The Intergenerational Transmission of Employers and the Earnings of Young Workers

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December 2021

Abstract

This paper investigates how the earnings of young workers are affected by individuals working for the same firm as their parent. My analysis of U.S. linked survey and administrative data indicates that 7 percent of young workers find their first stable job at a parent's employer. Using an instrumental variables strategy that exploits exogenous variation in the availability of jobs at the parent's employer, I estimate that working for a parent's employer increases initial earnings by 31 percent. The earnings gains are attributable to parents providing access to higher-paying firms. Individuals with higher-earning parents are more likely to work for their parent's employer and experience larger earnings gains when they do. Thus, the intergenerational transmission of employers increases the intergenerational persistence in earnings. Specifically, the elasticity of initial earnings with respect to parental earnings would be 10 percent lower if no one worked for their parent's employer.

Keywords: intergenerational mobility, labor market networks, job ladders
JEL Codes: D10, J31, J62

*E-mail: mstaiger@g.harvard.edu. I would like to thank my advisers John Haltiwanger, Sebastian Galiani, Judy Hellerstein, and Erika McEntarfer for their valuable feedback as well as Katharine Abraham, Rajshree Agarwal, Sandra Black, Sydnee Caldwell, Raj Chetty, John Coglianese, Melissa Kearney, Nuno Limão, Seth Murray, Giordano Palloni, Nolan Pope, John Sabelhaus, Claudia Sahm, John Shea, Bob Staiger, Doug Staiger, Cody Tuttle, Mateo Uribe-Castro, Daniel Vincent, John Wallis, Derek Wu, Moises Yi, Sammy Young, Emily Wiemers, and all the participants of the UMD 708 and U.S. Census Bureau seminar series. I would also like to thank the Kauffman Foundation, the Washington Center for Equitable Growth and the Economic Club of Washington, D.C. for generously providing me with funding. Any remaining errors are my own.
Disclaimer: Any analysis, opinions, and conclusions expressed herein are those of the author alone and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. See U.S. Census Bureau Disclosure Review Board bypass numbers CBDRB-: FY20-002, FY20-186, FY20-CED006-0020, FY20-CED0006-0025, FY21-CES011-001, FY21-242, and FY2022-CES010-005.

1 Introduction

Are labor market networks an important determinant of intergenerational mobility? Research on intergenerational mobility typically attributes differences in earnings by family background to differences in human capital (Mogstad and Torsvik, 2021). However, family connections in the labor market may also play a role. Indeed, a majority of jobs are found through a social contact (Ioannides and Loury, 2004) and the firm to which a worker matches is an important determinant of earnings (Manning, 2011). Despite their potential importance, it is not well understood how family connections in the labor market shape the intergenerational persistence in earnings.

My paper seeks to understand how the intergenerational persistence in earnings would change if firms were prohibited from hiring the children of current employees. My results shed light on one type of labor market network: Connections at the parent's current employer. Previous research finds that working for a parent's employer, which I refer to as the *intergenerational transmission of employers*, is not uncommon (Kramarz and Skans, 2014), particularly for individuals with high-income parents (Corak and Piraino, 2011). However, these descriptive patterns have ambiguous implications for intergenerational mobility. I advance the literature by estimating the causal effect of working for a parent's employer on earnings and use the estimates to quantify how the intergenerational persistence in earnings would change if no one worked for their parent's employer. I focus on the first stable job, which has important consequences for an individual's career.[1]

The intergenerational transmission of employers will increase the intergenerational persistence in earnings if individuals with higher-earning parents benefit more. However, the benefits–which depend on the likelihood and earnings consequences of working for a parent's employer–could be increasing or decreasing in parental earnings. On the one hand, higher-earning parents may be better able to provide access to high-paying jobs. On the other hand, individuals from disadvantaged backgrounds may be more reliant on their parents to find a decent-paying job. Which force dominates is an empirical

[1]Both theoretical (e.g., Jovanovic and Nyarko, 1997) and empirical (e.g., Von Wachter and Bender, 2006; Khan, 2010; Arellano-Bover, 2020) evidence suggests that early career experiences can have a large and persistent effect on earnings. Section 3.1 presents the definition of the first stable job.

question, which I answer by combining descriptive statistics of how common it is to work for a parent's employer with causal estimates of the earnings consequences of doing so.

I begin by showing that it is not uncommon for an individual to work for their parent's employer. I link survey data from the 2000 Decennial Census to administrative data from the Longitudinal Employer-Household Dynamics (LEHD) program and study 10 recent cohorts. I find that 7 percent of individuals work for a parent's employer at their first stable job, and 29 percent do so at some point between the ages of 18 and 30.[2] A number of pieces of evidence suggest that these patterns are driven by parents acting as a social contact to influence the job search or hiring process. For example, industries where it is most common to work for a parent's employer are the same industries where it is most common to find a job through a social contact. Also, individuals are significantly more likely to work for their parent's current employer compared to a past or future employer.

Next, I find large earnings benefits of working for a parent's employer. Estimating causal effects is difficult because individuals who work for a parent's employer likely differ from those who do not. In an ideal experiment, I would prohibit some firms from hiring the children of current employees and use this random assignment as an instrument. 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. The key assumption is that the hiring rate is related to the earnings of the child only through the effect on working for the parent's employer. My empirical model includes two-way fixed effects for the parent's employer and the local labor market to account for the possibility that the hiring rate could be related to time-invariant differences across firms or time-varying local labor market conditions. To provide initial support for the validity of the empirical strategy, 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 hiring conditions in earlier years and at other similar firms. I find that individuals earn 31 percent more at their first stable job when working for their parent's employer relative to their next best option.

[2]My estimates are broadly consistent with existing evidence from the United States (Stinson and Wignall, 2018), Canada (Corak and Piraino, 2011), and Denmark (Bingley et al., 2011).

These earnings gains appear to be explained by parents providing access to higher-paying firms. Following 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 33 percent more, which is virtually 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, 2003). 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. A narrative consistent with my results is that there is a group individuals who, without help from their parents, have limited labor market options and would end up at low-paying firms such as a fast food restaurant. However, their parents provide access to jobs at better-paying firms such as a manufacturing plant. Indeed, access to jobs in higher-paying industries explains 75 percent of the effect on individual earnings.

Lastly, I find that 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. I develop a methodology that uses the descriptive and causal estimates to quantify the difference between observed measures of the intergenerational persistence in earnings and measures that correspond to a counterfactual world in which no one worked for the employer of a parent.[3] I find that the elasticity of the initial earnings of an individual with respect to the earnings of their parents would be 10 percent lower if no one worked for the employer of a parent. My results are consistent with Eliason et al. (2019) and San (2020), who also find that parents provide access to higher-paying firms. In contrast to these two papers, I estimate the causal effect on earnings and quantify implications for the intergenerational persistence in earnings.[4]

Non-Black males with high-earning parents are the largest beneficiaries of working

[3]Corak and Piraino (2011) and Stinson and Wignall (2018) estimate a standard 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. My methodology is an improvement because it accounts for nonrandom selection into a parent's employer, whereas their approach does not.

[4]Eliason et al. (2019) and San (2020) study how parental connections affect overall earnings inequality and the earnings gap between ethnic groups, respectively.

for a parent's employer. Consistent with Chetty et al. (2020), I find that, conditional on parental earnings, Black males have lower expected earnings than White males. On average, the intergenerational transmission of employers explains 10 percent of this conditional Black-White gap in initial earnings. The intergenerational transmission of employers disproportionately benefits sons of high-earning parents but daughters of low-earning parents. On average, daughters benefit more than sons, and the gender pay gap in initial earnings would be 4 percent larger if no one worked 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 high-income backgrounds benefit the most 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. I show that parents also directly affect the labor market outcomes of their adult children by using their connections to provide access to jobs. Because parents may provide access to jobs outside of their current employer, my results raise the possibility that family connections, more broadly defined, could be an important determinant of intergenerational mobility in the United States.

My conclusions depend on the estimates of the earnings consequences, whose credibility is supported by a number of additional analyses. Existing evidence of the earnings consequences of working for a parent's employer–or, more generally, 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.[5] Reassuringly, I find that the correlation between the hiring rate and the outcomes of the child is strongest within industries in which the use of social contacts is most common. I also show that the results are robust

[5]Kramarz and Skans (2014) control for observable differences between children who do and do not work with their parents and find negligible earnings benefits in Sweden. Stinson and Wignall (2018) use data from the United States and find large benefits using an individual fixed effects estimator. While estimating the causal effect of finding a job through a social contact has proven difficult, a number of recent papers establish that social contacts can lead to employment and earnings gains (e.g., Beaman, 2012; Cingano and Rosolia, 2012; Schmutte, 2015; Caldwell and Harmon, 2019).

to controlling for the hiring conditions at the parent's past and future employers, which helps to address remaining concerns related to local labor market conditions. And while firms might offer higher wages when hiring more intensively, the results are robust to controlling for the earnings of other new hires, the earnings growth of existing employees, and the employment growth rate at the parent's employer. Lastly, an event study design, which relies on distinct assumptions, yields similar results: Workers who join their parent's employer enjoy a large increase in earnings driven by the firm pay premium.

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 (e.g, Schmeider et al., 2020; Lachowska et al., 2020) study workers who separate for exogenous reasons and find that earnings changes are related to changes in firm pay premiums. 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 describes how common it is to work for a parent's employer. Section 5 estimates the earnings consequences. Section 6 investigates implications for the intergenerational persistence in earnings. Section 7 concludes.

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 of the life-time 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 measures of life-time 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. This poses potential challenges to estimating the earnings benefits. Section 5.2 discusses this point in more detail.

Intuitively, the intergenerational transmission of employers will increase the intergenerational persistence in earnings if the average benefits are increasing in parental earnings (i.e., $\mathbb{E}[D_i\beta_i \mid y_p]$ is increasing in y_p). By iterated expectations, 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): $\mathbb{E}[D_i\beta_i] = \mathbb{E}[D_i]\mathbb{E}[\beta_i \mid D_i = 1]$. Thus, my goal is to estimate how these two objects vary with parental earnings, which I do in Sections 4 and 5.

I quantify how the the intergenerational transmission of employers affects the intergenerational elasticity of earnings (IGE), which is a common measure of the intergenerational persistence in earnings and 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 and use the following approximation:

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

where r_p is the percentile rank of parental earnings. The approximation relies on the insight that 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: $\mathbb{E}[D_i\beta_i y_p|r_p] \approx \mathbb{E}[D_i\beta_i|r_p]\mathbb{E}[y_p|r_p]$. I validate the methodology by showing that estimates of the IGE based on the micro data are virtually identical to estimates derived from the approximation. See Appendix C for details. Equations 2 and 3 illustrate that the intergenerational transmission of employers will increase the IGE (i.e., the covariance term will be positive) if individuals with higher-earnings parents are more likely to work for a parent's employer and experiences larger earnings gains when they do.

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 D 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-

[6]Magruder (2010) and Corak and Piraino (2012) 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.

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 at a parent's firm, which has theoretically ambiguous implications for the intergenerational persistence in earnings. On the one hand, working for a parent's employer increases the marginal returns to human capital investments by providing access to higher-paying firms. On the other hand, the marginal returns decline because higher-ability individuals are less likely to work for their parent's employer and benefit less when they do. Thus, parental investment decisions could either amplify or dampen the direct effect of the intergenerational transmission of employers on the intergenerational persistence in earnings. The 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 Hundred Percent Census Edited File (HCEF), which measures the relationship between parents and children who are living together in 2000 and (2) data from the LEHD program to measure labor market outcomes of both parents and their children between 2000 and 2016. The HCEF contains all responses from the 2000 Decennial Census Short Form and, in principle, includes all individuals living in the United States in 2000.[7] The LEHD is an employer-employee linked dataset produced by the U.S. Census Bureau and 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. The earnings records in the LEHD capture roughly 96 percent of private non-farm wage and salary employment in the United States (Abowd et al. 2009). The LEHD covers most jobs, but a notable exception is self-employment. While previous work,

[7]In practice, some individuals are not surveyed in the 2000 Decennial Census and non-respondents are more likely to be minorities or lower-income households. See Appendix B.1 for details.

such as Dunn and Holtz-Eakin (2000), documents strong patterns of intergenerational persistence in self-employment, I focus on more formal employer-employee relationships.

The sample frame is defined based on the HCEF and includes children who are living with their parents in 2000 and who were born after June 30th of 1982 and before July 1st of 1992.[8] The cohorts were chosen so as to focus on a set of individuals who are young enough to likely have lived with their parents in 2000–the oldest individual in the sample was 17 years old when data collection for the 2000 Decennial Census took place–but old enough to have likely entered the labor market by 2016–the youngest individual in the sample was 24 years old by the end of 2016. There are approximately 37 million individuals in the sample frame. See Appendix B.1 for details.

I implement two sets of sample restrictions. First, I require that the individuals and their parents found in the HCEF can be linked to the LEHD. In order to account for nonrandom attrition from the sample due to issues associated with linking records across the two data sources, I construct sample weights and use them to produce all descriptive statistics. Second, I drop cases in which the earnings of the children or parents are likely to be affected by coverage issues in the LEHD. Of the 37 million children in the sample frame, approximately 21 million (57 percent) meet the two sets of restrictions. Based on these sample restrictions and the source of earnings data, my analysis should be viewed as representative of working families, a category which excludes very low income households (approximately the bottom 10 percent of households) and very high income households (approximately the top 1 percent of households). See Appendix B.2 for details.

3.1 Measurement of Key Variables

I use observed earnings to identify when individuals enter the labor market. Conceptually, I define entry as the first period in which work becomes the primary activity. My empirical definition of entry is the first quarter in which the individual earns at least $3,300 per quarter–which approximately corresponds to working 35 hours per week at the federal

[8]Over 90 percent of individuals within this age range live with a parent in 2000. Children are individuals whose relationship to the household head is: son/daughter, adopted son/daughter or step son/daughter. I exclude individuals living in U.S. territories in 2000.

minimum wage–in the current and two consecutive quarters, and receives positive earnings from the same employer for those three quarters.[9] I refer to this employment spell as the first stable job. Approximately 80 percent of individuals (17 million individuals) that meet the sample restrictions have entered the labor market by the end of 2016.

There are many possible ways to define entry, but three pieces of evidence suggest that my approach is reasonable.[10] First, individuals experience a dramatic and persistent increase in earnings upon entry. Average quarterly earnings in the three years prior to entry is $1,258 compared to $6,597 in the three years after entry. Figure A.1 provides more detailed evidence by plotting the average quarterly earnings in the three years before and after entry. Second, the age of entry generally lines up with common perceptions of when individuals start their careers. For example, 89 percent of children enter the labor market between ages 18 and 26. Figure A.3 depicts the distribution of the age at which the children enter the labor market and compares this distribution to results based on an analogous measure constructed from the National Longitudinal Survey of Youth 1997 cohort (NLSY97).[11] The timing of entry is quite similar in the two data sources. Furthermore, 83 percent of workers in the NLSY97 data are not enrolled in school at the time of labor market entry, which suggests that my measure is not primarily picking up jobs held by students. Third, the first stable job is indeed stable as the average duration of employment at the first stable job exceeds two years.

I construct a measure of the lifetime earnings of the parents. 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), this approach problematic when using the LEHD since there is no way to distinguish between zero earnings and missing data.[12] Instead, I construct a measure of lifetime parental earnings by estimating a regression

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

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

[11] The analogous measure constructed from the NLSY97 is the first time an individual works at least 35 hours for 36 consecutive weeks (or three quarters). An alternative approach is to focus on labor market outcomes after all schooling is completed and I also present results for this definition of entry.

[12] Earnings data could be missing either because a state may not report to the LEHD in a given time period or because the job may not be covered in the LEHD frame.

of quarterly earnings on an individual fixed effect and a third degree polynomial in age within cells defined by the interaction between state of residence in 2000, sex, and race.[13] The measure of the lifetime earnings of each parent is the imputed value of earnings between ages 35 and 55. For one-parent households, parental earnings is the lifetime earnings of the parent. For two-parent households, parental earnings is the average of the lifetime earnings of both parents. The parental earnings percentile ranks are calculated within each cohort of children using sample weights.[14] See Appendix B.4 for details.

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] To simplify the discussion, 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. To reduce concerns related to measurement error, my main analysis focuses on the firm, but in some instances I use the establishment impute to measure the location of the job within a state.

4 Intergenerational Transmission of Employers

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 through fifth columns present results for individuals whose first stable job is at the employer of neither parent, the secondary earner, both parents, or the primary earner, respectively.[16] 7 percent of individuals work for a parent's employer at their first stable job and these individuals tend to stay at their first stable job longer, are less (more) likely to be employed

[13]The data are a panel measured at a quarterly frequency that include all strictly positive earnings records between 2000 and 2016 for the parents in the sample. Quarters with zero earnings are not included in the sample. I further restrict the panel to observations when the individuals are between the ages of 30 and 60 and drop individuals that have fewer than 4 quarters of strictly positive earnings over the entire time period. Parents not included in this sample are assumed to have zero lifetime earnings.

[14]Cohorts consist of individuals born between July 1st of year t and June 30th of year t+1.

[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 majority of earnings in that quarter.

[16]The primary earner is defined as the parent with the greatest earnings in the year prior to the quarter in which the child entered the labor market.

Table 1: Summary Statistics

		First Job at the Employer of			
	Full Sample	Neither Parent	Secondary Earner	Both Parents	Primary Earner
Demographics					
male	0.50	0.49	0.46	0.61	0.60
White non-Hispanic	0.79	0.78	0.83	0.84	0.79
Black non-Hispanic	0.08	0.08	0.05	0.02	0.07
Asian non-Hispanic	0.02	0.02	0.02	0.04	0.02
Hispanic	0.09	0.09	0.09	0.08	0.09
born in United States	0.97	0.97	0.97	0.96	0.97
parents are married	0.78	0.78	0.96	0.98	0.78
parental earnings / 1,000	51.42	51.26	53.15	67.28	51.28
First Stable Job					
age when job began	20.94	21.00	20.10	19.81	20.08
duration of job (quarters)	10.07	9.77	13.40	18.03	13.67
log of quarterly earnings	8.74	8.74	8.62	8.70	8.72
skilled services	0.37	0.37	0.45	0.31	0.37
unskilled services	0.46	0.47	0.36	0.31	0.28
manufacturing/production	0.18	0.16	0.19	0.39	0.36
500≤firm size	0.40	0.40	0.47	0.23	0.40
located in urban area	0.77	0.78	0.71	0.71	0.72
Sample Size					
proportion of full sample		0.93	0.02	0.01	0.04
observations	17,010,000	15,830,000	298,000	137,000	746,000

Notes: The table presents the average value of the variable defined in the row. Column 1 presents results for the full sample and columns 2-5 present results for the sample of children who, at their first stable job, work for the employer of neither parent, the secondary earner, both parents, or the primary earner, respectively.

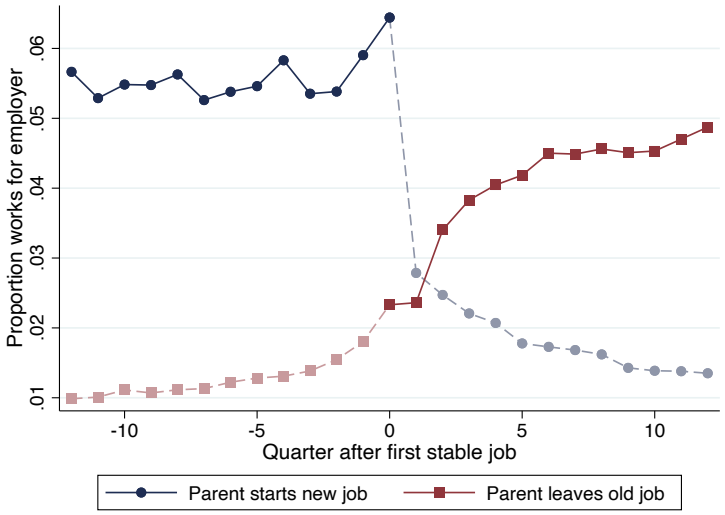
in the unskilled service (manufacturing/production) sector, and earn slightly less.[17]

One interpretation is that parents are a social contact and influence the hiring or job search process. This would be consistent with Loury (2006), who finds that 10 percent of young men found their current job through a parent, as well as with the finding that informal search methods are used frequently and affect where individuals work (e.g., Bayer et al., 2008; Hellerstein et al., 2011). However, there are other possible interpretations.

