persistence in earnings, this conclusion might differ in other contexts depending the characteristics of the labor market and the human capital accumulation process.

E.2 Extension with Parental Investment in Human Capital

Within economics, virtually all of the theoretical work on intergenerational mobility builds on the framework of Becker and Tomes (1976, 1986), in which the persistence of economic outcomes across generations is driven by investments human capital that are determined by optimizing behavior on the part of the parents. Even the two papers that have studied the role of parental labor market networks from theoretical perspective, Corak and Piraino (2010) and Magruder (2010), have used this approach. In contrast, I have ignored the decisions related to human capital investment and have instead focused on the component of earnings attributable to firm pay premiums. I refer to these effects on the firm pay premium, which are conditional on the human capital of the children, as the "direct effects." While I argue that this is most important feature to focus on, these channels are not mutually exclusive and may interact in interesting ways. I explore this possibility in this section by extending the stylized model to allow for parents to shape the human capital of their children through investments. I refer to the effects mediated by parental investment decisions as the "indirect effect" of the intergenerational transmission of employers.

I extend the model presented in Section E.1 to follow Becker and Tomes (1976, 1986) and allow parents make decisions regarding the optimal investments of the human capital of their children. For tractability I focus on the deterministic setting (z_i, η_i, ν_i, and u_i are equal to zero) and assume that children only accept job offers from their parents when the earnings benefits are positive ($c \geq 0$). Furthermore, I maintain the assumptions underlying equations E.1, E.2, and E.3. However, I do not impose the assumption stated in equation E.4, because the goal of this section is to derive the relationship between parental earnings and the human capital of the child as the result of optimizing behavior on the part of the parents. For notation, I use lower case letters to denote the log of upper case variables (for example, $h_i = log(H_i)$).

Parents care about their current period consumption, C_p, and the total financial resources of their children, which depends on the earnings of the children, Y_{ij}, and bequests, B_i, plus interest accrued at rate R. Parents solve the following problem:

$$\max_{C_p, C_i, B_i} \{v(C_p) + u(Y_{ij} + RB_i)\} \text{ subject to } C_p + S_i + B_i \leq Y_p \tag{E.10}$$

where S_i represents investment in the human capital of the children and $u(\cdot)$ and $v(\cdot)$ are continuous functions that both have the following properties: $u'(\cdot) > 0$, $u''(\cdot) < 0$ and $u'(0) = \infty$. This setup assumes that there are no credit constraints.

While there are a number of ways to generate intergenerational persistence in earnings in the absence of credit constraints, I follow Becker et al. (2018) and assume that there are complimentarities between the human capital of the parent and the production of human capital of the child. Specifically, investment translates into human capital according to the following production function, $H_i = H_p^{\sigma} S^{\alpha}$. Intuitively, this captures the fact that investments in human capital might be more productive if made by parents with higher ability. I also assume that $\alpha(1+\lambda) < 1$ which implies that there are diminishing returns to parental investment. The optimal level of investment in human capital is defined by the level at which the marginal rate of return is equal to the interest rate, $\frac{\partial Y_{ij}}{\partial S_i} = R$. Combining terms, the expression determining optimal investment can be rewritten as follows,

$$\alpha(1+\lambda) H_p^{\sigma(1+\lambda)} S_i^{\alpha(1+\lambda)-1} exp\{D_i \beta_i\} + H_p^{\sigma(1+\lambda)} S_i^{\alpha(1+\lambda)} \frac{\partial exp\{D_i \beta_i\}}{\partial S_i} = R \tag{E.11}$$

where the left-hand side represents the marginal returns to investments in human capital and the right-hand side represents the marginal returns to bequests.

