Intergenerational Occupation Choice*

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Abstract

Parents' labor market experiences are influential for children's later earnings and career trajectories. This paper examines a new channel through which these outcomes may be connected: risk-taking in career choices. The first section constructs a parsimonious empirical measure of lifetime earnings risk for 22 early career occupations observed in the Panel Study of Income Dynamics. Using linked parent and child data, the paper shows that parental layoffs are correlated with children earning less in their early careers and working in occupations with lower risk. This sorting channel can explain up to 13% of the earnings gap. These results are validated using an alternative measure of parents' exposure to macroeconomic shocks through their industry of employment.

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1. Introduction

One of the big questions economists and policymakers confront is how inequality is transmitted from one generation to the next. Understanding these patterns in intergenerational mobility has important implications for designing equitable policies, and has thus been the subject of much research (see overviews by Solon, 1999, Black & Devereux, 2011). One strand of this research has shown that parental layoffs and displacements have lasting effects on children's earnings and other outcomes later in life (Page *et al.*, 2009, Oreopoulos *et al.*, 2008). In order to successfully mitigate these effects, it is crucial to understand the intergenerational transmission mechanisms of labor market experiences.

This paper studies the role of occupation choice in the transmission of negative parental labor market shocks to children's lower earnings in adulthood. The key finding is that children whose parents experienced a layoff during their childhood go on to choose occupations that have lower risk, defined as lower variance in expected lifetime earnings, than their otherwise similar peers. These lower risk occupations are also associated with lower average expected lifetime earnings. The first part of the paper characterizes risk and return of starting occupations, documenting a tradeoff between the two occupational features. The second part uses these characteristics to study the effects of quasi-exogenous variation in parental layoffs and displacements on childrens' occupational characteristics. Finally, the last part of the paper uses an alternative measure of children's exposure to parental labor market shocks to test the validity of this transmission in other settings.

I use a parsimonious framework to define the risk and return of lifetime earnings within various starting occupations. I employ data from the Panel Study of Income Dynamics (PSID), which allows me to observe the earnings trajectories over time across individuals who started their careers in the same occupation. Similar to Boar (2021), I define occupation risk as the cross-sectional mean and volatility of lifetime earnings across individuals in the same starting occupation, in excess of what would be predicted by demographic characteristics. I find a positive relationship between return and risk using data on 22 occupation groups.

After constructing measures of risk and return, I evaluate whether parental experience affects these outcomes for young adults. I use the linked parent-child files from the PSID to identify roughly 4,600 parent-child pairs for whom the child is observed both during childhood and later as a working adult. I regress income in early adulthood on parental job loss (observed during ages 0 to 15), controlling for demographics and parental education and employment characteristics. My results confirm the finding that parental job loss leads to decreased earnings in early adulthood. Then, I use the same framework to evaluate the effect on the risk of the occupation these children choose. I find that parental layoffs are associated with working in lower-risk, lower-return occupations, particularly for children whose father was laid off. Using a back-of-the-envelope calculation, the occupation choice channel can explain up to 13% of the earnings gap in adulthood for children whose parents are laid off.

The focus on layoffs is a departure from the job displacement literature, which focuses on job losses that are due to firm closure, and therefore plausibly exogenous for the workers. I make this decision for two reasons. First, the number of displacements in my sample is small– about one-third the number of layoffs. I worry about drawing conclusions from such a small group of individuals. Second, research has shown that the negative consequences of job separation largely stem from periods of nonemployment in general rather than displacement in particular, and that people who are displaced are no more likely to experience periods of nonemployment than those separated for other reasons (Fallick *et al.*, 2019). However, focusing on layoffs generally runs the risk of conflating job loss with other parental characteristics. To alleviate this concern slightly, I exclude children whose parents were laid off more than one time and I use two variations of controls for parent characteristics. I also report results for the displaced subsample in the appendix.

As a further validation for the finding that negative parental experiences lead children to choose less risky occupations, I repeat my empirical analysis using relative exposure to negative macroeconomic conditions rather than layoffs. I exploit time-varying and cross-sectional growth in parents' primary industry of employment to show that children whose parents worked in relatively slow-growing industries earn 1-9 percentage points less than their peers in early adulthood. They work in occupations with 1-3 percentage points lower lifetime earnings risk, consistent with the results for parental layoffs.

Related Literature To my knowledge, this is the first paper to study how parent experience affects risk-taking in occupation choice. The most similar paper is Boar (2021), which studies whether parents' consumption decisions are influenced by the riskiness of the sector in which their children work. While this paper acknowledges that children's initial sector choice may be influenced by their family's financial resources, my paper tests this relationship more explicitly. **?** uses administrative data from Norway to document that children of high-income, high-wealth fathers experience steeper earnings growth but also more volatile earnings growth, suggesting that they are more likely to choose high-risk, high-return careers. This is consistent with my results, though I use quasi-exogenous variation to try to isolate the role of parental experiences.