Individuals are much more likely to work for their parent's employer relative to other similar firms. Table 1 indicates that individuals who work for a parent's employer are no more likely to work for large firms and over 70 percent of these individuals are located in urban areas. This suggests that the tendency to work for a parent's employer is

[17]I group two-digit North American Industry Classification System (NAICS) industry codes into three sectors: unskilled services, skilled services, and manufacturing/production. See Appendix B.5 for details.

Figure 1: Working for the Parent's Current, Past, and Future Employer



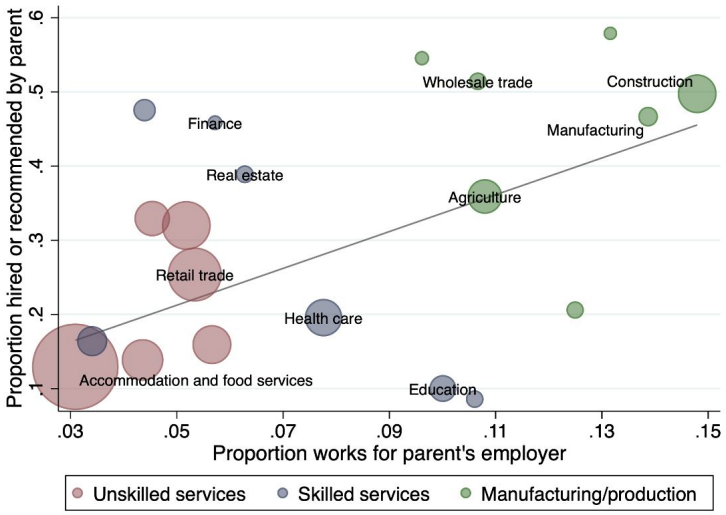
Notes: The circle (square) markers represent the sample of parents who start working for (separate from) a firm x quarters after their child finds their first stable job, where x is defined by the horizontal axis. Each point is the proportion of individuals who work for this firm. The darker shade identifies the sample in which the parent is still working for this firm at the time their child begins their first stable job.

not driven by cases in which a single employer dominates a local labor market. I also calculate the proportion of individuals who work for a firm in the same size category and in the same *neighborhood* (census tract) or *local labor market* (commuting zone and three-digit industry).[18] Individuals are 43 times more likely to work for the primary earner's employer compared to another firm in the neighborhood. Similarly, individuals are 70 times more likely to work for the primary earner's employer compared to another firm in the same local labor market. See panel A of Table 2.

Individuals are also more likely to work for the parent's current employer than past or future employers, which casts doubt on the possibility that individuals work for their parent's firms simply because they have similar skills or preferences. I identify parents who begin a new job or leave an old job within three years of their child entering the labor market. Figure 1 plots the proportion of children who work at that employer against the quarter in which their parent started or left the job. Parents have 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 (left) the firm before (after) their child entered the

[18]Firm size categories are: small (employees$<$ 50), medium (50 $\leq$employees$<$ 500), and large (500 $\leq$employees).

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.

labor market; this is depicted by the darker shading. Individuals are about 3 percentage points more likely to work for a firm if their parent started (stopped) working there four quarters before (after) compared to four quarters after (before) the child entered the labor market.[19] The fact that the child is more likely to work for these past and future employers of the parent relative to other employers in the same local labor market could be explained by the presence of other family connections at these firms.

The likelihood of working at 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 strongly positive (regression coefficient is 2.5 with a p-value of .001).[20]

The results suggest that individuals tend to work for their parent's firms because their parents act as social contacts. I am unable to determine precisely how parents

[19]The patterns for parents who separate are not as stark at time zero, possibly because these parents are separating from firms that lack good job opportunities.

[20]The 2008-2017 waves of the NLSY97 ask individuals if they found their current job through a friend or family. Figure A.4 shows a similarly strong industry-level correlation between this alternative measure and the proportion of individuals who work for their parent's firm.

provide access to jobs but the benefits to their child, as opposed to the employer, are more easily observed. Figures A.5 and A.6 illustrate that the industries in which working for a parent's employer is more common tend to offer higher wages and exhibit higher rates of unionization. Table A.1 links responses to the American Community Survey to a subset of records and shows that, conditional on parental earnings, individuals with lower levels of educational attainment are more likely to work for a parent's employer. Table A.2 shows that, conditional on the age of entry, working for a parent's employer is more likely when unemployment is high.[21] This is suggestive evidence that parents use their connections to help children with limited labor market opportunities.

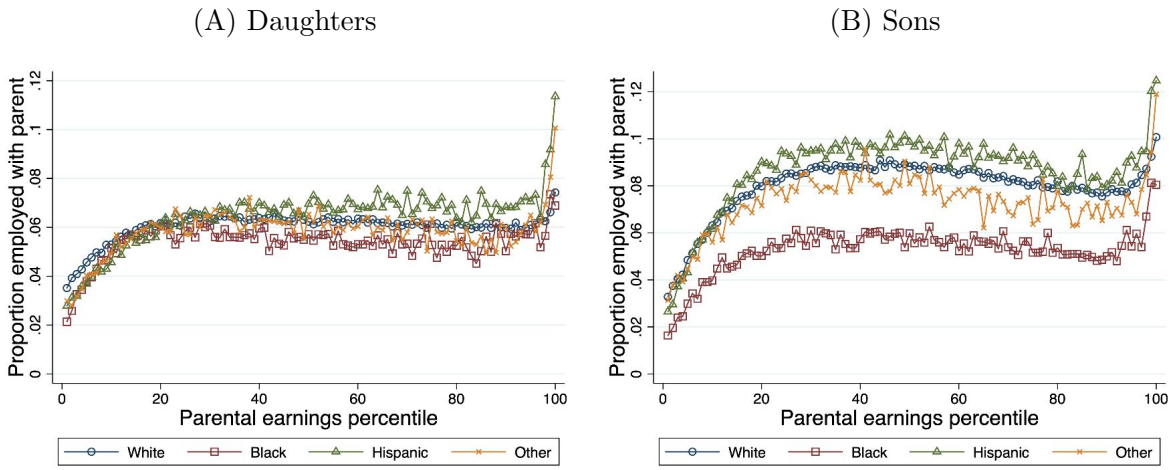
Individuals with higher-earning parents are more likely to work for their parent's employer, although the relationship is nonlinear.[22] Figure 3 presents the proportion of individuals who work for the employer of either parent at their first stable job by parental earnings, sex, and race/ethnicity. There is a strong positive association between the likelihood of working for a parent's employer and parental earnings in the bottom quintile and top decile of the parental earnings distribution and a weak (slightly negative for sons) association elsewhere. For daughters, the patterns are similar across the race/ethnicity categories. In contrast, Black sons are substantially less likely to work for the employer of a parent relative to other groups throughout the parental earnings distribution.

A plausible explanation for why children with higher-earnings parents are more likely to work for their parent's employer is that their parents are more likely to be employed and hold a position of authority within their employer. The percent of primary earners that are employed when their child enters the labor market rises steeply from 55 percent to 84 percent between the 1st and 20th percentiles of the parental earnings distribution and eventually plateaus at 94 percent. The percent of primary earners whose earnings are in the top percentile within their firm rises gradually from 4 percent to 14 percent between the 1st and 90th percentiles of the parental earnings distribution and then rises

[21] I condition on the age of entry because older individuals are less likely to work for the employer of a parent and average age of entry is older later in the sample period (when unemployment is higher).

[22] Sons are more likely to work for the employer of a parent at their first stable job relative to daughters, with 7.8 percent of sons doing so compared to 6.0 percent of daughters. Individuals are about twice as likely to work with the parent of the same sex (see Table 3).

Figure 3: Intergenerational Transmission of Employers



Notes: The figures plot the proportion of individuals whose first stable job is at the employer of either parent. Statistics are reported separately by sex, the percentile of parental earnings, and race/ethnicity. All statistics are calculated using sample weights.

steeply to 41 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.[23]

The nonlinear relationship between the intergenerational transmission employers and parental earnings is also present in longer-run measures. Within the sample of individuals who turn 30 by the end of 2016, 28 percent of daughters and 29 percent of sons work for the employer of a parent between the ages of 18 and 30. These estimates are consistent with Stinson and Wignall (2018), who find that 22 percent of sons have shared an employer with their father by the time they are 30 years old. Figure A.8 presents how these estimates vary across the parental earnings distribution and illustrates that the nonlinear patterns observed at the first stable job are replicated in these longer-run measures.

5 Earnings Consequences

There are two channels through which working for a parent's employer could affect wages. First, parents may provide access firms that pay all workers higher wages; possibly by

[23]Figure A.7 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.

sharing information about job openings as in Mortensen and Vishwanath (1995). 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 the causal effect 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 if they are searching for a job in labor markets with higher levels of unemployment. These patterns suggest that a naive comparison between individuals who do and do not work for their parent's employer would understate the earnings benefits. More generally, an empirical strategy that identifies causal parameters must account for the possibility that the characteristics and outside options of individuals are related to the probability that they end up working for their parent's employer.

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 using the hiring rate at the parent's employer measured just before their child 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. There are two immediate concerns. First, the hiring rate at the parent's employer could be correlated with local labor market conditions that directly affect the earnings of the child. Second, the hiring rate could also be correlated with characteristics of the parent's employer that are correlated with the outcomes of the child.

I include two-way fixed effects in the empirical model to address these two concerns.

Specifically, I estimate the following equation via two-stage least squares,

$$\begin{aligned} D_i &= \pi^1 + \gamma Z_{j(p)t-1} + X_i\Gamma^1 + \delta^1_{j(p)} + \lambda^1_{l(j(p),t)} + u_i \\ y_{ij} &= \pi^2 + \beta_i D_i + X_i\Gamma^2 + \delta^2_{j(p)} + \lambda^2_{l(j(p),t)} + v_i \end{aligned} \tag{4}$$

where t is the quarter in which the individual starts their first stable job; $\delta_{j(p)}$ 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 state, two-digit industry, and calendar year; X_i is a vector of demographic characteristics; and u_i and v_i are regression residuals, which are clustered at the level of the parent's employer.[24] The instrument, $Z_{j(p)t-1}$, is the average quarterly hiring rate at the parent's employer in the four quarters prior to the quarter in which the child begins their fist stable job. By taking the average hiring rate over the preceding four quarters, I avoid measuring the hiring rate in the quarter in which the child starts their first job and ensure that the hiring rate is not affected by seasonal variation.

I implement two sample selection criteria when estimating equation 4. First, I require that the parent is employed with at least one year of tenure at the time the child enters the labor market. The tenure restriction helps address concerns that children and parents might be responding to common economic shocks affecting firms in the local labor market. Second, I drop singleton observations because they do not contribute to the identification of the model and retaining them would bias estimates of the standard errors.[25]

The identifying variation comes from the difference across firms in the differences in the hiring rate over time. The first stage compares individuals whose parents work for the same employer 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 employer is hiring less, and whether this difference is larger relative to individuals whose

[24]The vector of demographic characteristics includes: the log of the annual earnings of the parent in the year prior to entry; a fixed effect for the cohort of the child; and an interaction between the sex of the child and their race (White, Black, Native American, Asian, Pacific Islander, and other), ethnicity (Hispanic and non-Hispanic), and an indicator equal to one if born in the United States.

[25]A singleton refers to an observation which has a unique value of a fixed effect. If there only existed one observation for a given parent's employer, then the outcome would be perfectly predicted by the employer fixed effect and this observation would not contribute to the identification of any other coefficients.

parents' employer experiences a smaller decline in hiring.

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.[26] 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).

Column 3 of Table 2 illustrates that the hiring conditions at the parents firm are strongly related to outcomes of the child. Panels B and C present estimates from the first-stage and reduced-form specifications, respectively. The first stage implies that a 10 percentage point increase in the hiring rate at the parent's employer leads to a 1.2 percentage point increase in the likelihood that the child works there. The estimate is highly significant with an associated F-statistic of 1,434.[27] Similarly, a 10 percentage point increase in the hiring rate leads to a 3.2 percent increase in initial earnings.[28]

In contrast to contemporaneous hiring conditions at the parent's firm, hiring conditions in earlier years and at other similar firms are unrelated to outcomes of the child. Columns 1 and 2 of Table 2 present the first-stage and reduced-form estimates for specifications in which I replace all variables related to the parent's employer with variables

[26] 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.

[27] To assess magnitude of the first stage, note that a one standard deviation increase in the residualized hiring rate leads to an 8 percent increase in the probability of working for the parent's employer.

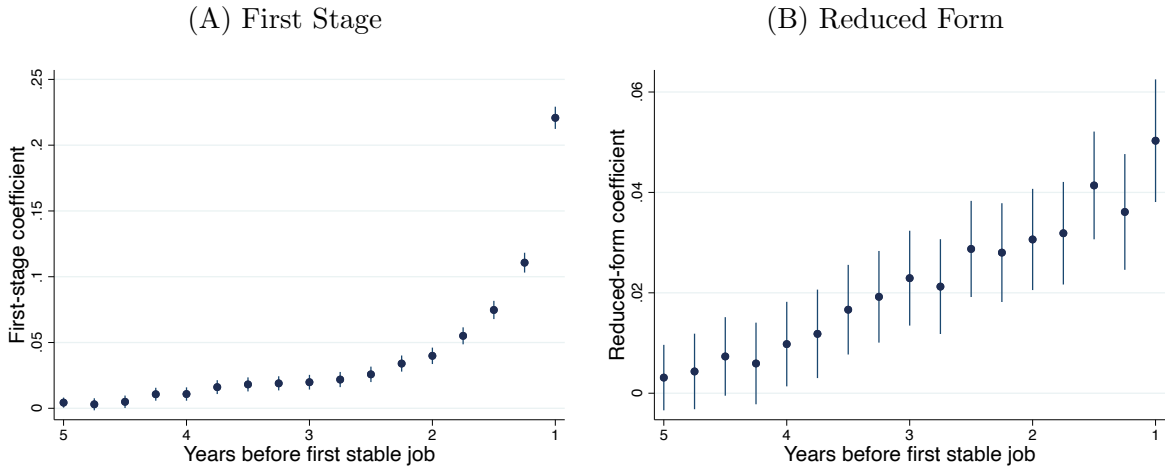
[28] Initial earnings are measured during the first full-quarter of employment at the first stable job. A full-quarter employment spell occurs when a worker receives strictly positive earnings from the same employer in the current, previous and subsequent quarter and variation in earnings is less likely to be driven by differences in the duration of an employment spell within a quarter. The definition of the first stable job implies that every worker experiences a full-quarter employment spell in the second quarter at their first stable job.

Table 2: Hiring Rate at Other Firms

	Placebo Firms		
	Neigborhood	Labor Market	Parent's Employer
	(1)	(2)	(3)
A. Proportion			
works at same employer	0.0013	0.0008	0.0561
B. First Stage			
hiring rate	0.0003**	0.0002*	0.1187***
	(0.0001)	(0.0001)	(0.0031)
F-statistic	10	6	1,434
C. Reduced Form			
hiring rate	-0.0016	0.0018	0.0364***
	(0.0015)	(0.0015)	(0.0033)
observations	10,470,000	10,530,000	11,460,000

Notes: Column 3 presents results for the employer of the parent who is the primary earner. The results in columns 1 and 2 are estimated by replacing all variables associated with the parent's employer with the placebo firm. The placebo firm is from the same neighborhood (size cateogry and census tract) and local labor market (size cateogry, three-digit industry, and commuting zone) as the parent's firm for columns 1 and 2, respectively. Standard errors are presented in parentheses.
*** p≤0.001, ** p≤0.01, * p≤0.05

Figure 4: Hiring Rate in Earlier Years



Notes: Panels A and B present estimates from the first-stage and reduced-form specifications, respectively. The horizontal axis defines the time at which the hiring rate at the primary earner's employer is measured, which ranges from one to five years before the start of the first stable job. 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 job. The vertical bars denote the 95 percent confidence intervals.

related to a placebo firm drawn from the same neighborhood and local labor market, respectively. The hiring rate at the placebo firms is unrelated to the earnings of the child, which provides initial evidence that time-varying local labor market conditions do not bias my results. Figure 4 plots estimates from different variants of the first-stage and reduced-form specification in which the hiring rate is measured one to five years prior to when the child begins their first stable job. Hiring conditions immediately before the child enters the labor market are strongly correlated with the outcomes of the child whereas hiring conditions five year before are unrelated to the outcomes of the child.

5.1 Effect on Initial Earnings

Table 3 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 6 indicates that working for the primary earner's employer leads to a 31 percent increase in initial earnings.[29] For context, the standard deviation of initial log earnings among individuals who do not work for their parent's employer is 0.427. Column 5 shows that working for the secondary earner's employer leads to a similarly large increase in earnings.[30] Columns 1 through 4 present estimates for subsamples defined by the sex of the child and the sex of the parent. While individuals are more likely to work for the parent of the same sex, they experience similarly large earnings gains regardless of which parent they work with. The magnitude of the effects are similar across all subgroups but the effects for the primary earner are the most precisely estimated. I therefore focus on the primary earner in the subsequent analyses.

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 twice as large as the union wage

[29]Regressing log initial earnings on an indicator for working for a parent's emlpoyer and controlling for the same set of covairates and fixed effects yields a point estimate (standard error) of 0.032 (0.002). These estimates could be negatively biased if low-ability children with limited labor market opportunities are more likely to work for their parent's employer. It is plausible that these estimates would suffer severely from bias since the data lack meaningful measures of human capital.

[30]In order to avoid estimating effects of working with the primary earner, I limit the sample to cases in which the secondary earner does work work at the same employer as the primary earner.

Table 3: Effect of Working for Parent's Employer on Initial Earnings

	Fathers		Mothers		Secondary Earner	Primary Earner
	(1)	(2)	(3)	(4)	(5)	(6)
works for parent's employer	0.522***	0.326***	0.281***	0.336***	0.291***	0.307***
	(0.102)	(0.039)	(0.056)	(0.075)	(0.081)	(0.029)
first-stage F-statistic	388	761	371	392	365	1,434
proportion works for parent's employer	0.019	0.052	0.047	0.036	0.042	0.056
children in sample	daughters	sons	daughters	sons	all	all
observations	3,511,000	3,691,000	4,150,000	4,168,000	4,447,000	11,460,000

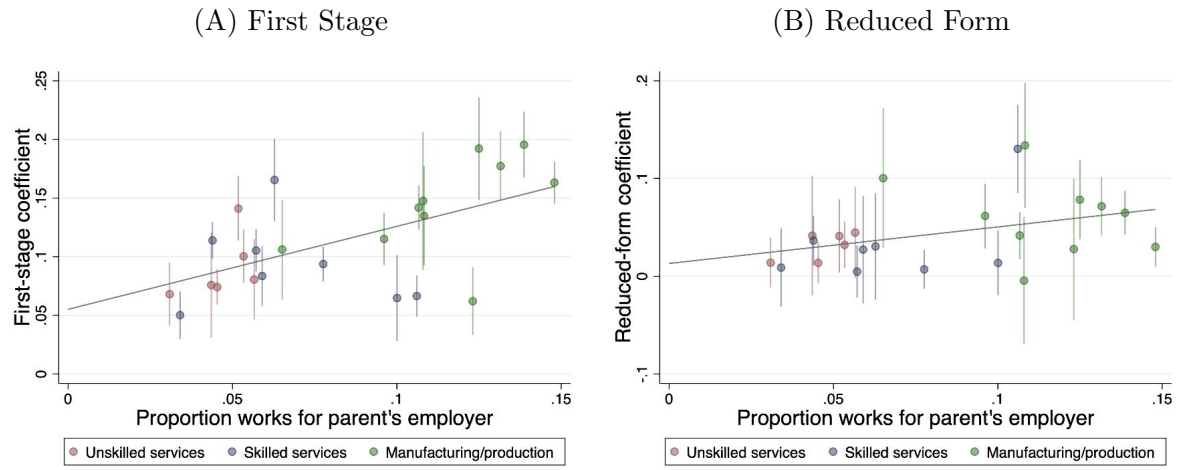
Notes: Each column presents estimates from a separate regression in which the two-stage least squares specification is estimated on a different sample. The column headers define the parent and the second to last row defines the children included in the sample. The outcome variable in all columns is the log of the first full-quarter earnings at the first stable job. Standard errors are presented in parentheses. *** p≤0.001, ** p≤0.01, * p≤0.05

premium (Farber et al., 2018) and about two standard deviations of the inter-industry wage premium (Katz and Summers, 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 school educated workers–which is about 68 log points (Acemoglu and Autor, 2011). In the context of the United States, Stinson and Wignall (2018) 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 22 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. (2019), who use more recent data from Sweden.