To understand how the transmission of employers shapes the investment decision it is useful to consider three cases. As a starting point consider the case in which parents do not account for employer transmission when making investment decisions ($exp\{D_i\beta_i\} = 1$ and $\frac{\partial exp\{D_i\beta_i\}}{\partial S_i} = 0$). Under these conditions is it straight forward to show that the optimal level of investment is given as:

$$S_i' = [\frac{R}{\alpha(1+\lambda)}]^{1/[\alpha(1+\lambda)-1]} H_p^{\sigma(1+\lambda)/[1-\alpha(1+\lambda)]} \tag{E.12}$$

Thus, the optimal level of parental investment is increasing in the human capital of the parent and decreasing in the interest rate and it produces the following relationship between the human capital of the child and the earnings of the parent, $h_i = x + \theta y_p$, where $x = \frac{-\sigma}{1-\alpha(1+\lambda)} log(\frac{R}{\alpha(1+\lambda)})$ and $\theta = \frac{\sigma/(1+\lambda)-(1-\alpha)}{1-\alpha(1+\lambda)}$. Note that this linear relationship is exactly the one assumed in equation E.4.

How will this relationship change if parents consider the possibility of helping their child to secure a job within their employer when making investment decisions? In a step towards answering this question, consider a second case in which parents account for the fact that the transmission of employers might affect the level of earnings ($exp\{D_i\beta_i\} \neq 1$) but they do not account for the fact that investments might affect the gains associated with transmission ($\frac{\partial exp\{D_i\beta_i\}}{\partial S_i} = 0$). Under these assumptions, the optimal level of investment is defined as, $S_i'' = S_i' \times exp\{\frac{D_i\beta_i}{1-\alpha(1+\lambda)}\}$ and it follows that,

$$s_i'' - s_i' = \frac{D_i\beta_i}{1-\alpha(1+\lambda)} \geq 0 \tag{E.13}$$

Because $\exp\{D_i\beta_i\} \geq 0$ and $\alpha(1+\lambda) < 0$, this mechanism leads to an increase in parental investment. Intuitively, the transmission of employers provide access to firms that pay higher wages and thus parents who expect their children to work with them will expect a higher rate of return on investments in human capital.[54]

In the third case I allow for the investment decisions of parents to also depend on the anticipated effects of a rise in human capital on the gains of working for a parent's employer ($\frac{\partial exp\{D_i\beta_i\}}{\partial S_i} \neq 0$).[55] Because $\frac{\partial exp\{D_i\beta_i\}}{\partial S_i} < 0$, it is immediately apparent that if we were to plug in S_i'' into equation E.11 the sum of the terms of the left hand side would be less than the interest rate on the right hand side. Furthermore, under the assumption that $\gamma < 0$, both $\alpha(1+\lambda)H_p^{\sigma(1+\lambda)}S_i^{\alpha(1+\lambda)-1}exp\{D_i\beta_i\}$ and $H_p^{\sigma(1+\lambda)}S_i^{\alpha(1+\lambda)}\frac{\partial exp\{D_i\beta_i\}}{\partial S_i}$ are (weakly) decreasing in S_i, and it follows that the optimal level of investment in case 3 is less than the optimal level in case 2, $S_i''' < S_i''$. In the mechanism highlighted in this case, the intergenerational transmission of employers reduces the incentive to invest in human capital because the earnings gains associated with working the parents' employer are declining in the human capital of the child (both along intensive and extensive margins).

Taken together, the total indirect effect of the intergenerational transmission of employers on the level of parental investment is theoretically ambiguous.[56] On the one hand,

[54]Different assumptions could lead to alternative conclusions. For example, both Corak and Piraino (2012) and Magruder (2010) assume that the effect of networks on earnings is additive in levels, which leads them to conclude that parental investment decisions are unaffected by the presence of parental labor market networks.

[55]As in case 2, I continue to allow for the possibility that $exp\{D_i\beta_i\} \neq 0$.

[56]This follows from the fact that I have shown that $S_i' \leq S_i''$ and $S_i''' < S_i''$. Thus the total effect

the transmission of employers will increase the marginal returns to human capital investments by providing access to high-paying firms. On the other hand, the marginal returns are pushed down by the fact that higher-ability children are less likely to work with their parents and experience smaller earnings gains when they do.

The implications for intergenerational mobility are similarly ambiguous. For simplicity, consider the case in which $\theta(1+\lambda) < 1$ and $\phi > -\theta\gamma(1+\lambda)$, which implies that the direct impact of employer transmission will increase IGE. Because these conditions imply that $D_i\beta_i$ is increasing in parental earnings, children from high income families will tend to be the greatest beneficiaries of working with their parents (being more likely to do so and experiencing earnings gains when they do). The mechanism highlighted in case 2 will amplify the disparities between children from high and low income households while the mechanism highlighted in case 3 will mitigate these differences. The total indirect effect on intergenerational mobility will depend on which force dominates.