This research contributes to a literature measuring career risk. Cubas & Silos (2017) disentangles the industry risk premium from sorting based on industry-specific skills. Dillon (2018) estimates a measure of occupation risk that allows for occupation switching as an insurance mechanism. Saks & Shore (2005) construct a measure of career risk that is related to education decisions. My paper builds on this work by taking occupation risk as given and studying it as an outcome of interest.

My work also relates to the large set of papers examining the long-term impacts of childhood experiences. A large body of work shows that health shocks during childhood can have lasting effects on outcomes in adulthood. See, for example, Almond *et al.* (2009), Almond & Mazumder (2011), and others. Chetty & Hendren (2018) and related papers have shown that the neighborhoods in which children grow up influence their adult outcomes. More specifically, my paper builds on the job displacement literature which studies how parental job loss during childhood affects adult labor market outcomes (Oreopoulos *et al.*, 2008, Page *et al.*, 2009). **?** studies the effects of parental job loss on children's career choices, with a focus on college major decisions and social ties to the labor market, rather than risk. My paper combines this childhood experience literature with the outcome of occupation risk and return to provide a potential mechanism for the observed earnings gaps and career choices.

This paper also touches on the literature about economic experience and risk taking.

Several papers have studied heterogeneity in individuals' risk preferences and how they vary across families or correlate to observed behaviors (Barsky *et al.*, 1997, Kimball *et al.*, 2009). Shigeoka (2019) uses geographic variation in Japan to show how exposure to adverse economic conditions influences risk tolerance and some observed behaviors, such as business ownership. These papers rely on survey questions that elicit individuals' risk preferences by asking them how they would respond to hypothetical income trade-offs. My paper will advance this literature by taking occupation risk as given and studying how these heterogeneous preferences map into actual labor market choices. Malmendier & Nagel (2011) uses survey data to demonstrate that individuals' financial market experiences influence their future financial decisions. Poor past performance tends to make them less likely to take risks. My contribution is testing this finding in the labor market, which is a more consequential source of income for many people than financial markets.

Outline The rest of the paper proceeds as follows. Section 2 discusses the measurement of occupation risk and return, Section 3 describes the empirical framework, Section 4 describes the data, Section 5 presents results for parent layoffs, Section 6 presents results for macroeconomic exposure, and Section 7 concludes.

2. Characterizing occupations

2.1. Framework

As a starting point for my analysis, I assume that individuals enter the labor market and choose an initial occupation that will provide a stream of earnings over their career. The reason for focusing on starting occupation is two-fold. First, there is no obvious way to categorize individuals into occupations systematically, as they could theoretically change occupations every year. Characterizing occupations based on workers who stay in their occupations for long periods of time may not be appropriate as these workers might be better matched to their jobs than the general pool of workers to choose that occupation at any point in time. Since all workers must start somewhere, looking at first occupation provides a somewhat natural way of dividing the workforce into occupations, even if these are not permanent. It also makes sense from an entry-decision framework.

The second reason I focus on starting occupations is because I want to study the early-career decisions of individuals who had negative parental employment experiences in their childhood. If I characterize occupations based on the individuals who hold those occupations at the prime of their careers, ascribing those attributes to the young adults who choose those careers may be inappropriate, as young adults in particular tend to change occupations more than older individuals (Kambourov & Manovskii, 2008).

Next, I identify the salient pecuniary characteristics of occupations. Using a similar framework to Boar (2021), I assume that individuals enter the labor market with a prediction of what their lifetime earnings will be based on their demographic characteristics and education. In particular,

$$y_{ijt} = f(\boldsymbol{X}_{it}, t) + \epsilon_{ijt}, \tag{1}$$

where y_{ijt} is real annual labor income of individual i in year t who started their career in occupation j; $\boldsymbol{X}_{it}$ are observable demographic characteristics, including race, an age polynomial, gender, and educational attainment, but notably excludes occupation. Then ϵ_{it} may be interpreted as the annual real earnings of individual i in excess of what would be predicted by their demographics and macroeconomic conditions alone, which is captured by $\hat{y}_{it}$.[1]

For each individual, I aggregate (1) over the life cycle to construct lifetime earnings, expressed in annual terms

$$Y_{ij} = \frac{1}{T} \sum_{t} \frac{y_{ijt}}{R^{t-t_0}}, \tag{2}$$

where Y_{ij} is lifetime earnings of individual i who started their career in occupation j at time t_0. Discount rate R is assumed constant for simplicity. I then use equation (1) to decompose

[1] Because I did not condition on occupation in $f(\cdot)$, the residuals need not be mean zero within occupation.

lifetime earnings into two components:

$$\hat{Y}_i = \frac{1}{T}\sum_t \frac{f(\boldsymbol{X}_{it}, t)}{R^{t-t_0}} \tag{3}$$

$$\varepsilon_{ij} = \frac{1}{T}\sum_t \frac{\epsilon_{ijt}}{R^{t-t_0}}, \tag{4}$$

where $\hat{Y}_i$ is predicted lifetime earnings of i conditional on demographics and aggregate conditions, and ε_{ij} is the excess lifetime return of individual i, and $Y_{ij} = \hat{Y}_i + \varepsilon_{ij}$.