5.2 Validity of the Instrumental Variables Strategy

The results ought to be muted for parents who work for firms that are unlikely to hire through social contacts. Motivated by Figure 2, which shows that there is substantial variation in the use of social contacts by industry, I estimate an alternative specification and interact the hiring rate at the parent's employer with that firm's industry. Figure

Figure 5: Heterogeneity by Parent's Industry



Notes: The figures present estimates from a modified version of the (A) first-stage and (B) reduced-form specifications in which the hiring rate is interacted with the industry of the primary earner's employer. Each point represents the coefficient on the interaction term and the horizontal axis represents the proportion of individuals in a given industry who work for a parent's employer. The vertical bars denote the 95 percent confidence intervals.

5 plots the coefficients on the interaction terms against the proportion of individuals employed in that industry who work for a parent's employer. The correlation between the hiring rate at the parent's employer and the outcomes of the child is significantly stronger for parent's employed in industries where it is more common to work for a parent's employer.[31] Figure A.9 presents analogous results from the second stage. There is no similar gradient and the 95 percent confidence interval for 20 of the 24 estimates contains the main point estimate from column 6 of Table 3. These results support the plausibility of the independence assumption. If the hiring rate were related to the earnings of the child primarily through some other channel–e.g., local labor market conditions– then there would be no clear reason why the reduced form would be stronger in industries in which the use of social contacts is more common.

The results are robust to controlling for hiring conditions at past or future employers of the parent. I identify primary earners who have a past employer that still exists

[31]Regressing the point estimates against the proportion of individuals who work for the parent's employer yields a positive coefficient significant at the 10 percent level for both the first stage and the reduced form. I also estimate a model in which, instead of using industry interactions, I interact the hiring rate with the industry-level measure of the proportion of individuals who work for the parent's employer. The interaction term is significant at the 0.1 percent for both the first stage and reduced form.

Table 4: Controlling For Hiring Rates at Past and Future Employers

	Past Employers			Future Employers		
	(1)	(2)	(3)	(4)	(5)	(6)
works for parent's employer	0.361***	0.361***	0.359***	0.375***	0.362***	0.355***
	(0.062)	(0.068)	(0.068)	(0.075)	(0.081)	(0.081)
hiring rate at other firm			0.010*			0.015***
			(0.005)			(0.004)
first-stage F-statistic	417	400	399	346	298	297
fixed effects for other firm		X	X		X	X
observations	3,661,000	3,661,000	3,661,000	2,402,000	2,402,000	2,402,000

Notes: The table presents estimates from the baseline specifciation and specifications that add controls for the hiring rate, local labor market fixed effects, and firm fixed effects for the past and future employer of the primary earner. Within columns 1-3 and 5-6 the sample is restricted to cases where the parent had a past or future employer, respecitvely. The outcome variable in all columns is the log of the first full-quarter earnings at the first stable job. Standard errors are presented in parentheses. *** p≤0.001, ** p≤0.01, * p≤0.05

when their child enters the labor market. Columns 1-3 of Table 4 present estimates from the baseline specification as well as specifications that control for the contemporaneous hiring rate, local labor market fixed effects, and firm fixed effects associated with the past employer. Controlling for the hiring rate at the past employer does not affect the estimated effect of working for the parent's current employer. Columns 5-7 present similar findings for future employers. This robustness suggests that the estimates are not biased by time-varying local labor demand conditions. The fact that the coefficient on the hiring rate at the past and future employers is positive could be explained by other social contacts at these firms, which would be consistent with Figure 1.

Two additional results suggest that time-varying local labor market conditions do not bias my estimates. First, the estimates are robust to defining local labor markets fixed effects at the commuting zone level (instead of the state). While about half of parents work for a firm with multiple establishments, which could be located across the state, I can measure the precise location of single-establishment firms. Estimating the baseline specification on this sample yields a point estimate (standard error) of 0.183 (0.031). Estimating an alternative specification that includes commuting zone by industry by year

fixed effects yields a point estimate (standard error) of 0.164 (0.033).[32] Second, the estimates are robust to including controls for aggregate local hiring conditions. Specifically, I include a vector of controls that interacts the three sector-specific hiring rates within the commuting zone of the parent's employer with with the sector of parent's employer. The resulting point estimates (standard error) from the first and second stage are 0.118 (0.003) and 0.297 (0.029), respectively.

While the firm fixed effects control for time-invariant characteristics of the firm, firms might offer higher wages when hiring more intensively. I assess this concern by controlling for the log of average earnings of all new hires at the parent's employer in the preceding year. This only reduces the main estimates from 0.307 to 0.299 (see column 2 of Table A.3). However, changes in the earnings of new hires might partially reflect a change in the composition of workers being hired. Columns 3 and 4 of Table A.3 take an alternative approach and control for the earnings growth of the parents and all workers at the employer, respectively, in the year prior to entry. The idea is that changes in offer wages are likely to be correlated with earnings growth for current workers. Again, the estimated earnings benefits are largely unaffected. Lastly, column 5 of Table A.3 shows that the results are also robust to controlling for the growth in employment in the year prior to entry (point estimate is 0.307). Thus, time-varying wage setting policies do not appear to bias my results, which may be because firm pay policies are highly persistent (Lachowska et al., 2020) or because the local labor market fixed effects absorb this variation.

It is potentially problematic that the hiring rate could affect when or even whether an individual finds their first stable job. To assess this concern, I construct a sample of parents who are employed at the same firm when the child is between the ages of 18 and 22, which is the five-year period in which the most children enter the labor market. I define the instrument as the hiring rate at parent's employer in the year the child turns 18 and define the local labor market fixed effect as the interaction between the two-digit industry of the parent's employer, the state in which the employer is located, and the

[32]Using the establishment impute, I also estimate the alternative specification (with the commuting zone by industry by year fixed effects) on the full sample. This yields a point estimate (standard error) of 0.278 (0.030).

cohort of the child. Thus, both the sample and the covariates in the empirical model are defined independent of when or whether the child enters the labor market.

Evidence from this alternative specification argues against concerns related to the hiring rate affecting when or whether the child enters the labor market. I regress an indicator for whether the child enters the labor market on the hiring rate and the vector of covariates and find that the hiring rate is unrelated to the probability of ever finding a first stable job; the point estimate (standard error) is -0.005 (0.003). Thus, variation in the hiring rate does not appear to affect whether an individual finds a first job. I then limit the sample to children who enter the labor market and estimate the effect of working for a parent's employer on initial earnings using the two-stage least squares estimator. The point estimate (standard error) from the alternative specification is 0.324 (0.090). The similarity to my main estimates suggests that conditioning on entry or measuring the hiring rate in the four quarters prior to entry does not introduce bias.

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 household, which limits the identifying variation to comparisons between siblings. Both regressions are estimated on the same subsample, which retains cases for which at least two siblings entered 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 household by employer fixed effect are 0.199 (0.040) and 0.155 (0.045), respectively (see Table A.4). The two estimates are qualitatively and quantitatively similar, which suggests that the results are not driven by unobserved differences across households.

The hiring rate at the parent's employer could be related to earnings through some other channel. For example, 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, if the hiring rate is correlated with other measures of parental financial well-being, individuals might stay in school longer absent financial constraints. Both mechanisms ought to delay entry into the labor market.

However, the estimates in Table A.5 illustrate that working for a parent's employer leads individuals to find their first stable job almost a year earlier and makes them slightly less likely to be employed in the three years prior to entry, which might indicate a smoother transition between school and work. Thus, there is no evidence that the earnings gains are driven by an increase in educational attainment or in the time spent searching for a job. This is consistent with Hilger (2016) and Fradkin et al. (2018) who find that parental job loss during adolescence does not meaningfully impact educational attainment or job quality through extended search.

5.3 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 5, where the outcome is the AKM firm fixed effect of the child's employer.[33] Working for the parent's employer leads individuals to work for firms that pay all workers 32.6 percent more, which is approximately a one standard deviation improvement in the firm effect. A comparison to the main results in Table 3 reveals that the effect on individual earnings is virtually identical. For individuals whose parents work for firms with pay premiums that are above the median, the effect (standard error) on individual log earnings is 0.549 (0.036) compared to only 0.073 (0.036) for individuals whose parents work for lower-paying firms. Individuals who work for their parent's employer end up at higher-paying firms, with an average AKM firm effect that is 11.7 log points greater relative to those who do not work for their parent's employer. However, the estimated effect on the firm premium (32.6 log points) exceeds this difference implying that, absent parental connections, those who work for their parent's employer would have ended up at relatively lower-paying firms. This suggests that individuals who work for their parent's

[33]AKM refers to the decomposition developed by Abowd et al. (1999). I estimate the AKM firm fixed effect using code adapted from Crane, Hyatt, and Murray (2021) and based on national data that excludes the young workers in my sample. 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. See Appendix B.6 for details.

employer have more limited outside options.

I provide additional evidence of that parents provide access to higher-paying firms by focusing on outcome variables 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.[34] In these models more productive firms poach workers from less productive firms by offering higher wages. Consistent with this class of models, columns 2-4 of Table 5 illustrate that working for the employer of a parent leads individuals to start their careers on a higher run of the firm job ladder as defined by productivity, wages, and the proportion of hires made through poaching flows.[35] Column 4 suggests 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.

Part of the effect on the firm pay premium is explained by parents providing access to employers in higher-paying industries. Columns 7-9 of Table 5 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 43 percentage points and increases the probability of working in the manufacturing/production sector by 37 percentage points. The effect on the industry of employment has large predicted earnings consequences. Table A.6 presents estimates in which the outcome variable is the industry-level earnings premium (estimated analogously to the firm-level pay premium). Working for a parent's employer increases the two-

[34]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 (e.g., 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.

[35]The outcomes in columns 2-4 correspond to the rank of time-invariant characteristics of the first stable employer relative to the national distribution of firms. See Appendix B.7 for details. For examples of papers that use similar measures to define job ladders, see Haltiwanger et al. (2021), Haltiwanger et al. (2018), and Bagger and Lentz (2019).

Table 5: Effect on Employer Characteristics

		National Rank					Sector		
	employer pay premium	revenue per worker	poaching hires	average earnings	log firm size	firm age in years	unskilled services	skilled services	manufacturing/ production
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
works for parent's employer	0.327***	4.767*	9.217***	25.060***	-1.979***	-3.040***	-0.433***	0.062*	0.372***
	(0.025)	(2.118)	(1.638)	(1.741)	(0.244)	(0.866)	(0.036)	(0.031)	(0.028)
control mean	-0.094	51.75	55.33	42.47	6.72	22.78	0.375	0.460	0.165
control s.d.	0.367	27.52	23.38	26.53	3.40	12.28	0.484	0.498	0.371
observations	11,460,000	9,391,000	11,460,000	11,460,000	11,460,000	11,460,000	11,460,000	11,460,000	11,460,000

Notes: The table presents estimates from the two-stage least squares specifcation. Each column presents estimates from a separate regression for a different outcome. Standard errors are presented in parentheses.
*** p≤0.001, ** p≤0.01, * p≤0.05

Table 6: Effect on Earnings and Job Mobility Three Years After Entry

	First Move in Three Years			Annual Earnings After Entry		
	stay	j2j	j2n	year one	year two	year three
	(1)	(2)	(3)	(4)	(5)	(6)
works for parent's employer	0.174***	-0.182***	0.008	7,363***	7,226***	4,790***
	(0.034)	(0.033)	(0.038)	(1,002)	(1,284)	(1,440)
control mean	0.286	0.279	0.435	26,460	25,660	26,740
control s.d.	0.452	0.449	0.496	15,660	19,290	21,130
observations	10,200,000	10,200,000	10,200,000	10,200,000	10,200,000	10,200,000

Notes: The table presents estimates from the two-stage least squares specifcation. Each column presents estimates from a separate regression for a different outcome. Standard errors are presented in parentheses.
*** p≤0.001, ** p≤0.01, * p≤0.05

and six-digit industry pay premium by 0.167 and 0.230, respectively. Thus, 75 percent of the effect on individual earnings is explained by individuals working in higher paying (six-digit) 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 information to their children about where to look for high-paying jobs.

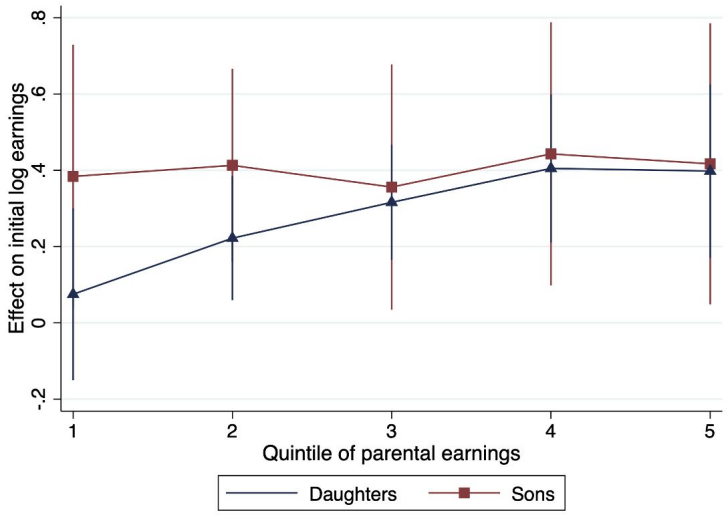
Working for a parent's employer leads individuals to stay at their first employer longer. Column 1 of Table 6 indicates that working for a parent's employer increases the probability of remaining at the first employer for at least three years by 17.4 percentage points. Columns 2 and 3 illustrate that this effect is entirely 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 6 illustrate that the earnings benefits of working for a parent's employer are quite persistent. Working for the parent's employer leads to an increase of \$7,363 in the first year after entry into the labor market. The effects are persistent but by the third year the magnitude of the effect falls to \$4,790. Figure A.10 presents estimates of the effect on annual earnings one to six years after entry for a group of individuals for whom I am able to observe these outcomes. There is less statistical precision in the later years but the point estimates suggest that the earnings benefits are quite persistent, with annual earnings benefits that exceed \$5,000 even six years after entry.

Figure 6 investigates heterogeneous effects by estimating the main specification on subgroups of workers defined by sex and the quintile of parental earnings.[36] In general, individuals with higher-earnings parents experience larger gains. However, this appears to be driven by sons, as daughters with low-earnings parents experience similarly large gains

[36]See Table A.7 for the results in table form with the first-stage F-statistic.

Figure 6: Heterogeneous Effects by Sex and Parental Earnings



Notes: Each point represents an estimate from a separate regression estimated on a distinct sample defined by the sex of the child and the quintile of parental earnings. The vertical bars depict the 95 percent confidence interval.

compare to daughters from high-earnings parents. The effects are somewhat imprecise and the differences are generally statistically insignificant.

5.4 Interpreting the Local Average Treatment Effect

If the three identifying assumptions are satisfied, the two-stage least squares estimator identifies a LATE. This section provides a theoretical argument for why the LATE may be a reasonable approximation of the ATT in my context. I then present empirical evidence to assess the plausibility of this interpretation.

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.[37] 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

$$\underbrace{\mathbb{E}\big[\beta_i | \{\eta_i^A < \beta_i\}, \{\underline{z} < \eta_i^O < \bar{z}\}\big]}_{\text{LATE}} = \underbrace{\mathbb{E}\big[\beta_i | \{\eta_i^A < \beta_i\}, \{Z_i < \eta_i^O\}\big]}_{\text{ATT}} \tag{5}$$

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 D develops a stylized behavioral model and provides a more detailed discussion of the intuition by focusing on a specific case of equation 5.

The assumptions that imply the equality of the LATE and ATT also imply that the estimated treatment effects should not be sensitive to the variation exploited in the instrument; I test that implication here. To do so, I regress the instrument on the covariates

[37] 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 $x \in \{O, A\}$.

from equation 4 and compute the residualized value, which is the source of identifying variation.[38] I then compute terciles based on the residualized instrument, partitioning the sample into periods in which employers have a relatively low, medium, and high rate of hiring. I estimate equation 4 on samples defined by different combinations of the three terciles. The point estimate (standard error) is 0.436 (0.048), 0.310 (0.029), and 0.228 (0.114) when excluding observations from third, second and first terciles, respectively (see Table A.8). While there is some variation across the samples, the point estimates are large and positive regardless of range of variation exploited in the instrument.

An alternative approach to assessing the representativeness of the two-stage least squares estimates is to characterize the compliers. My data lack variables that strongly predict individual earnings benefits, but I can estimate the size of the complier population. The methodology developed by Abadie (2003) applies to binary instruments, so I construct three binary instruments which are equal to one when the residualized hiring rate exceeds the 25th, 50th, and 75th percentiles. The estimated effect on log earnings when using these three binary instruments is 0.44, 0.42, and 0.25, respectively. The fact that these estimates are qualitatively similar to those obtained using the continuous instrument provides some evidence that the complier population for these instruments is not fundamentally different. For the three instruments, I find that 3.6, 2.8, and 16 percent of the population is in the complier population, respectively.[39] Given that 5.6 percent of individuals in the estimation sample work for their parent's employer, the compliers represent a meaningful percentage of the treated population.[40] Thus, the results provide additional evidence that the instrumental variables estimates are informative of the ATT.

5.5 Alternative Empirical Strategy

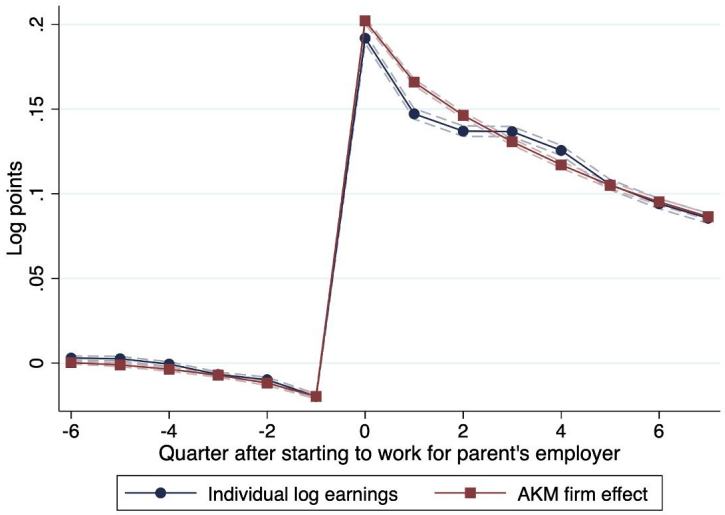
To assess the robustness of my findings, I use an event study design that relies on an entirely distinct set of assumptions. I identify a set of individuals who work for their parent's employer at some point between their second and fourth years of labor market

[38] The distribution of the residualized hiring rate is both symmetric and smooth (see Figure A.11).

[39] Table A.9 presents estimates of the size and characteristics of the complier population.

[40] These estimates suggest that 49, 25, and 69 percent of the individuals who work for their parent's employer are in the complier population defined by the three binary instruments, respectively.

Figure 7: Event Study



Notes: The series represent estimates from separate event study regressions where the outcome is individual log earnings or the firm fixed effect. The dashed lines denote the 95 percent confidence interval.

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, tenure, and experience. I then estimate the following equation,

$$y_{it} = \alpha_i + \phi_{m(i)t} + \gamma X_{it} + \sum_{k \geq 6} D_{it}^k \beta^k + u_{it} \tag{6}$$

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 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 is 16 quarters in length and includes the eight quarters with strictly positive earnings before and after the event.

Figure 7 plots the estimates of β^k and illustrates that the main results are robust to using the event study empirical strategy. Individuals experience a 21.2 log point increase in earning in the quarter in which they join their parent's employer. They also experience a 22.2 log point increase in the firm premium associated with their employer. These

estimates are not directly comparable to my main results since they do not correspond to outcomes at the first stable job but rather an early-career job. Regardless, the qualitative and quantitative similarity offers support to my main conclusion: Working for a parent's employer leads to a large increase in earnings that is driven by the firm pay premium.

6 Intergenerational Persistence in Earnings

Sections 4 and 5 show that individuals with higher-earning parents are more likely to work for a parent's employer and experience larger earnings gains when they do. This suggests that the intergenerational transmission of employers increases the intergenerational persistence in earnings. This section uses the methodology described in Section 2 to quantify how the intergenerational persistence in earnings would change if no one worked for their parent's employer.