E.3 References

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(difference between S_i' and S_i''') will depend on whether the mechanism highlighted in case 2 or 3 is stronger.

Appendix F Quantifying and Correcting for Bias

This section defines conditions under which the parent's future employer can be used to detect and correct for violations of the exclusion restriction. Consider the following system of equations,

$$Y_i = \beta D_i + \lambda O_i + u_i \tag{F.1}$$

$$D_i = \delta Z_i + v_i \tag{F.2}$$

where i is the individual; Y_i is initial earnings at the first job; D_i is an indicator equal to one if the individual works for their parent's employer at their first job; Z_i is the hiring rate at the parent's employer; and O_i, u_i, and v_i are unobserved variables. Furthermore, assume that $\mathbb{E}[Z_i u_i] = 0$, $\mathbb{E}[Z_i v_i] = 0$, $\mathbb{E}[Z_i O_i] = 0$, and $\mathbb{E}[O_i v_i] = 0$. Thus, instrumenting for D_i using Z_i yields a consistent estimate of β.

Instead of observing Z_i, assume I actually observe Z_i^*, where

$$Z_i^* = Z_i + O_i. \tag{F.3}$$

Z_i represents factors specific to the parent's employer, while O_i represents factors common to all firms in the local labor market. Let $\hat{\beta}^{2sls}$ denote the two-stage least squares coefficient obtained by instrumenting for D_i using Z_i^*. Then,

$$plim\ \hat{\beta}^{2sls} = \beta + \frac{\lambda \sigma_O^2}{\delta \sigma_Z^2} \tag{F.4}$$

Thus, the two-stage least squares estimator is inconsistent due of the omitted variable. Furthermore, the magnitude of the bias is increasing in both λ and σ_O^2.

Now assume that I also observe the hiring rate at the parent's future employer. As with the parent's current employer, let the observed hiring rate be

$$M_i^* = M_i + O_i, \tag{F.5}$$

where $\mathbb{E}[M_i u_i] = 0$, $\mathbb{E}[M_i v_i] = 0$, $\mathbb{E}[M_i O_i] = 0$, and $\mathbb{E}[M_i Z_i] = 0$. M_i now represents factors specific to the parent's future employer and O_i is the omitted factor common to all firms in the local labor market. The key assumption is that hiring conditions at the parent's future employer have no direct impact on earnings (i.e., M_i does not appear in equation F.1). Thus, any correlation between initial earnings and hiring conditions at the parent's future employer operates through the omitted variable.

Let $\hat{\Delta}^{Y|X}$ denote the coefficient from a regression of Y on X. Then,

$$plim\ \hat{\Delta}^{D|Z^*} = \delta \frac{\sigma_Z^2}{\sigma_Z^2 + \sigma_O^2}, \tag{F.6}$$

$$plim\ \hat{\Delta}^{Y|Z^*} = \beta\delta \frac{\sigma_Z^2}{\sigma_Z^2 + \sigma_O^2} + \lambda \frac{\sigma_O^2}{\sigma_Z^2 + \sigma_O^2}, \tag{F.7}$$

and

$$plim\ \hat{\Delta}^{Y|M^*} = \lambda \frac{\sigma_O^2}{\sigma_M^2 + \sigma_O^2}. \tag{F.8}$$

Equations F.6 and F.7 correspond to the first stage and reduced form and equation F.8 corresponds to the reduced form using the hiring rate at the parent's future employer.

Under the assumption that $\sigma_Z^2 = \sigma_M^2$ (which is reasonable since the current and future employers are similar), it follows that

$$plim\ \frac{\hat{\Delta}^{Y|Z^*} - \hat{\Delta}^{Y|M^*}}{\hat{\Delta}^{D|Z^*}} = \beta. \tag{F.9}$$

In this way, I can use the parents' future employers to adjust for violations of the exclusion restriction.

A key assumption in this setup is that the hiring rate at the parent's future employer has no direct effect on earnings. To the extent that working for the future employer produces earnings gains, then this method overstates the bias, since some of the positive association between Y_i and M_i^* would be attributable to the effect of a different treatment.