Panel A of Table 7 presents estimates of the IGE. Columns 1-3 present estimates for daughters, sons, and the full sample. The elasticities, which range from 0.13 to 0.16, are substantially lower than typical estimates of IGE from the literature (Black and Devereux 2011). To investigate this discrepancy, I produce alternative estimates of the IGE, which measure the earnings of the children in 2016 (when the children are between the ages of 24 and 35). Panel A of Table A.10 presents estimates based on samples that include children with zero earnings in 2016 (by taking the hyperbolic sine of earnings) and the estimates of the IGE are closer to 0.4, which is comparable to other estimates from the United States. Thus, the low estimates of the IGE appear to be an artifact of focusing on labor market outcomes at the time of entry. Panel B of Table A.10 presents estimates of the IGE for children with strictly positive earnings in 2016. The IGE is 0.235 for this sample, which is similar to the estimates based on initial earnings. These results highlight the fact that the IGE is sensitive to how observations with zero earnings are dealt with and suggests that my estimates of the IGE based on initial labor market outcomes are lower primarily because, by design, all children have strictly positive earnings.

Panels B and C of Table 7 indicate that the intergenerational transmission of employer

Table 7: Intergenerational Elasticity of Earnings

	sample		
	daughters	sons	all
	(1)	(2)	(3)
A. Observed			
IGE	0.1565	0.1298	0.1430
	(0.0002)	(0.0003)	(0.0002)
B. No One Works with Primary Earner			
percent change in IGE	-2.04	-10.79	-4.73
	(6.52)	(5.02)	(3.30)
C. No One Works with Either Parent			
percent change in IGE	-3.87	-23.09	-9.68
	(12.25)	(9.39)	(6.16)
observations	8,416,000	8,591,000	17,010,000

Notes: Panel A presents the estimated IGE. Panels B and C present the percent by which the IGE would change if no one worked for the employer of the primary earner or either parent, respectively. Standard errors are presented in parentheses and are calculated using the delta method and take into account the uncertainty in the estimated earnings consequences.

leads to a modest increase in the intergenerational persistence in earnings. Specifically, column 3 of Panel B suggests that the IGE would be 5 percent lower if no one worked for the employer of the parent who is the primary earner.[41] Panel C indicates that the IGE would be about 10 percent lower if no one worked for the employer of either parent.[42] Columns 1 and 2 indicate that if no one worked for the employer of either parent the IGE for daughters and sons would be 4 percent and 23 percent lower, respectively. The intergenerational transmission of employers has a larger effect on the IGE for sons because, relative to daughters, both the probability of working for a parent's employer and the earnings consequences are more strongly related to parental earnings. The standard errors suggest that there is some uncertainty regarding the magnitude of these effects.

The event study estimates produce similar results. Figure A.14 plots the effect of

[41]Estimates of the ATT can be found in Table A.7. I allow all estimates of the ATT to vary by parental earnings quintile. For the counterfactual estimates presented in column 3 of Table 7 I use the pooled estimates of the ATT presented in Panel A of Table A.7. For the counterfactual estimates in columns 1 and 2, I use the appropriate sex-specific estimates. Figure A.13 presents the proportion of individuals who work for the employer of the primary earner, secondary earner, or both parents.

[42]For the case of working for the employer of the secondary earner, I assume that the effect of working for the employer of the secondary earner is the same as working for the employer of the primary earner within each subgroup. As previously discussed, this appears to be true, at least in the full sample.

joining a parent's employer by sex and quintile of parental earnings estimated via the event study specification from equation 6. The effect is increasing in parental earnings, ranging from about 7 log points for individuals with parents in the lowest quintile of earnings to about 20 log points for individuals with parents in the highest quintile. Using these estimates in the counterfactual exercise implies that, if no one worked for the employer of either parent, the IGE would be 12.3 percent (0.33) and 18.3 percent (0.40) lower for daughters and sons, respectively (standard errors in parentheses). The estimates are similar to those in Panel C, although the magnitude is larger for daughters because there is a stronger association between parental earnings and the event study estimates.

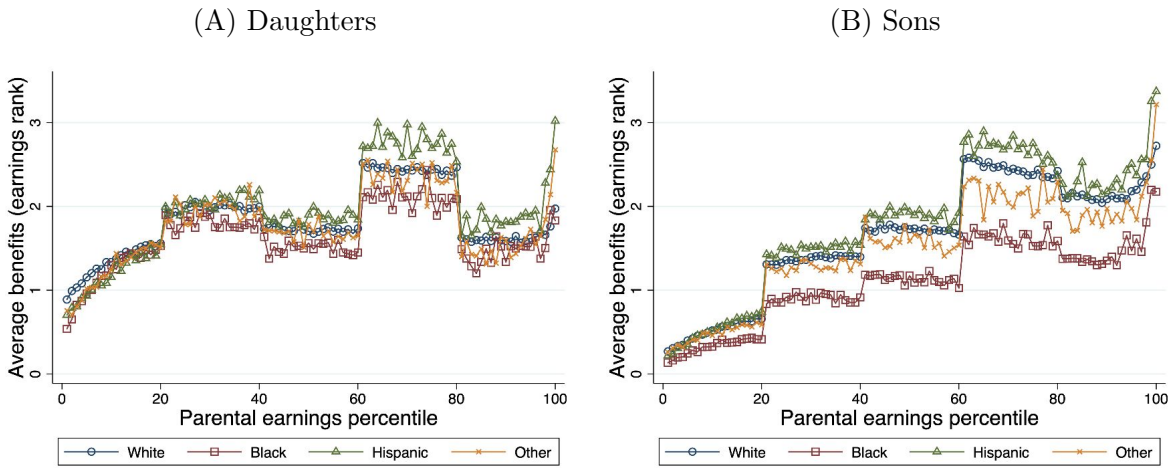
In addition to the IGE, I consider an alternative measure of the intergenerational persistence in earnings: the conditional expected rank (CER). The CER is defined as, $E[r_{ij}|r_p]$, where r_{ij} is the percentile rank of the earnings of the child, calculated within cohorts and using sample weights. Figure 8 presents the average earnings benefits–defined as $\mathbb{E}[D_i\beta_i]$–by sex, race/ethnicity, and parental earnings.[43] The benefits are largest for non-Black males whose parents are in the top two quintiles of the earnings distribution. The results by race/ethnicity should be interpreted with some caution since I do not have sufficient power to estimate earnings consequences by parental earnings, sex, and race/ethnicity and instead assume that, within groups defined by sex and the parental earnings quintile, average treatment effects do not differ by race/ethnicity.

Conditional on parental earnings, Black sons earn less than White sons, and this gap would be slightly smaller if no one worked for the same employer as a parent. Consistent with Chetty et al. (2020), I find that, conditional on parental income, Black males have lower expected income compared to White males. Specifically, conditional on the percentile of parental earnings, the expected rank of the initial earnings of Black sons is, on average, 5.8 percentiles lower relative to White sons. The estimates from Figure 8 suggest that this gap would decline by about 10 percent if no one were to work for the same employer as a parent.[44] While other factors are clearly at play, my results suggest

[43]The two-stage least squares estimates of the effect of working for the employer of the primary on the earnings rank of the children are presented in table A.11.

[44]Figure A.16(A) plots the CER for Black and White sons against the percentile of parental earnings. The dashed lines below represent the counterfactual CER. A.16(B) presents the proportion of the Black-

Figure 8: Average Benefits of Working for Parent's Employer



Notes: Each point presents the average earnings benefits from working for the employer of either parent for the sub group defined by sex, parental earnings, and race/ethnicity. The benefits are equal to the causal effect times the proportion who work for their parent's employer.

that young Black males are at a relative disadvantage, in part, because they are less likely to have an employed father who can help them find work.

The gap between the initial earnings of sons and daughters would be slightly larger if no one worked for a parent's employer. Conditional on the percentile of parental earnings, the expected earnings rank of daughters is, on average, 4.5 percentiles lower relative to sons. Figure 8 illustrates that daughters with low-earning parents benefit more from working for a parent's employer while sons with high-earnings parents benefits more.[45] Averaging across the parental earnings distribution indicates that the earnings gap between sons and daughters would be 4 percent larger if no one worked for a parent's employer.

7 Conclusion

I use linked survey and administrative data to investigate how working for a parent's employer affects the earnings of young workers. I start with a descriptive analysis, and

White gap (vertical distance between the solid lines in Panel A) that is explained by the intergenerational transmission of employers at each percentile of the parental earnings distribution.

[45]Panel A of Figure A.17 plots the observed and counterfactual CER by sex and the percentile of parental earnings. Panel B plots the expected benefits by sex and the percentile of parental earnings.

find that 7 percent of individuals work for a parent's employer at their first stable job and 29 percent do so at some point between the ages of 18 and 30. This tendency is best explained by parents influencing the hiring or job search process to help children who have limited options in the labor market. I then use an instrumental variables strategy, which exploits exogenous variation in the availability of jobs at the parent's employer, and find that working for the employer of a parent increases earnings by 31 percent. These large earnings benefits appear to be explained by parents providing access to higher-paying firms. Individuals with higher-earning parents are more likely to work for the employer of a parent, and benefit more when they do, and thus the intergenerational transmission of employers increases the intergenerational persistence in earnings. Specifically, the elasticity of the initial earnings of an individual with respect to the earnings of their parents would be 10 percent lower if no one worked for the employer of a parent.

The key takeaway from my paper is that parents influence the earnings of their children by using their connections to provide access to higher-paying firms. The literature on intergenerational mobility typically attributes differences in earnings by family background to differences in human capital but my findings suggest that access to jobs through social contacts may also be important. While connections that operate within the parent's employer are clearly not the main determinant of the intergenerational persistence in earnings, parents may also provide access to jobs at other firms through social contacts such as friends, former co-workers, or classmates. Understanding the importance of these broader family connections should be a priority for future research.

My results relate to the normative assessment of whether rates of intergenerational mobility are too low in the United States, an assessment which depends on whether the economic system that produces the intergenerational persistence in earnings is equitable and efficient. 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.[46] Thus, from an equity standpoint, my finding that individuals from high-income

[46]According to the definition developed by Roemer (1998), a society provides equality of opportunity if the outcomes of individuals are not systematically determined by factors for which they are not

families disproportionately benefit from their parents' connections should raise concerns about the relatively low levels of intergenerational mobility in the United States.[47] My results do not speak directly to the implications for efficiency and future research should aim to understand whether the use of family connections in the labor market leads to gains or losses in productivity.

My results are also informative of the positive assessment of what would be required to achieve equality of opportunity. One view is that the United States is a meritocracy, where economic rewards are determined by hard work and ability. According to this view, efforts to expand economic opportunity should aim to equip everyone with the skills they need to succeed in the labor market. Government programs such as Head Start, which provides access to early childhood education, and the Pell Grant program, which helps students pay for college, are both examples of programs that promote the development of skills for individuals from disadvantaged backgrounds. However, my results challenge a purely meritocratic view of the labor market, as individuals from high-income families are likely to earn more not only because they are more skilled, but also, because their parents are able to 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.

responsible. Determining what to hold someone responsible for is a subjective judgment. But most people in the United States would likely agree that individuals should not be responsible for their parents' lack of connections in the labor market.

[47] 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).

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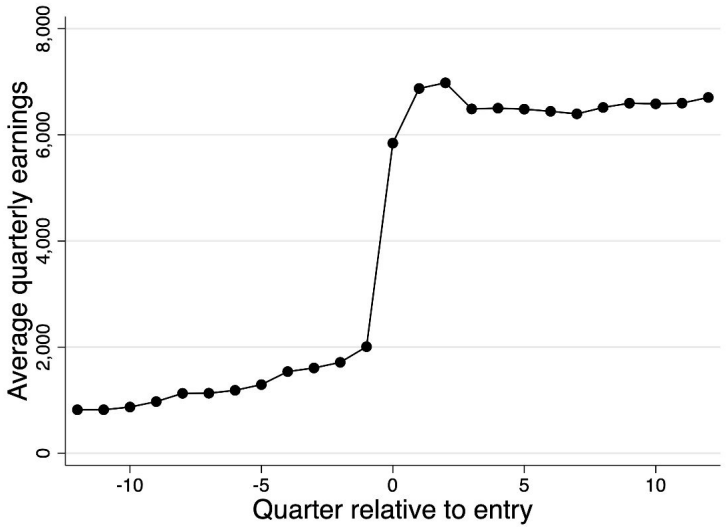
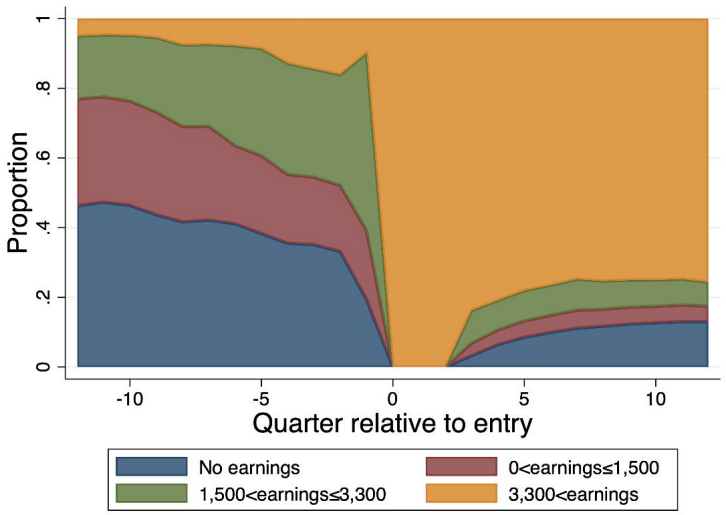
Appendix A Additional Empirical Results

Figure A.1: Earnings Before and After Entry

(A) Average Earnings

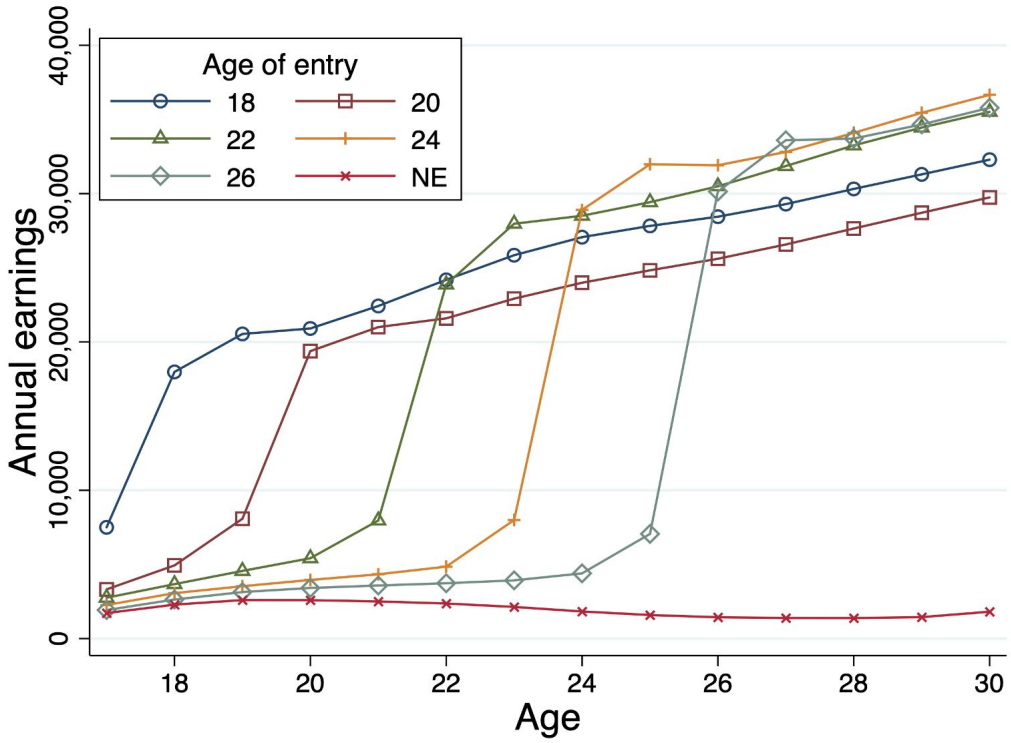


(B) Earnings Categories



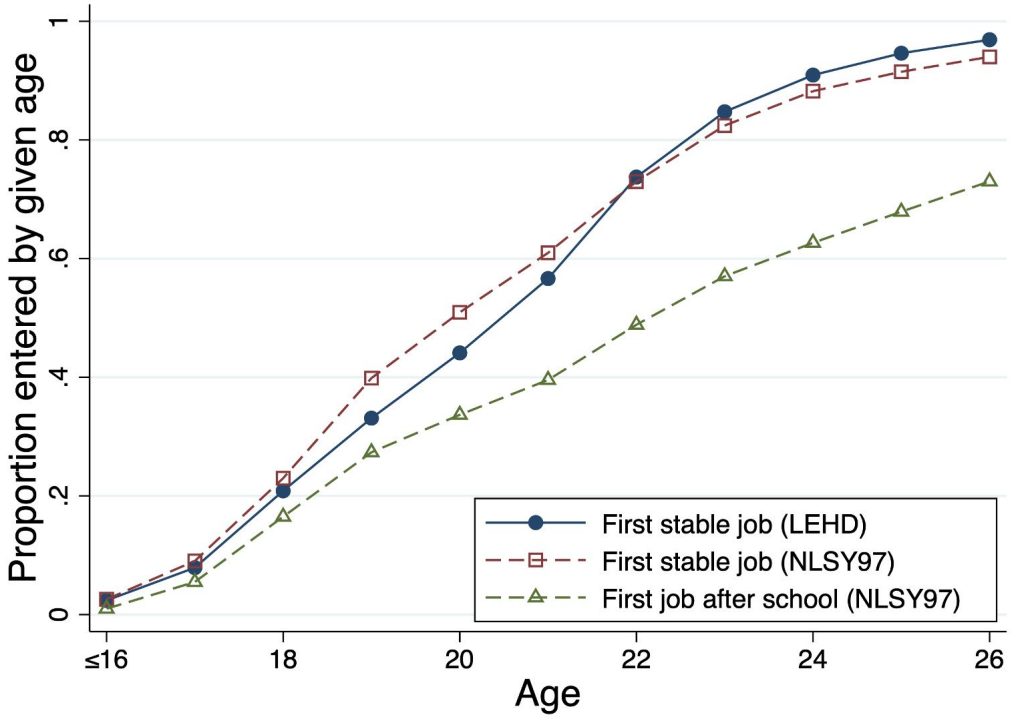
Notes: Both figures plot earnings in the 12 quarters before and after entry. Panel A plots the average quarterly earnings and Panel B plots the proportion of individuals with quarterly earnings in one of four mutually exclusive categories. All statistics are calculated using sample weights.
Source: Author's calculations based on matched data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Figure A.2: Age-Earnings Profile by Age of Entry



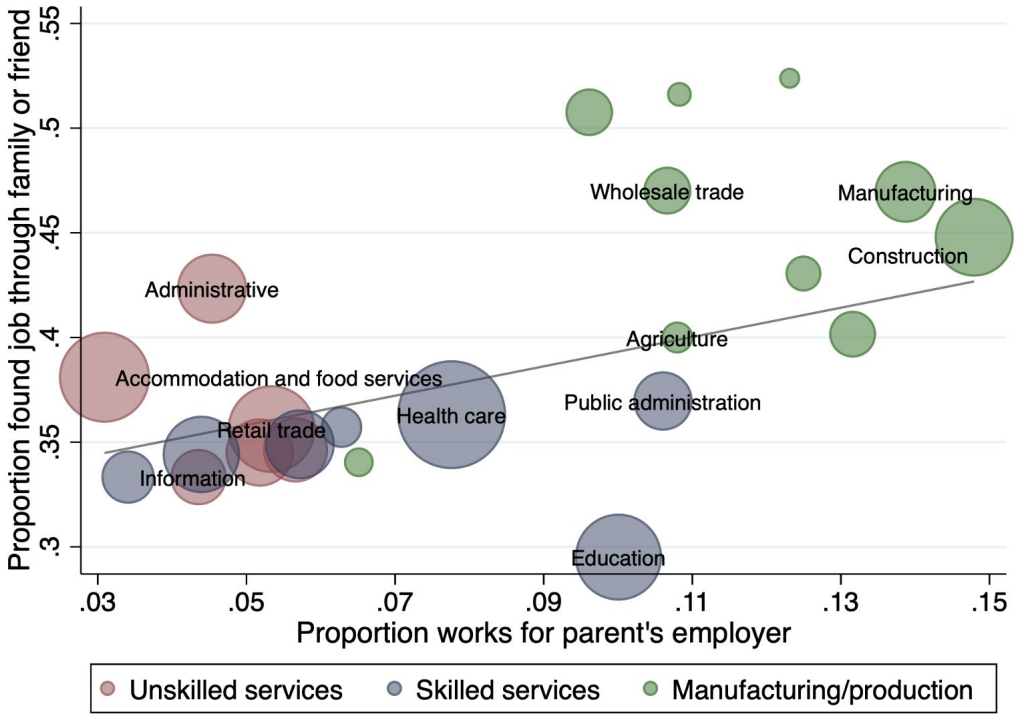
Notes: The figure plots the average annual earnings by age for different groups of workers defined by the age they were when they entered the labor market. The category, NE, is a group of workers that never entered the labor market. The sample includes all children who turned 30 by 2016 and all statistics are calculated using sample weights.
Source: Author's calculations based on matched data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Figure A.3: 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. All statistics are calculated using sample weights.
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.4: Industry-Level Association with Job Finding through Family or Friends



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 that were found through a family or friend.
Source: Author's calculations based on matched data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files. The variable represented by the vertical axis is calculated from the 2008-2017 waves of the National Longitudinal Survey of Youth 1997.

Table A.1: Intergenerational Transmission of Employers and Education

	works for parent's employer				
	(1)	(2)	(3)	(4)	(5)
less than high school	0.055***	0.061***	0.048***	0.023*	0.055***
	(0.003)	(0.004)	(0.006)	(0.009)	(0.002)
high school	0.043***	0.054***	0.047***	0.042***	0.048***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)
some college	0.020***	0.027***	0.024***	0.025***	0.024***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
parental earnings quartile	first	second	third	fourth	all
observations	180,000	183,000	177,000	165,000	705,000

Notes: Each column presents estimates from a separate regression. The outcome variable is an indicator equal to one if the first stable job is at the employer of either parent. The main independent variables include indicator variables for the highest level of education: less than high school, high school or equivalent, and some college or Associate degree. Bachelor's degree or advanced degree is the omitted educational category. Each regression controls for the interaction between the sex of the individual and the percentile of the parental earnigns distribution. All results are based on the sample of individuals who respond to the American Community Survey after they turn 25. Columns 1 through 4 present estimates based on the sample of individuals whose parents are in the first through fourth quartiles of the parental earnigns distribution, respectively. Column 5 includes all indviduals.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics, 2000 Decennial Census files and responses to the American Community Survey.
*** p≤0.001, ** p≤0.01, * p≤0.05

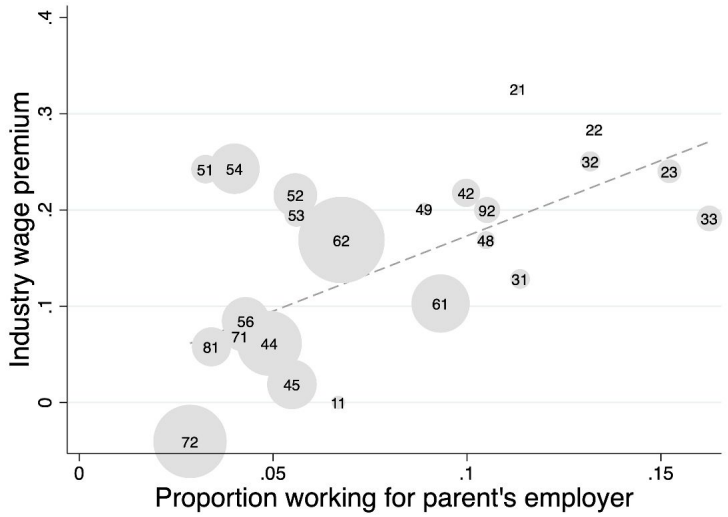
Table A.2: Intergenerational Transmission of Employers and Unemployment

	works for parent's employer			
	(1)	(2)	(3)	(4)
unemployment rate	-0.068**	0.128***	0.191***	0.064*
	(0.022)	(0.024)	(0.032)	(0.031)
covariates				
age of entry		X	X	X
quarter of entry			X	
county				X
observations	17,010,000	17,010,000	17,010,000	17,010,000

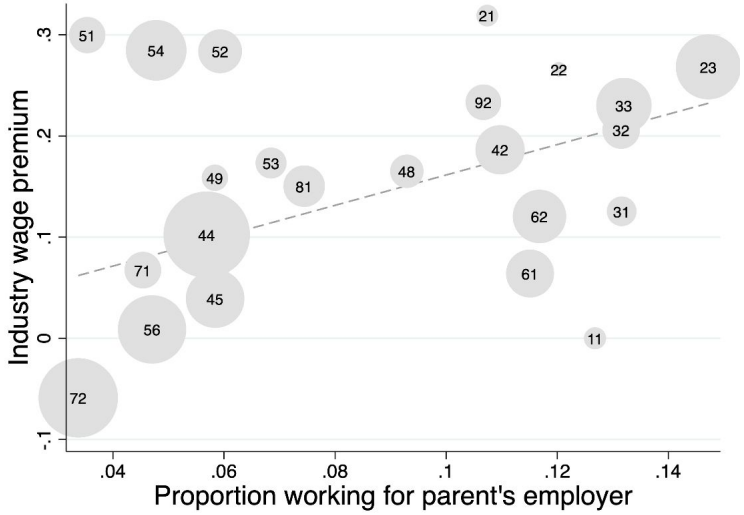
Notes: Each column presents estimates from a separate regression. The outcome variable is an indicator equal to one if the first stable job is at the employer of either parent. The main independent variable is the county-level unemployment rate, which ranges from zero to one, measured in the year in which the child enters the labor market. The different columns include additional covariates as indicated by the rows below the estimates. The covariates include fixed effects for: the age of entry, the quarter of entry, the county in which the individual entered the labor market. Standard errors are two-way clustered at the county and quarter of entry.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files and unemployment data from the U.S. Bureau of Labor Statistics.
*** p≤0.001, ** p≤0.01, * p≤0.05

Figure A.5: Intergenerational Transmission of Employers and Industry Wage Premiums

(A) Daughters



(B) Sons

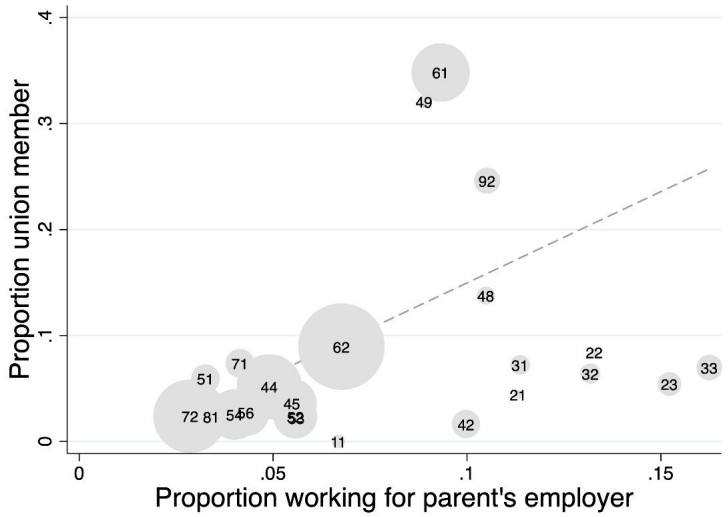


Notes: Panels A and B present results for daughters and sons, respectively. Each point on the plot presents information related to an industry, measured as the two-digit North American Industry Classification System code. The horizontal axis represents the proportion of individuals in a given industry who work for the employer of either parent at their first stable job, where this proportion is calculated separately for sons and daughters. The vertical axis is the industry-level wage premium. The wage premium is estimated using data from the Current Population Survey (CPS) by regressing log wages on an set of industry dummies (Agriculture, Forestry, Fishing, and Hunting is the omitted industry category) and controlling for year fixed effects, a third order polynomial in potential experience and fixed effects for the level of education. The sample from the CPS includes all employed individuals between the ages of 26 and 35 and regressions are estimated separately for males and females. The size of the marker is proportional to the number of individuals whose first stable job is in that industry.

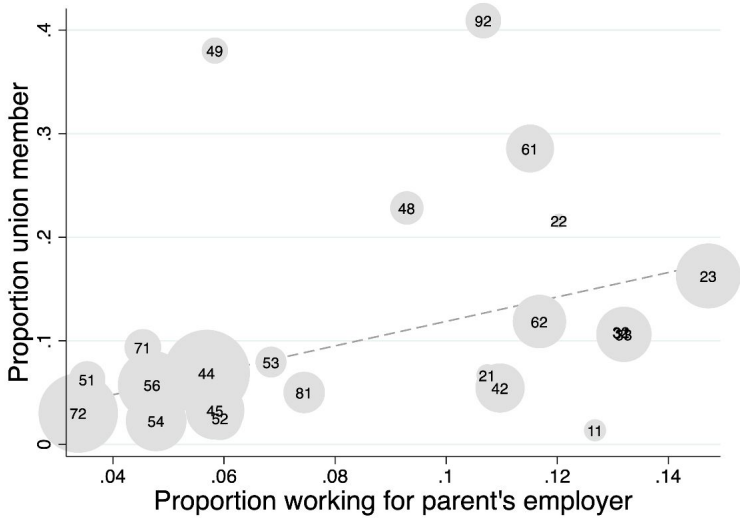
Source: Author's calculations based on matched data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files and publicly available data from the Current Population Survey.

Figure A.6: Intergenerational Transmission of Employers and Union Membership

(A) Daughters



(B) Sons

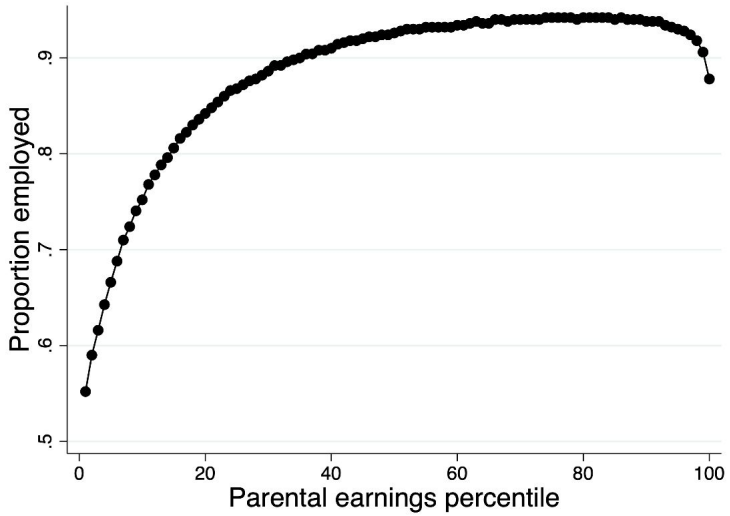


Notes: Panels A and B present results for daughters and sons, respectively. Each point on the plot presents information related to an industry, measured as the two-digit North American Industry Classification System code. The horizontal axis represents the proportion of individuals in a given two-digit industry who work for the employer of either parent at their first stable job, where this proportion is calculated separately for sons and daughters. The vertical axis presents proportion of individuals within that industry that are a member of a union. This statistic is calculated separately for males and females using data from the Current Population Survey, which include a sample of employed individuals between the ages of 26 and 35. The size of the marker is proportional to the number of individuals whose first stable job is in that industry.

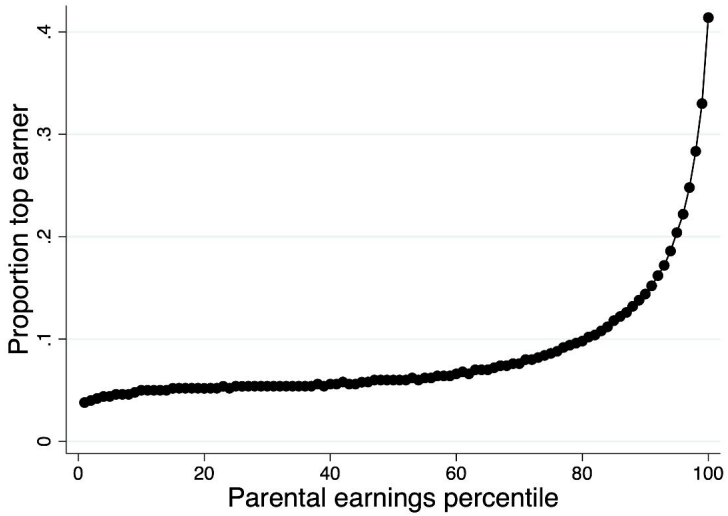
Source: Author's calculations based on matched data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files and publically available data from the Current Population Survey.

Figure A.7: Correlates with Parental Earnings

(A) Parent is Employed



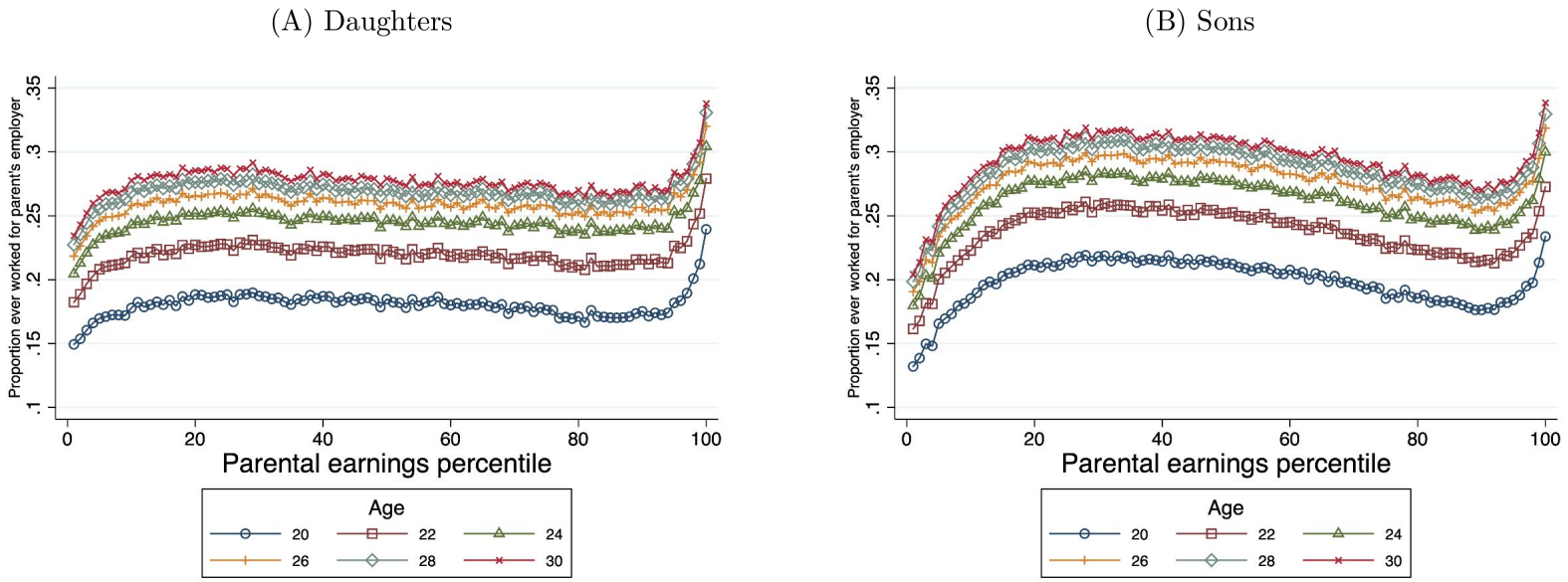
(B) Parent is Top Earner within Employer



Notes: This figure describes the labor market outcomes of the parent who is the primary earner in the quarter in which their child enters the labor market. Panel A presents the proportion of parents (primary earner) that are employed. Panel B presents the proportion of parents (primary earner) whose earnings are in the top percentile of the within employer earnings distribution. All statistics are presented separately for each percentile of the parental earnings distribution and are calculated using sample weights.

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

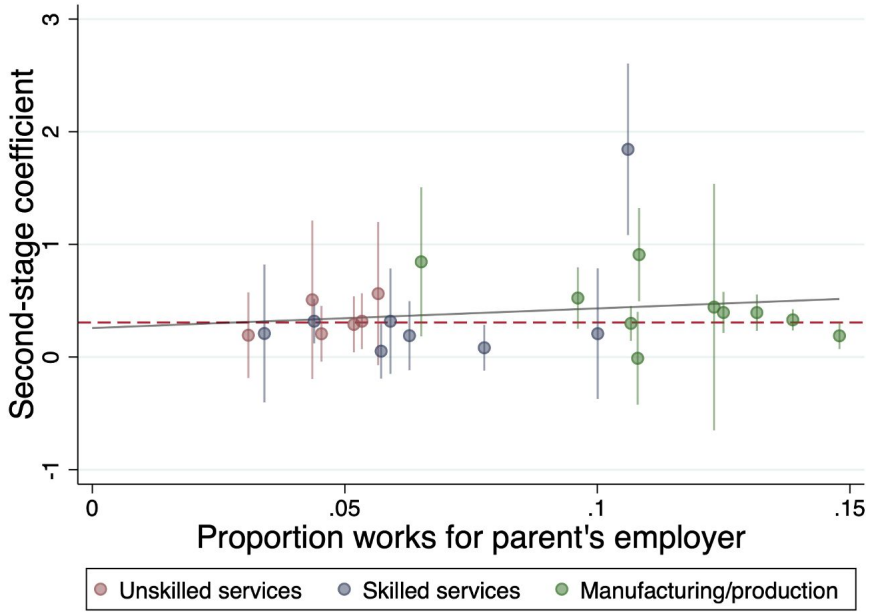
Figure A.8: Long-Run Measures of the Intergenerational Transmission of Employers



Notes: Each line in the plot the proportion of individuals who have ever worked for an employer of either parent between the ages of 18 and the age indicated in the legend. Each statistic is reported separately by the percentile of the parental earnings distribution. Panels A and B present results for the sample of daughters and sons, respectively. The results are based on a subsample that include children who turned 30 by 2016. All statistics are calculated using sample weights.

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

Figure A.9: Heterogeneity in Second Stage by Parent's Industry



Notes: The figures present the second stage estimates from a modified specification in which the hiring rate is interacted with the industry of the primary earner's employer. Each point represents the coefficient on the interaction term and the horizontal axis represents the proportion of individuals in a given industry who work for a parent's employer. The solid line depicts the linear fit and the dashed line depicts the point estimate from the full sample. The vertical bars denote the 95 percent confidence intervals.