Appendix G Interpreting the LATE

This section provides a theoretical argument for why the LATE may be a reasonable approximation of the ATT in my context.

Let $Y_i(d, z)$ denote the potential outcome of individual i who has the treatment status $D_i = d \in \{0, 1\}$ and instrument value $Z_i = z \in \{\underline{z}, \bar{z}\}$ where $\underline{z} < \bar{z}$. Let D_{zi} denote the treatment status of i when $Z_i = z$. Furthermore, assume the following: (Independence) $\{Y_i(D_{\bar{z}i}, \bar{z}), Y_i(D_{\underline{z}i}, \underline{z}), D_{\bar{z}i}, D_{\underline{z}i}\} \perp\!\!\!\perp Z_i$, (Exclusion) $Y_i(d, \underline{z}) = Y_i(d, \bar{z}) \equiv Y_{di}$ for $d = \{0, 1\}$, (First Stage) $\mathbb{E}[D_{\bar{z}i} - D_{\underline{z}i}] \neq 0$, and (Monotonicity) $D_{\bar{z}i} \leq D_{\underline{z}i}\ \forall\ i$. Under these assumptions, the instrumental variables estimator identifies a LATE, which is the average treatment effect for the compliers (i.e., the population for which $D_{\bar{z}i} < D_{\underline{z}i}$).

In the standard selection framework of Roy (1951), the LATE will likely depend on the specific values of the instruments, since selection into treatment is determined by a single agent who weighs the benefits (treatment effects) against the costs (instruments). To see this more formally, consider the selection model in which $D_{zi} = \mathbb{1}\{\beta_i > z\}$, where $\beta_i = Y_{1i} - Y_{0i}$ is the individual-level treatment effect. It immediately follows that the LATE, which is $\mathbb{E}[\beta_i | \underline{z} < \beta_i < \bar{z}]$, will generally depend on the values of the instruments.

In my context, selection is determined by the choices of more than one agent—the young worker and their parent's employer—and this potentially breaks the link between the instruments and the treatment effects. To see why, consider an alternative selection model in which the individual works for their parent's employer if and only if the employer makes them a job offer and they choose to accept the offer. The employer's decision to make an offer depends on the instruments and is defined as, $O_{zi} = \mathbb{1}\{\eta_i^O > z\}$. The child's decision to accept the offer depends on the benefits and is defined as, $A_{zi} = \mathbb{1}\{\beta_i > \eta_i^A\}$. Where η_i^O and η_i^A are unobserved error terms whose values are defined independent of D_i and Z_i.[57] Treatment status is then defined as, $D_{zi} = O_{zi} \times A_{zi}$.

The LATE and ATT are equal if the employer's decision to make an offer is unrelated to the child's decision to accept. Formally, if $\{\eta_i^O, \eta_i^A\} \perp\!\!\!\perp Z_i$ and $\{\beta_i, \eta_i^A\} \perp\!\!\!\perp \eta_i^O$, then

$$\underbrace{\mathbb{E}\big[\beta_i | \{\eta_i^A < \beta_i\}, \{\underline{z} < \eta_i^O < \bar{z}\}\big]}_{\text{LATE}} = \underbrace{\mathbb{E}\big[\beta_i | \{\eta_i^A < \beta_i\}, \{Z_i < \eta_i^O\}\big]}_{\text{ATT}} \tag{G.1}$$

Under these conditions, both the compliers and the individuals working for their parent's employer are a random sample of individuals who would accept an offer from their parent's employer if made one. Importantly, because of the multi-agent nature of the selection problem, the LATE and ATT may be equivalent even in the presence of selection on gains and selection bias. Appendix E develops a stylized behavioral model and provides a more detailed discussion of the intuition by focusing on a specific case of equation G.1.

G.1 References

Roy, Andrew Donald. "Some thoughts on the distribution of earnings." *Oxford economic papers 3, no. 2* (1951): 135-146.

[57] More formally, let $\eta_i^x(d, z)$ denote the potential outcome with treatment status $D_i = d$ and instrument value $Z_i = z$. Then I assume that $\eta_i^x = \eta_i^x(d, z)$ for $x \in \{O, A\}$.