Table A.3: Control for Changes in Offer Wages

	log of quarterly earnings				
	(1)	(2)	(3)	(4)	(5)
works for parent's employer	0.307***	0.299***	0.312***	0.342***	0.307***
	(0.029)	(0.029)	(0.028)	(0.031)	(0.030)
added covariates	none	new hire earnings	earnings growth of parent	earnings growth of all employees	employment growth
observations	11,460,000	11,460,000	11,460,000	11,460,000	11,460,000

Notes: Each column presents estimates from a separate regression estimated by two-stage least squares. The outcome variable is the log of the first full-quarter of earnings at the first stable job. The endogenous variable is an indicator equal to one if the child works for their parent's employer (primary earner) at the first stable job. The excluded instrument is the average quarterly hiring rate at the parent's employer in the four quarters prior to the quarter in which the individual enters the labor market. Column 1 reproduces the main results and columns 2-5 extend the baseline specification to include controls for the log of average earnings of stable new hires in the year before entry, the average quarterly earnings growth of the primary earner in the year before entry, the average annual earnings growth of all workers in the year before entry, and the average quarterly employment growth rate in the year prior to entry, respectively. All specifications include a fixed effect for the parent's employer; a fixed effect for the year of entry by two-digit industry code of parent's employer by state of parent's employer; and a vector of covariates that includes log annual earnings of the parent in the year prior to entry, a fixed effect for the cohort of the child, and interactions between the sex of the child and race, ethnicity, and an indicator equal to one if born in the United States. Standard errors are clustered at the level of parent's employer and are presented in parentheses.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.
*** p≤0.001, ** p≤0.01, * p≤0.05

Table A.4: Household Fixed Effects

	log of quarterly earnings	
	(1)	(2)
works for parent's employer	0.199***	0.155***
	(0.040)	(0.045)
fixed effect	employer	household
control mean	8.757	8.757
observations	4,476,000	4,476,000

Notes: Each column presents estimates from a separate regression estimated by two-stage least squares. The outcome variable is the log of the first full-quarter of earnings at the first stable job. The endogenous variable is an indicator equal to one if the individual works for their parent's employer (primary earner) at the first stable job. The excluded instrument is the average quarterly hiring rate at the parent's employer in the four quarters prior to the quarter of entry. The specification in column 1 includes a fixed effect for the parent's employer whereas the specification in column 2 includes a fixed effect for the parent's employer by household. Both specifications are estimated on the same sample (which drop singleton observations) and include a fixed effect for the year of entry by two-digit industry code of parent's employer by state of parent's employer; and a vector of covariates that includes log annual earnings of the parent in the year prior to entry, a fixed effect for the cohort of the child and interactions between the sex of the child and race, ethnicity, and an indicator equal to one if born in the United States. Standard errors are clustered at the level of parent's employer and are presented in parentheses.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.
*** p≤0.001, ** p≤0.01, * p≤0.05

Table A.5: Effect on Timing of Entry

	average in three years prior to entry		
	quarterly earnings (1)	quarters worked (2)	quarter of entry (3)
works for parent's employer	-84.870	-0.066**	-3.973***
	(61.840)	(0.020)	(0.570)
control mean	1,269	0.612	13.170
observations	11,460,000	11,460,000	11,460,000

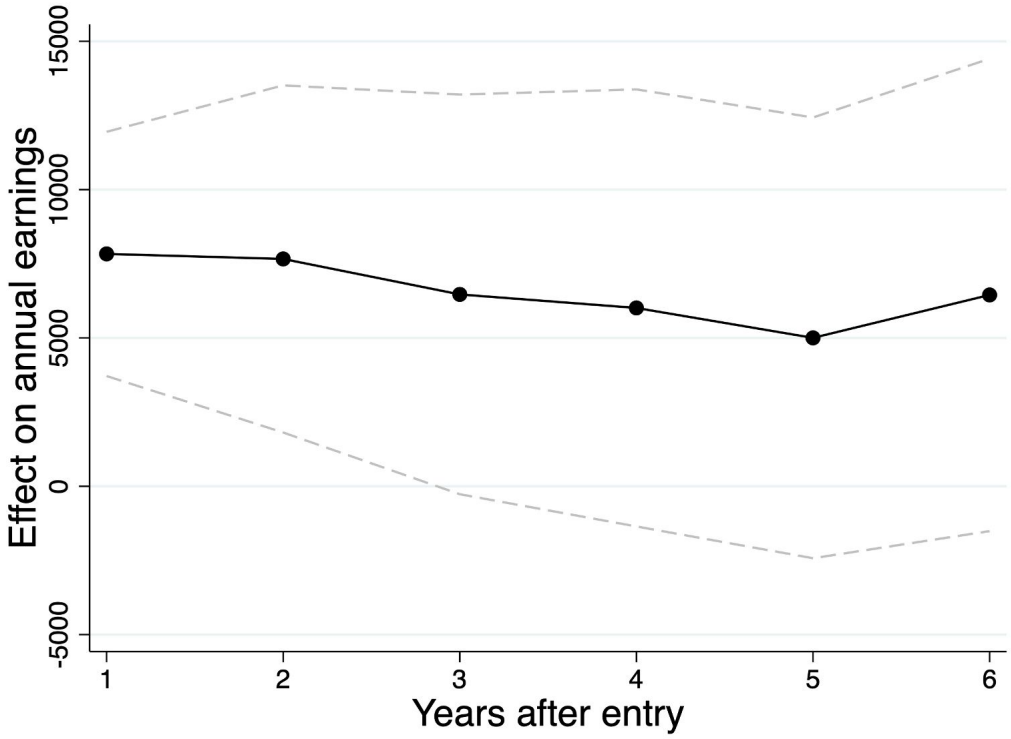
Notes: Each column presents estimates from a separate regression estimated by two-stage least squares. The outcome variables in columns 1 and 2 are average quarterly earnings and employment in the three years pior to entry, respectively. The outcome variable in column 3 is the quarter of entry relative to the expected quarter of high school graduation (based on birth cohort). The endogenous variable is an indicator equal to one if the child works for their parent's employer (primary earner) at the first stable job. The excluded instrument is the average quarterly hiring rate at the parent's employer in the four quaters prior to the quarter in which the individual enters the labor market. All specifications include a fixed effect for the parent's employer; a fixed effect for the year of entry by two-digit industry code of parent's employer by state of parent's employer; and a vector of covariates that includes log annual earnings of the parent in the year prior to entry and interactions between the sex of the child and race, ethnicity, and an indicator equal to one if born in the United States. The specificaitons in columns 1 and 2 also include a fixed effect for the cohort of the child. Standard errors are clustered at the level of parent's employer and are presented in parentheses.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.
*** p≤0.001, ** p≤0.01, * p≤0.05

Table A.6: Effect on Industry and Employer Pay Premium

	Industry Pay Premium				Employer Pay
	two-digit	three-digit	four-digit	six-digit	Premium
	(1)	(2)	(3)	(4)	(5)
works for parent's employer	0.167***	0.200***	0.208***	0.230***	0.304***
	(0.013)	(0.015)	(0.016)	(0.016)	(0.024)
control s.d.	0.178	0.208	0.222	0.232	0.366
observations	11,460,000	11,460,000	11,460,000	11,460,000	11,460,000

Notes: Each column presents estimates from a separate regression estimated by two-stage least squares. The outcome variables in columns 1-4 are the estimated pay premiums associated with the two-digit, three-digit, four-digit and six-digit industry codes, respectively. The outcome variable in column 5 is the estimated pay premiums associated with the employer. The endogenous variable is an indicator equal to one if the child works for their parent's employer (primary earner) at the first stable job. The excluded instrument is the average quarterly hiring rate at the parent's employer in the four quarters prior to the quarter in which the individual enters the labor market. All specifications include a fixed effect for the parent's employer; a fixed effect for the year of entry by two-digit industry code of parent's employer by state of parent's employer; and a vector of covariates that includes log annual earnings of the parent in the year prior to entry, a fixed effect for the cohort of the child and interactions between the sex of the child and race, ethnicity, and an indicator equal to one if born in the United States. Standard errors are clustered at the level of parent's employer and are presented in parentheses.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.
*** p≤0.001, ** p≤0.01, * p≤0.05

Figure A.10: Long-Run Effects



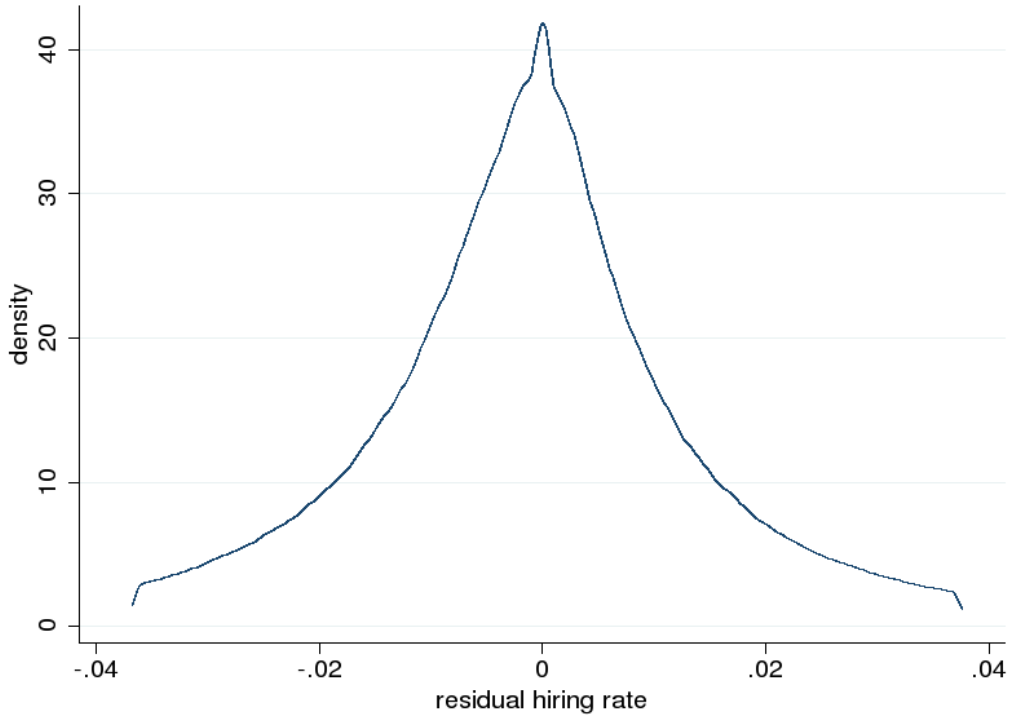
Notes: Each point on the figure represents an estimate from a separate regression. The outcome is the annual earnings x years after entry, where x refers to the coordinate on the horizontal axis. The endogenous variable is an indicator equal to one if the child work for their parent's employer (primary earner) at the first stable job. The excluded instrument is the average quarterly hiring rate at the parent's employer in the four quarters prior to the quarter in which the individual enters the labor market. All specifications include a fixed effect for the parent's employer; a fixed effect for the year of entry by two-digit industry code of parent's employer by state of parent's employer; and a vector of covariates that includes log annual earnings of the parent in the year prior to entry, a fixed effect for the cohort of the child and interactions between the sex of the child and race, ethnicity, and an indicator equal to one if born in the U.S. Standard errors are clustered at the level of parent's employer and are used to construct the 95 percent confidence interval, which is denoted by the dashed lines. All regressions are estimated on a sample of 3,441,000 individuals who are expected to graduate high school in 2004 or earlier and who entered the labor market between the year in which they were expected to graduate high school and six and a half years later. The F-statistic from the first stage is 364.
Source: Author's calculations based on matched data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Table A.7: Heterogeneous Effects by Sex and Parental Earnings

	log of quarterly earnings					
	(1)	(2)	(3)	(4)	(5)	(6)
A. All						
works for parent's employer	0.189*	0.273***	0.234***	0.362***	0.328***	0.307***
	(0.082)	(0.063)	(0.062)	(0.077)	(0.085)	(0.029)
F-statistic	238.9	358.0	446.8	330.4	316.2	1,434
observations	1,350,000	1,987,000	2,297,000	2,462,000	2,487,000	11,460,000
B. Daughters						
works for parent's employer	0.384*	0.413***	0.356*	0.443*	0.417*	0.424***
	(0.176)	(0.129)	(0.164)	(0.176)	(0.188)	(0.057)
F-statistic	64.3	131.2	100.0	106.1	130.9	679.8
observations	586,000	876,000	1,029,000	1,128,000	1,152,000	5,387,000
C. Sons						
works for parent's employer	0.075	0.222**	0.316***	0.405***	0.398***	0.312***
	(0.115)	(0.083)	(0.077)	(0.099)	(0.116)	(0.036)
F-statistic	97.7	198.3	245.7	176.9	161.3	854.2
observations	600,000	909,000	1,067,000	1,149,000	1,148,000	5,501,000
Sample Description						
parental earnings quintile	first	second	third	fourth	fifth	all

Notes: This table presents estimates on subsamples defined by the interaction between the quintile of parental earnings (defined by the column) and sex (defined by the panel). The outcome in all columns is the log of the first full quarter of earnings at the first stable job. The endogenous variable is an indicator equal to one if the individual works for their parent's employer (primary earner) at the first stable job, which is instrumented for using the average quarterly hiring rate at the parent's employer in the four quarters prior to entry. All specifications include a fixed effect for the parent's employer, a fixed effect for the year of entry by two-digit industry code of parent's employer by state of parent's employer, and the standard vector of demographic characteristics. Standard errors are clustered at the level of parent's employer and are presented in parentheses.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.
*** p≤0.001, ** p≤0.01, * p≤0.05

Figure A.11: Residualized Hiring Rate



Notes: This figure presents the kernel density of the residuals from a regression of the average quarterly hiring rate at the parents' (primary earner) employer in the four quarters prior to entry on a fixed effect for the parents' employer; a fixed effect for the year of entry by two-digit industry code of parents' employer by state of parents' employer; and a vector of covariates that includes log annual earnings of the parent in the year prior to entry, a fixed effect for the cohort of the child and interactions between the sex of the child and race, ethnicity, and an indicator equal to one if born in the United States. Standard errors are clustered at the level of parents' employer. The distribution is winsorized at the 5^{th} and 95^{th} percentiles according to the Census Bureau's rules.
Source: Author's calculations based on matched data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Table A.8: Heterogeneity by Residualized Hiring Rate

	log of quarterly earnings		
	(1)	(2)	(3)
works for parent's employer	0.436***	0.310***	0.228*
	(0.048)	(0.029)	(0.114)
estimation sample			
first tercile	X	X	
second tercile	X		X
third tercile		X	X
first stage F-stat	999	1,429	212
observations	7,304,000	7,606,000	7,308,000

Notes: Each column presents estimates from a separate regression estimated by two-stage least squares. The outcome variable is the log of the first full-quarter earnings at the first stable job. The endogenous variable is an indicator equal to one if the child works for their parent's employer (primary earner) at the first stable job. The excluded instrument is the average quarterly hiring rate at the parent's employer in the four quarters prior to the quarter in which the individual enters the labor market. The sample is partitioned into terciles based on the residualized hiring rate. The row below the estimates indicates whether observations from a given tercile are included in the estimation sample. All specifications include a fixed effect for the parent's employer; a fixed effect for the year of entry by two-digit industry code of parent's employer by state of parent's employer; and a vector of covariates that includes log annual earnings of the parent in the year prior to entry, a fixed effect for the cohort of the child and interactions between the sex of the child and race, ethnicity, and an indicator equal to one if born in the United States. Standard errors are clustered at the level of parent's employer and are presented in parentheses.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.
*** p≤0.001, ** p≤0.01, * p≤0.05

Table A.9: Characteristics of Compliers

	works for parent's employer		Characteristics of Compliers		
	no	yes	IV(p25)	IV(p50)	IV(p75)
	(1)	(2)	(3)	(4)	(5)
A. Individual					
male	0.50	0.60	0.54	0.54	0.51
White non-Hispanic	0.74	0.74	0.73	0.74	0.74
Black non-Hispanic	0.09	0.08	0.10	0.11	0.10
Asian non-Hispanic	0.03	0.02	0.03	0.03	0.03
Hispanic	0.11	0.13	0.12	0.10	0.10
other	0.03	0.03	0.03	0.03	0.03
born in United States	0.96	0.96	0.97	0.98	0.97
B. Parent and their Employer					
skilled services	0.49	0.38	0.49	0.48	0.66
unskilled services	0.15	0.26	0.20	0.16	0.10
manufacturing/production	0.35	0.36	0.31	0.36	0.25
tenure of parent	23.96	22.63	24.52	25.27	26.71
earnings rank within employer	68.49	77.93	63.97	51.65	65.40
parental earnings rank	55.47	54.40	58.48	66.39	60.33
Sample Size					
proportion of full sample	0.94	0.06	0.04	0.03	0.15

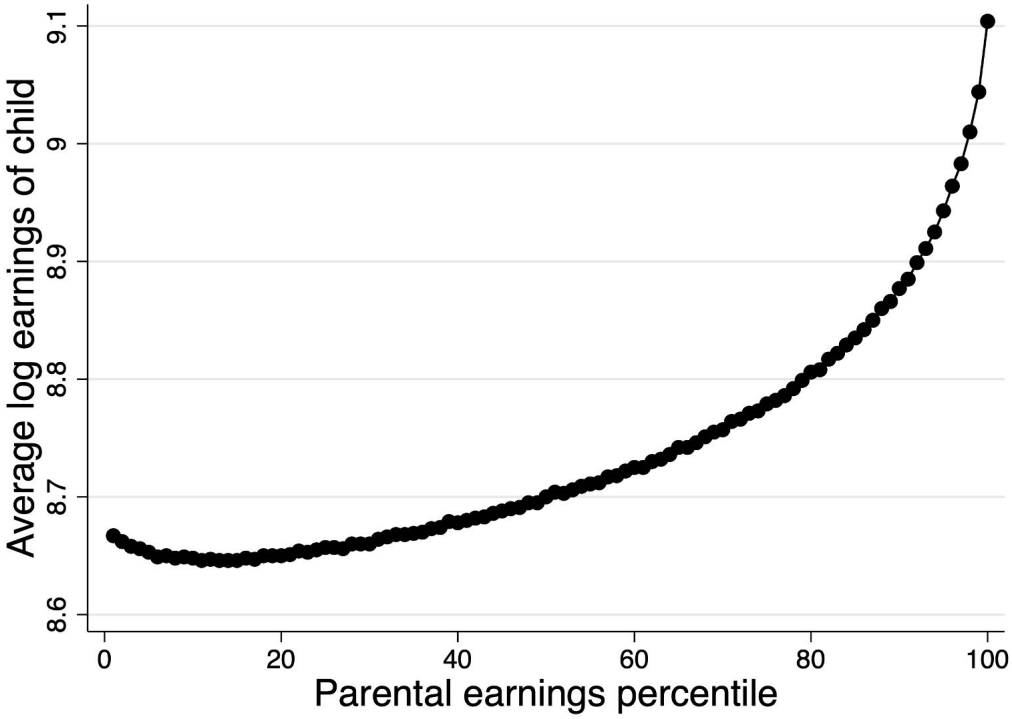
Notes: Each row presents estimates for the variable defined in the first column.Columns 1 and 2 present the average value of the variable for the sample of individuals who do not and do work for the employer of their parent at their first stable job, respectively. Columnns 3-5 present the average characteristics of the compliers for the case in which the instrumental variable is a binary variable equal to one if the residualized hiring rate exceeds the 25th, 50th, and 75th percentile, respectively. The complier characteristics are estimated using the methodology described by Abadie (2003). I winsorize the estimates of κ at the 1st and 99th percentiles to reduce the influence of outlier values. Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Table A.10: Intergenerational Elasticity of Earnings Using Long-Run Earnings

	earnings of child in 2016		
	(1)	(2)	(3)
Panel A. Including Zero Earnings			
log of parental earnings	0.378	0.417	0.396
	(0.002)	(0.002)	(0.001)
sample	daughters	sons	all
observations	8,416,000	8,591,000	17,010,000
Panel B. Excluding Zero Earnings			
log of parental earnings	0.2499	0.2203	0.2348
	(0.0006)	(0.0005)	(0.0004)
sample	daughters	sons	all
observations	7,412,000	7,706,000	15,120,000

Notes: Columns 1 through 3 present results based on a sample of daughters, sons, and all children, respectively. The estimates in Panel A are the coefficients from a regression in which the independent variable is the log of parental earnings and the dependent variable is the inverse hyperbolic sine of the earnings of the child in 2016. The samples used to estimate the regressions in Panel A include children who have zero earnings in 2016. The estimates in Panel B are the coefficients from a regression in which the independent variable is the log of parental earnings and the dependent variable is the log of the earnings of the child in 2016. The samples used to estimate the regressions in Panel B do not include children who have zero earnings in 2016. All regressions are estimated via weighted least squares using sample weights.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

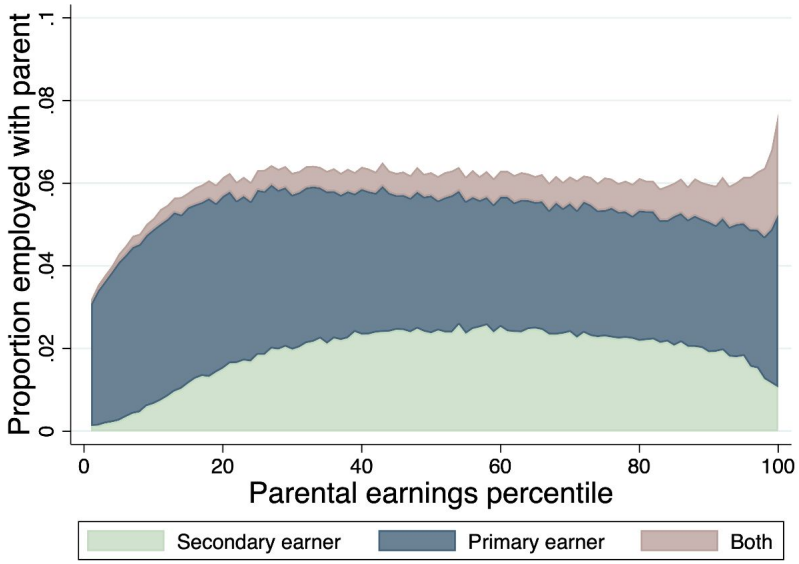
Figure A.12: Log Earnings of Parents and Children



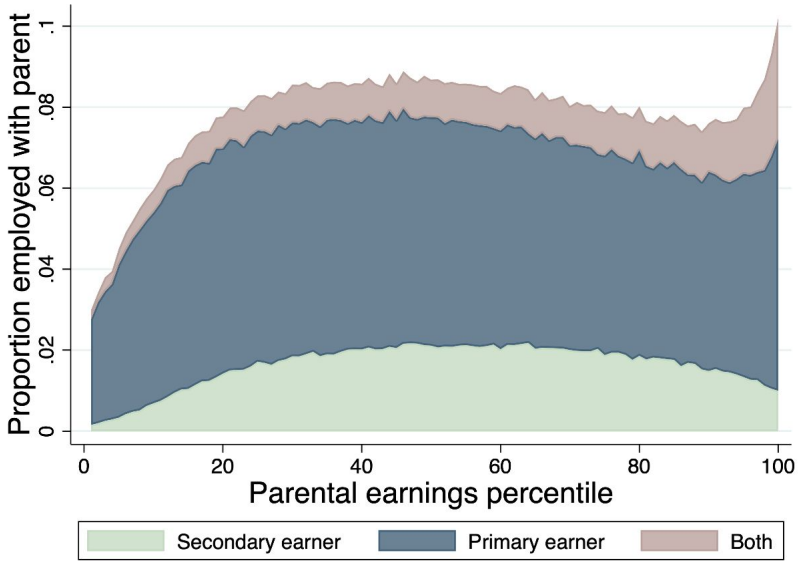
Notes: The figure plots the average log earnings of the children against the average log earnings of the parents. Each point represents the average outcome of individuals and their parents for a given percentile of the parental earnings distribution. The horizontal and vertical axes correspond to the average value of log parental earnings and the average value of the log of the first full-quarter of earnings at the first stable job of the child, respectively. All statistics are calculated using sample weights.
Source: Author's calculations based on matched data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Figure A.13: Intergenerational Transmission of Employers by Parental Earnings

(A) Daughters



(B) Sons



Notes: The figures plot the proportion of children whose first stable job is at the same employer as the secondary earner only, primary earner only, or both parents, respectively. Each statistic is reported separately by the percentile of the parental earnings distribution. Panels A and B present results for the sample of daughters and sons, respectively. All statistics are calculated using sample weights.

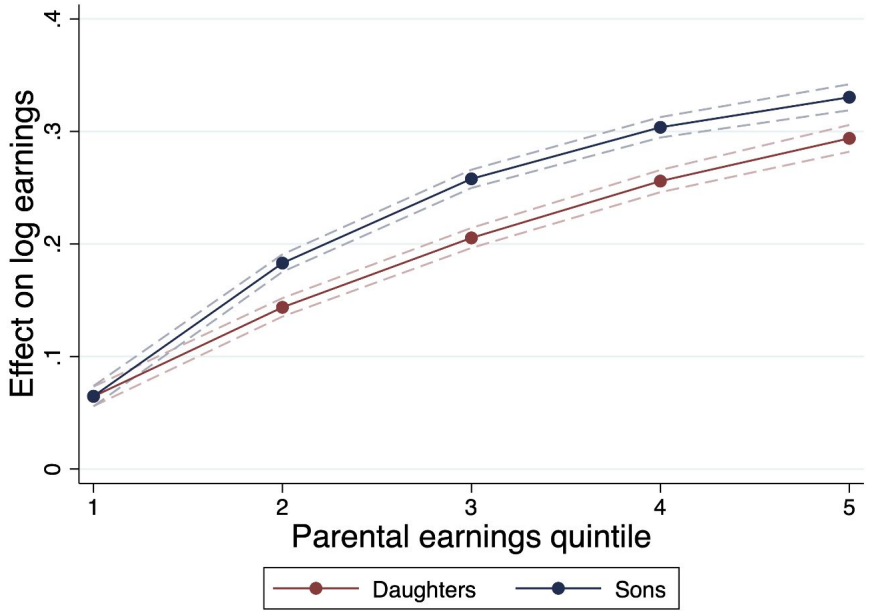
Source: Author's calculations based on matched data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Table A.11: Effect on Earnings Rank by Sex and Parental Earnings

	percentile earnings rank					
	(1)	(2)	(3)	(4)	(5)	(6)
A. All						
works for parent's employer	14.30*	20.64***	15.93***	28.96***	20.63***	21.64***
	(05.88)	(04.70)	(04.42)	(05.34)	(05.46)	(01.97)
F-statistic	238.9	358.0	446.8	330.4	316.2	1434.1
observations	1,350,000	1,987,000	2,297,000	2,462,000	2,487,000	11,460,000
B. Daughters						
works for parent's employer	25.25*	31.27***	27.32*	39.76***	26.58*	31.13***
	(12.49)	(09.68)	(12.06)	(12.55)	(12.30)	(04.02)
F-statistic	64.3	131.2	100.0	106.1	130.9	679.8
observations	586,000	876,000	1,029,000	1,128,000	1,152,000	5,387,000
C. Sons						
works for parent's employer	08.23	15.95**	19.61***	29.59***	27.04***	21.72***
	(08.23)	(06.06)	(05.37)	(06.70)	(07.31)	(02.46)
F-statistic	97.7	198.3	245.7	176.9	161.3	854.2
observations	600,000	909,000	1,067,000	1,149,000	1,148,000	5,501,000
Sample Description						
parental earnings quintile	first	second	third	fourth	fifth	all

Notes: This table presents estimates based on subsamples defined by the interaction between the quintile of parental earnings (defined by the column) and sex (defined by the panel). The outcome varable is the percentile rank of the individual's earnings at their first stable job. The endogenous variable is an indicator equal to one if the individual works for their parent's employer (primary earner) at the first stable job. The excluded instrument is the average quarterly hiring rate at the parent's employer in the four quarters prior to the quarter of entry. All specifications include a fixed effect for the parent's employer; a fixed effect for the year of entry by two-digit industry code of parent's employer by state of parent's employer; and a vector of covariates that includes log annual earnings of the parent in the year prior to entry, a fixed effect for the cohort of the child and interactions between the sex of the child and race, ethnicity, and an indicator equal to one if born in the United States. Standard errors are clustered at the level of parent's employer and are presented in parentheses.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.
*** p≤0.001, ** p≤0.01, * p≤0.05

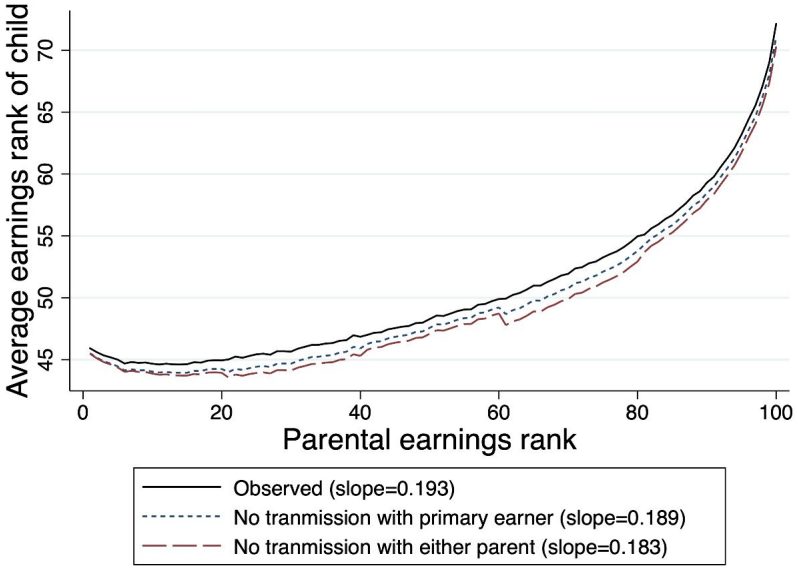
Figure A.14: Estimates from Event Study Design by Sex and Parental Earnings



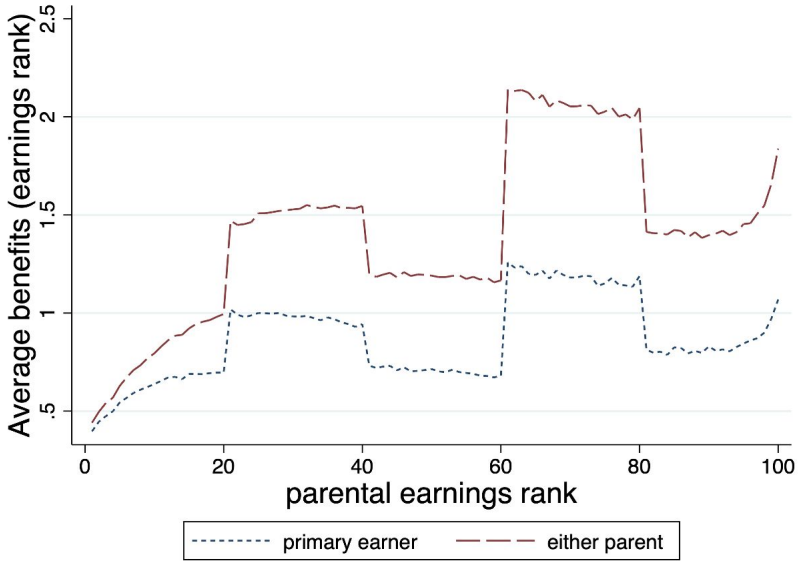
Notes: For each subgroup defined by sex (daughters and sons) and parental earnings quintile, I estimate the event study specification in which log quarterly earnings is the outcome variable and the empirical equation includes controls for an individual fixed effect, a matched pair by quarter fixed effect, and a quadratic in experience. The estimates in the figure are the difference between the effect in time zero minus the effect in time negative one, which captures the increase in log earnings in the period in which the individual joins the parent's employer. Standard errors are clustered at the level of the match pair and the dashed lines denote the 95 percent confidence interval.
Source: Author's calculations based on matched data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Figure A.15: Conditional Expected Rank

(A) Observed and Counterfactural



(B) Difference

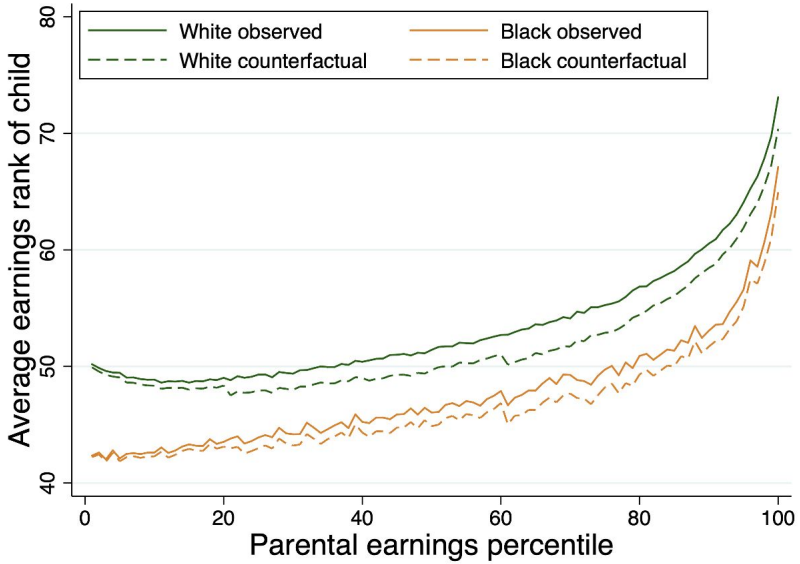


Notes: The solid line in Panel A presents the conditional expected rank measure, which is the average percentile rank the of earnings at the first stable job of the child for each percentile of the parental earnings distribution. The dashed lines represent the counterfactual measures that correspond to the two different scenarios in which no individual works for the employer of the primary earner or either parent. Panel B plots the difference between the observed and counterfactual measure for each percentile of the earnings distribution. The treatment effects used to construct the counterfactual estimates are estimated via two-stage least squares and are estimated separately by the quintile of the parental earnings distribution. All statistics, aside from the two-stage least squares estimates, are calculated using sample weights.

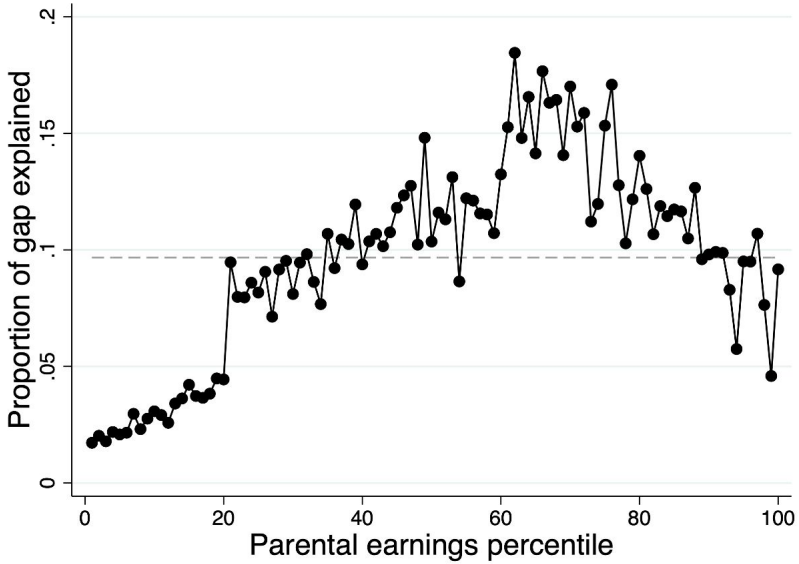
Source: Author's calculations based on matched data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Figure A.16: Black-White Earnings Gap for Sons

(A) Observed and Counterfactural



(B) Explained by Employer Transmission

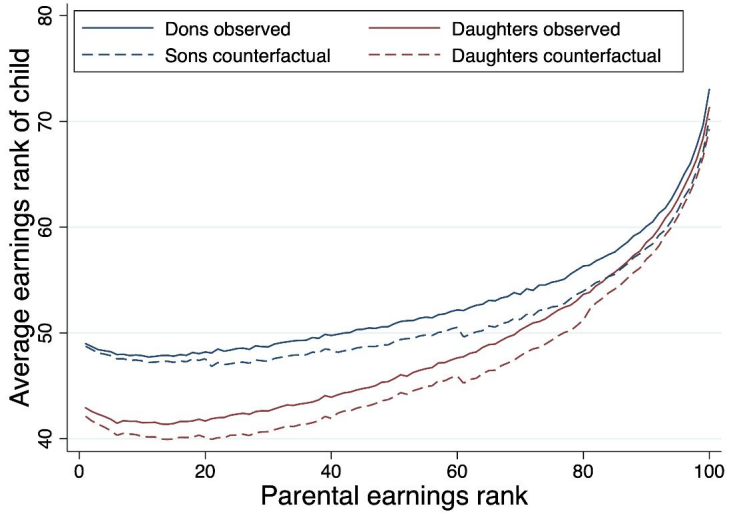


Notes: The solid lines in Panel A present the conditional expected rank (CER) separately for White and Black sons. The dashed lines represent the counterfactual CER that correspond to the counterfactual in which no individual works for the employer of either parent. Panel B plots the proportion of the Black-White earnings gap that is explained by the transmission of employers for each percentile of the parental earnings distribution. The dashed line represents the average across all percentiles. The treatment effects used to construct the counterfactual estimates are estimated via two-stage least squares and are estimated separately by the quintile of the parental earnings distribution and sex of the child. All statistics, aside from the two-stage least squares estimates, are calculated using sample weights.

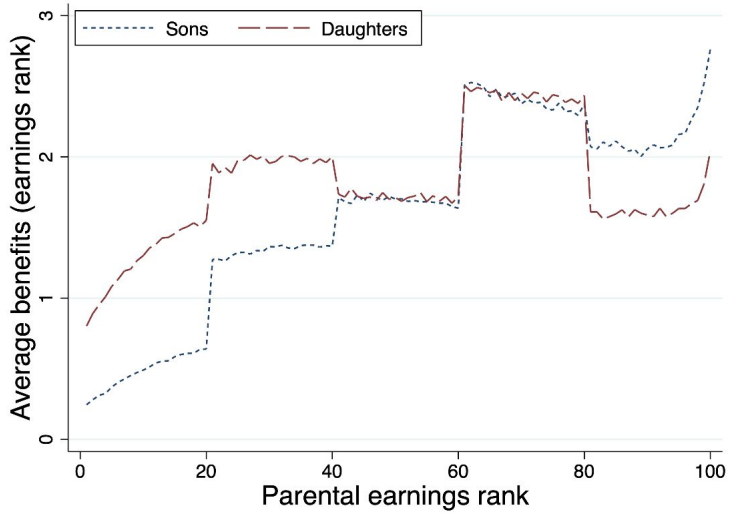
Source: Author's calculations based on matched data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Figure A.17: Gender Earnings Gap

(A) Observed and Counterfactural



(B) Expected Benefits



Notes: The solid lines in Panel A present the conditional expected rank (CER) separately for sons and daughters. The dashed lines below them represent the counterfactual CER that correspond to the counterfactual in which no individual works for the employer of either parent. Panel B plots the expected earnings benefit, which is the difference between the observed and counterfactual CER. The treatment effects used to construct the counterfactual estimates are estimated via two-stage least squares and are estimated separately by the quintile of the parental earnings distribution and the sex of the child. All statistics, aside from the two-stage least squares estimates, are calculated using sample weights.

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

Appendix B Details on Data

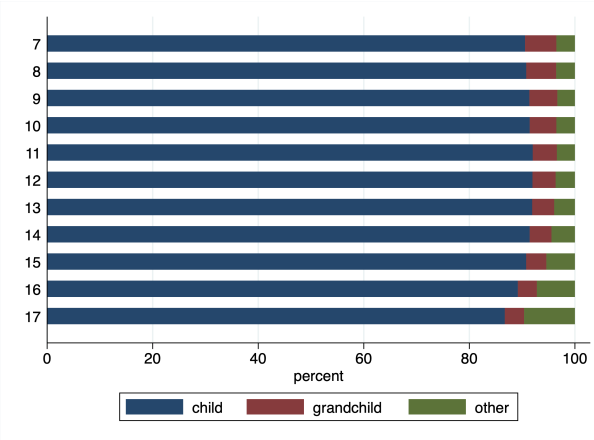
B.1 Sample Frame

The Hundred Percent Census Edited File (HCEF) is an edited version of the Hundred Percent Census Unedited File, which contains all household and person records included in the 2000 Decennial Census. Edits are applied to remove duplicate observations and to ensure consistency between the long and short-form files. While the Decennial Census surveys aim to interview everyone who resides in the United States, in practice, the sample frame considered in my paper does not include all children (within the appropriate age range) living in the United States in 2000. In addition to coverage issues in the 2000 Decennial Census discussed in the text and by Mulry (2007) and the technical report "Coverage Evaluation of Census 2000: Design and Methodology", some children do not live with their parents. Specifically, 91 percent of individuals younger than 18 lived with their parents in 2000. The remaining 9 percent individuals will be excluded from my sample since I require that the parent is the head of household.[48]

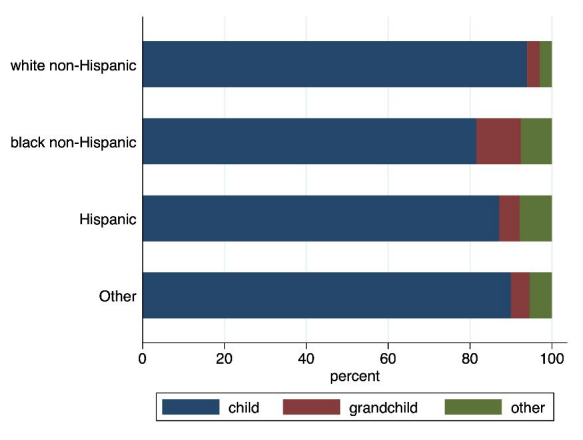
Panel A and B of Figure B.1 depict the share of individuals whose relationship to the household head is defined as a child by age in 2000 and race/ethnicity, respectively. While my sample frame excludes some individuals for these two reasons, it does include the vast majority of children who fall within the age range. Nevertheless, I point out that the results in this paper aim to be representative of the sample frame and I make no attempts to adjust for additional differences between the sample frame and other populations.

Figure B.1: Relationship to Head of Household

(A) By Age in 2000



(B) By Race/Ethnicity



Notes: The figures present the proportion of children born between 1982 and 1992 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/ethnicity of the child.
Source: Author's calculations based on a 5 percent sample from the 2000 Decennial Census obtained from IPUMS, see Ruggles et al. (2019).

[48]This statistic is based on the authors own calculations using a 5 percent sample of the 2000 Decennial Census made available through IPUMS, see Ruggles et al. (2019).

B.2 Sample Restrictions

I make several key sample restrictions in the move from the sample frame to the analysis sample, all of which are summarized in Table B.1. First, I implement a number of restrictions to ensure that I can accurately link the records of the children from the HCEF to the data from the Longitudinal Employer-Household Dynamics (LEHD) program. Individuals are identified by a Protected Identification Key (PIK), which the Census Bureau generates using personally identifiable information.[49] I use the PIK to link person records between the HCEF and the LEHD and to attach employer characteristics to jobs. Various types of measurement error in the HCEF may prevent a PIK from being accurately assigned to an individual. In order to ensure that each child is accurately assigned a PIK, I require that a unique PIK be assigned to the individual and the year and month of birth recorded in the Individual Characteristic File (ICF) match those recorded in the HCEF.[50] The decision to retain only observations with unique non-missing PIKs and matching year and month of birth between the HCEF and the LEHD is conservative, in the sense that it may drop some individuals who could accurately be linked across the two datasets. The justification for doing this is to limit measurement error in intergenerational relationships, which would arise if PIKs were incorrectly assigned to the child or either parent. While these restrictions reduce sample size, they do not introduce bias to the extent that the sample weights account for the selected nature of the sample. 79 percent of the children in the sample frame satisfy these restrictions.

Second, I implement a number of restrictions to ensure that I accurately measure the relationship between children and parents and link parental records to the LEHD. To ensure that the relationship between children and parents is accurately measured in the HCEF, I require that the household contains no more than 15 individuals in the HCEF. To ensure that I am able to link the records of the parents to the LEHD files, I require that a unique PIK be assigned to both parents and the year and month of birth recorded in the ICF match those recorded in the HCEF for both parents.[51] 62 percent of the children in the sample frame satisfy the restrictions in this and the preceding paragraph.

I construct sample weights in order to address the possibility that the first two sample restrictions produce a selected sample. Specifically, using a dataset that includes every child in the sample frame, I estimate the propensity score as the probability of satisfying the first two sample restrictions as a function of observable characteristics that include: sex, relationship to head of household (biological child, adopted child or step child), race (White, Black, Native American, Asian, or other), Hispanic ethnicity, number of parents in the household in 2000, and a vector of observable characteristics of the census tract in which the household resided in at the time of the 2000 Decennial Survey (share of parents that are single parents, median household income, poverty rate, proportion of residents who were living in the same house five years ago, urban/rural, proposition of households receiving public assistance). The sample weights are the inverse of the estimated propensity score.

[49] See Wagner and Layne (2014) for a description of the methodology by which PIKs are assigned to individual observations.

[50] The ICF contains a record for every individual that ever appears in the LEHD and contains basic observable characteristics such as race, sex, and date of birth. The primary source for the date of birth variable is the Person Characteristic File (PCF), which is drawn from information recorded from transactions with the Social Security Administration.

[51] Parents are defined as the household head and either their spouse or unmarried partner. Note that edits applied to the HCEF imply that there are at most two parents in each household.

Table B.1: Sample Restriction Criteria

Exclusion Criteria	Observations Remaining: number	Observations Remaining: percent
none (sample frame with no restrictions)	37,120,000	100
child not assigned a unique PIK or the year and month of birth recorded in the HCEF does not match the date of birth in the Social Security Administration transaction file	29,165,000	79
head of household and spouse (or unmarried partner) is not assigned a unique PIK, the year and month of birth recorded in the HCEF does not match the date in the LEHD or there are more than 15 individuals in the household	23,169,000	62
the state in which the child resided in began reporting to the LEHD less than a year prior when they are expected to graduate high school or the year child entered the labor market, or if parental earnings is below the 5^{th} percentile	21,321,000	57
child did not enter the labor market by the end of 2016	17,010,000	46

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 cummulative 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.

Third, I implement a set of restrictions to ensure that the measurement of key labor market outcomes are not impacted by coverage issues in the LEHD. Since much of the analysis focuses on the labor market outcomes associated with first stable jobs, I drop children if their first stable job is likely to not be covered in the LEHD. Specifically, I identify the state in which children reside in in the year they are expected to graduate from high school and retain observations only if the state was participating in the LEHD for more than a year prior to that year and the year child entered the labor market. Since an important dimension of the project is to study differences across the parental earnings distribution, I also drop parents for whom I cannot reliable measure earnings. Specifically, I construct a long-run measure of parental earnings (discussed in detail in Appendix Section B.4) and I drop parents whose earnings is below the 5^{th} percentile. The percentile is calculated on a dataset with all previously discussed sample restrictions and also conditional on the child entering the labor market. For parents below this threshold, it is difficult to distinguish between low earnings and earnings missed in the LEHD and I find that measures of earnings and other economic indicators (such as the poverty rate of median value in the census tract in which the household lived in 2000) start to diverge for these households. These two sets of restrictions drop an additional 1.9 million children,

which leaves 57 percent of the sample frame.

Lastly, much of the analysis is restricted to a set of children who enter the labor market. I define entry as the first quarter in which the individual earns at least $3,300 per quarter for three consecutive quarters and receives positive earnings from the same employer for those three quarters. 46 percent of the children in the sample frame satisfy the restrictions in this and the preceding paragraphs.

B.3 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 winsorizing the data–editing or dropping earnings records above some percentile of the distribution. The issue with 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.[52] Then define earnings growth as:

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

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 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 95^{th} percentile of the distribution. Let $\Delta(p95)$ denote the 95^{th} percentile, then the earnings variable used in this paper is defined as:

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

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

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

B.4 Measuring Parental Earnings

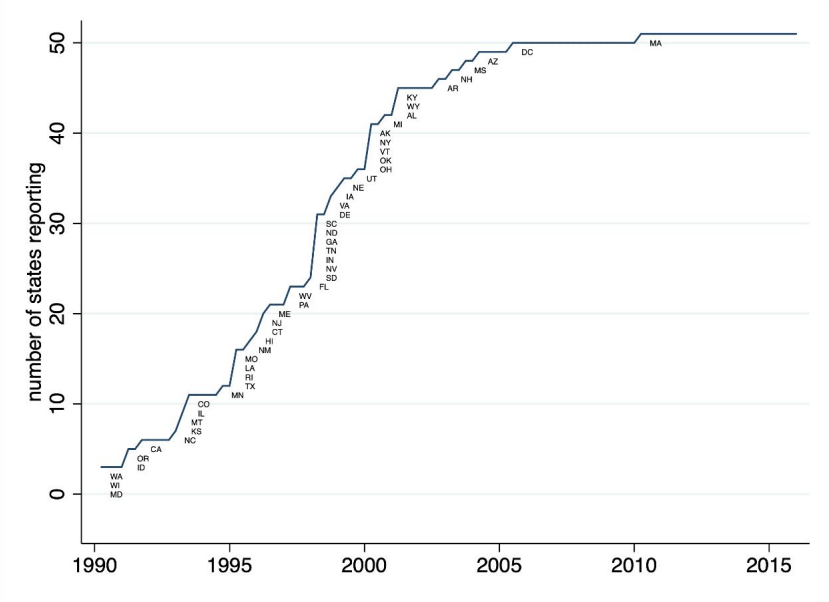
The ideal dataset would contain earnings data for each worker over their entire working life, and lifetime earnings would simply be calculated as the sum of all observed earnings. However, the LEHD fall short of the ideal data because some sources of earnings are not included in the data and because 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. Even using comprehensive income data derived from the 1040 tax forms, there are various issues with their 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.

There are also a number of additional issues that are specific to the LEHD. The main challenge is that it is not clear how to interpret missing data because it is difficult to distinguish between zero earnings and missing earnings. There are two main reasons why earnings data from the LEHD might be missing for a given individual in a given quarter. First, data availability in the LEHD varies on a state-by-state basis. While all states are currently reporting, coverage is less complete for years further in the past. Figure B.2 illustrates when the different states entered the program. While the residential data in the LEHD can be used to identify whether workers are living in a state that participates in the LEHD, imperfect coverage of these data and workers who commute across state boundaries make it difficult to accurately flag workers whose earnings are missing due to a lack of state reporting.

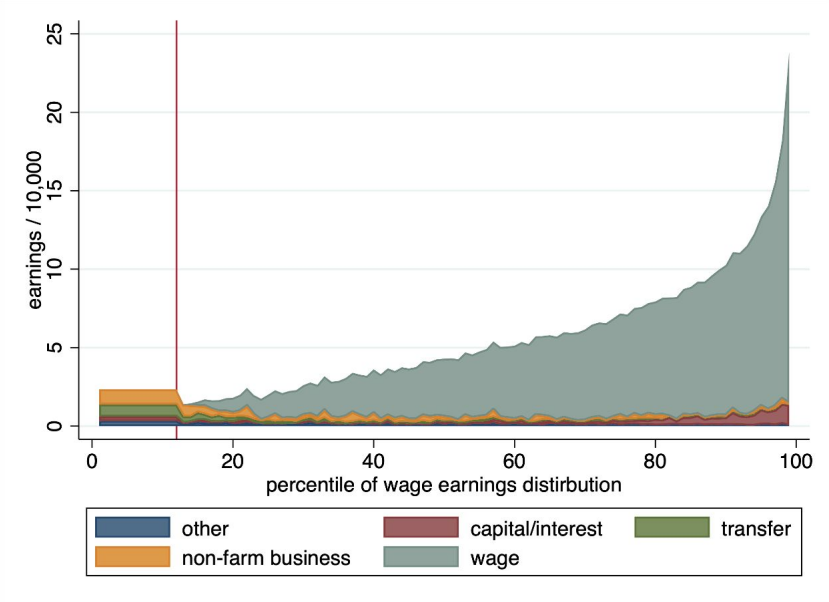
Second, while most earnings (96 percent of salary employment) are covered under the UI system, the LEHD systematically misses some sources of earnings. Measurement issues at the bottom of the wage earnings distribution are of particular concern. Figure B.3 demonstrates this point by using data from the 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. Below the vertical line marks the set of households with no wage earnings (12 percent of household in this sample have no reported wage earnings). Below the 25^{th} percentile, alternative sources of income start becoming an increasingly more important source of total household income, so much so that 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

Figure B.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 B.3: Source of Earnings Across the Wage Earnings Distribution



Notes: The figure presents the average household earnings 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. Percentiles below the vertical line have zero wage earnings. 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, see Ruggles et al. (2019).

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. While Figure B.3 seems to indicate that wage earnings represent the primary source of earnings at the top of the distribution, Smith et al. (2019) find that non-wage earnings become increasingly important in the top 1 percent of earners. Taken together, the measure of parental earnings constructed using earnings data from the LEHD should be seen as representative of working families, which excludes roughly the bottom 10 percent and top 1 percent of earners.

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:

$$y_{it} = \alpha_i + \beta^g X_{it} + u_{it} \tag{B.3}$$

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, race/ethnicity (White non-Hispanic, Black non-Hispanic, Asian non-Hispanic, Hispanic, and other), and state of residence in 2000. 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 30 and 60 and drop individuals that have fewer than 4 quarters of strictly positive earnings over the entire time period.

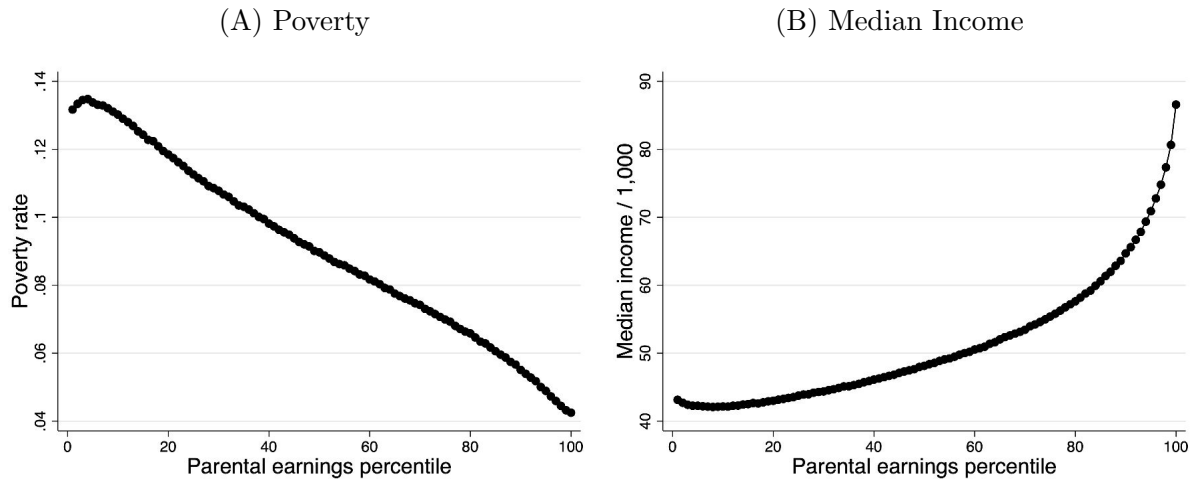
I use the estimates from this model to construct a measure of lifetime earnings for each parent. I predict the value of earnings for each quarter between the ages of 35 and 55 and define lifetime earnings as the average of these values. Individuals with either missing or negative values are assigned a lifetime earnings of zero. For single-headed households parental earnings is simply the lifetime earnings of the parent. For two-parent households, parental earnings is the average of the lifetime earnings of both parents.[53]

Much of the analysis relies on percentile ranks of parental earnings. Thus, it is critical that the estimates of lifetime earnings preserve the rank of the true values of lifetime earnings. While I do not have an objective measure of lifetime earnings against which to validate my measure, I do have other proxies. In particular, I use the HCEF to identify the census block group in which all households reside in 2000 and measure characteristics of those neighborhoods. I focus on poverty rate and median income, since these are likely to be correlated with lifetime earnings. Figure B.4 plots the average value of these neighborhood level variables against the percentile of the lifetime earnings distribution (percentiles are calculated within cohorts of children). If all measures are proxies of lifetime earnings then there should be a monotonic relationship between the variables. The figure illustrates that this is true for most of the distribution. The one exception is that very bottom of the distribution, where parental earnings may be measured with more error. But overall, the figure indicates a strong relationship between the measure of parental earnings used in this paper and other measures of economic status and thus should alleviate concerns related to measurement error.

If the imputed measure of parental earnings is a multiple of the true lifetime earnings value, then the estimates of IGE will be unaffected. However, if the error is not multiplicative, or differs across individuals, then measurement error may affect the estimates

[53]The choice to take the average earnings across parents is in line with the assumptions made by Chetty et al. (2014).

Figure B.4: Parental Earnings and Neighborhood Characteristics



Notes: The figure plots the average characteristic of the census block group of residence in 2000 for each percentile of the parental earnings distribution. The characteristics in Panel A and B are poverty rate and median income, respectively.

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

of IGE. A main concern is that my measure is unable to account for differences in labor force participation. By failing to account for periods of nonemployment, my measure will produce artificially high levels of lifetime earnings for parents who have many periods of zero earnings. This may reduce the elasticity of the initial earnings of a child with respect to parental earnings in the lower parts of the distribution. For this reason, it is useful to compare the results with elasticities to those using percentiles. It is worth pointing out that the issue of measuring the earnings of low-income households is not unique to my setting. For example, Chetty et al. (2014) find that their estimates of the IGE are sensitive to the inclusion of the households below the 10^{th} percentile.

B.5 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 manufacturing/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).

B.6 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,

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

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.[54] The estimate, $\hat{\Psi}_{j(i,t)}$, is a time-invariant measure of the firm pay premium.

I estimate equation B.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 for workers between the ages of 15 and 65.[55] I drop children from the 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. In practice this happens in a very small fraction of cases. In order to avoid disclosure issues related to releasing results on multiple samples, I impute missing data with the mean value of individuals who do not work at the employer of a parent and include a control for imputed values in the empirical specification.

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.

B.7 Firm-Level Variables

B.7.1 Hiring Rate

To measure the hiring rate used as the instrumental variable, 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.

[54] 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.

[55] 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.

B.7.2 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 B.2, where "+" denotes positive earnings and "0" denotes zero earnings at the employer at quarter t.

Table B.2: 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 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.

A small fraction of employers have insufficient observations to calculate this measure. In order to avoid disclosure issues related to releasing results on multiple samples, I impute missing data with the mean value of individuals who do not work at the employer of a parent and include a control for imputed values in the empirical specification.

B.7.3 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.

B.7.4 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.

B.7.5 Firm Age and Size

Measures of firm age and firm size are derived from the Longitudinal Business Database (LBD).[56] 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.[57]

[56]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.

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

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Appendix C 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,

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

and

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

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

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

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,

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

where equation C.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,

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

Where this approximation relies on the same assumption used to derive equation 3. Table C.1 compares the estimates of the IGE from the micro data, in Panel A, to the approximated values, in Panel B. The approximated values are virtually identical to the actual values, which suggests that the methodology performs well in this context.

Standard errors for the counterfactual estimates in Table 7 are estimated via the delta method. Specifically, let

$$\begin{aligned} \Gamma(\vec{B}) &= \frac{\rho(y_{ij}, y_p) - \rho(y_{ij(0)t}, y_p)}{\rho(y_{ij}, y_p)} \times 100 \\ &= \Big(\frac{100}{\rho(y_{ij}, y_p)var(y_p)}\Big) \sum_{q=1}^{5} \hat{\beta}^q \Big[\frac{1}{100}\Big(\sum_{k=(q-1)*20+1}^{q*20} \mathbb{E}[y_p|r_p = k]\mathbb{E}[D_i|r_p = k]\Big) - \mathbb{E}[y_p]\mathbb{E}[D_i]/5\Big] \end{aligned} \tag{C.6}$$

where $\vec{B} = [\hat{\beta}^1, \hat{\beta}^2, \hat{\beta}^3, \hat{\beta}^4, \hat{\beta}^5]$ is a 1×5 vector where the components are the effects conditional on parental earnings for the five parental earnings quintiles. Then we have,

$$\frac{\partial\Gamma(\vec{B})}{\partial\beta^q} = \frac{100}{\rho(y_{ij}, y_p)var(y_p)} \times \Bigg[\frac{1}{100} \sum_{k=(q-1)*20+1}^{q\times 20} \big(E[y_p|r_p = k]E\big[D_i|r_p = k\big]\big) - E[y_p]E[D_i]/5\Bigg] \tag{C.7}$$

Assuming independence between the β^k estimates, leads to the following expression by

the delta method,

$$se(\Gamma(\vec{B})) = \sum_{k=1}^{5} var(\beta^k) \times [\frac{\partial \Gamma(\vec{B})}{\partial \beta^k}]^2 \tag{C.8}$$

where $var(\beta^k)$ is simply the square of the standard error from Table A.7.

Table C.1: Approximation of the Intergenerational Elasticity of Earnings

	(1)	(2)	(3)
A. Individual-Level Data			
$\rho(Y_i, Y_{p(i)})$	0.157	0.130	0.143
B. Approximation			
$\rho(Y_i, Y_{p(i)})$	0.155	0.131	0.143
sample	daughters	sons	all

Notes: The results in columns 1-3 corresopnd to daughters, sons, and all children, respectively. Panel A presents the estimated coefficient from a regression of the log of the first full-quarter of earnings at the first job of the child on the log of parental earnings. The regression is estimated via weighted least squares with sample weights applied. Panel B presents the approximations of the values in Panel A.
Source: Author's calculations based on data from the Longitudinal Employer-Household Dynamics and 2000 Decennial Census files.

Appendix D Stylized Model

D.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,

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

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 actual employer can be written as,

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

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 the following equation:

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

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.[58] Furthermore, the relationship between the human capital of the child and earnings of the parent is characterized by,

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

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 parents' employer makes a job offer to the child and zero otherwise. The offer decision depends on the instrument, $z_i \in \{z', z''\}$ 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.[59] 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

[58] 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 $\beta_i = (\frac{\lambda}{1+\lambda} - \lambda\theta)y_p + [\lambda/(1+\lambda)](\lambda\nu_p - u_p) - [\lambda x + \lambda\eta_i + \nu_i]$.

[59] 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,

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

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

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

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

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.[60] For this reason, I rely on the approximation methodology derived in Appendix C.

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*

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

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,*

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

where the first and third inequalities hold by the law of iterated expectations and the second inequality holds as a result of $O_i \perp\!\!\!\perp \beta_i$.[61]

[60] 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 $A_i = \mathbb{1}\{(\frac{\lambda}{1+\lambda} - \lambda\theta) y_{pj(1)} + (\frac{\lambda}{(1+\lambda)})(\nu_p/\lambda - u_p) > c + \lambda x + \lambda\eta_i + \nu_i\}$.

[61] 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,*

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

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.

D.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 (2012) 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 consider a model in the vein Becker and Tomes (1976, 1986) in which 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 D.1, D.2, and D.3. However, I do not impose the assumption stated in equation D.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 examples, $h_i = log(H_i)$).

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:

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

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,

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

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:

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

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 $x = \frac{-\sigma}{1-\alpha(1+\lambda)} log\big(\frac{R}{\alpha(1+\lambda)}\big)$ and $\theta = \frac{\sigma/(1+\lambda)-(1-\alpha)}{1-\alpha(1+\lambda)}$. Note that this linear relationship is exactly the one assumed in equation D.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,

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

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.[62]

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 ($\frac{\partial exp\{D_i\beta_i\}}{\partial S_i} \neq 0$).[63] 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 D.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.[64] On the one hand,

[62] 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.

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

[64] 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.

D.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.