Note that I have not conditioned on occupation in constructing $\hat{Y}_i$. Thus there can be some portion of ε_{ij} that comes from the choice of occupation j. I use this observation to define the return and risk of occupation j as the cross-sectional mean and volatility of excess lifetime earnings (ε_{ij}) across individuals with the same starting occupation j,

$$\text{Lifetime earnings return} = \mathbb{E}_j[\varepsilon_{ij}] \tag{5}$$

$$\text{Lifetime earnings risk} = \mathbb{V}_j[\varepsilon_{ij}] \tag{6}$$

$$\tag{7}$$

To illustrate why these features are relevant, consider the perfect capital market benchmark in which individuals choose occupations to maximize lifetime consumption, subject to a lifetime budget constraint,

$$\max_j \left\{ \mathbb{E} \sum_{\tau=0}^{T} \frac{u(c_\tau)}{R^\tau} \right\} \tag{8}$$

$$\text{s.t.}$$

$$\frac{1}{T}\sum_{\tau=0}^{T} c_\tau = \hat{Y}_i + \varepsilon_{ij}$$

Lifetime earnings risk and return are relevant features of occupations in this simple framework as they provide information about the mean and variance of the budget constraint. This simple framework excludes many other relevant features of career choice, but it is informative about the pecuniary component of career choice nonetheless.

2.2. Data and limitations

I estimate these measures using longitudinal data on labor income from the PSID.[2] My sample includes individuals with positive labor income for at least ten years. Labor income includes transfers from unemployment compensation and workers' compensation when available. I also restrict the sample to observations with positive hours unless they report non-zero unemployment or worker's compensation. I exclude retired individuals, students, and those are out of the labor force for other reasons during periods in which they are not labor force participants. I exclude individuals during years in which their occupation or industry is missing, unless they report being unemployed. I winsorize log income and exclude the top and bottom one percent.

I assign each individual to a starting occupation based on the first occupation in which they are observed working after finishing school and by age 30. My focus on starting occupations thus excludes individuals from the original survey who were over age 30 in 1968 and individuals who marry into PSID families after age 30. I define occupations using 22 groups of 2010 Census occupation codes, as described in Table 1. After all of these restrictions, I have a sample of 141,053 observations corresponding to 6,760 individuals. Table 2 shows some descriptive statistics of the sample.

If I observed every individual over their full lifetime, I could directly implement the measures discussed above. Instead, I often observe fragments of individuals' careers. In particular, my sample gets thinner at mid-career through retirement. In order to implement equation (2) in my sample directly, I must assume that the distribution of missing data points and the wage profile over the life cycle are not systematically different across occupations.

To the extent that these assumptions are valid, then this measure is an appropriate approximation of lifetime earnings. Indeed, under the strong assumption of perfect consumption smoothing and perfect capital markets, then annual lifetime earnings would be an appropriate measure of annual consumption. If the wage profile is different across oc-

[2] I use waves from 1968 to 2017.

Table 1: Occupation categories

Occupation	2010 Census codes	Number of entrants
Management, business, and financial		
Management	[0010,0430]	424
Business and financial	[0500,0900]	131
Professional and related		
Computer and math	[1000,1240]	85
Engineering and architecture	[1300,1560]	146
Sciences	[1600,1965]	62
Community	[2000,2060]	73
Legal	[2100,2160]	32
Education	[2200,2550]	328
Arts	[2600,2960]	102
Health	[3000,3540]	241
Services		
Healthcare support	[3600,3655]	233
Protection	[3700,3955]	115
Food	[4000,4160]	455
Building maintenance	[4200,4250]	230
Personal care	[4300,4650]	231
Sales and office		
Sales	[4700,4965]	600
Office	[5000,5940]	1,112
Natural resources, construction, and maintenance		
Agriculture	[6000,6130]	89
Construction and mining	[6200,6940]	409
Installation, maintenance, and repair	[7000,7630]	233
Production, transportation, and material moving		
Production	[7700,8965]	904
Transportation	[9000,9750]	528

Note: The table reports the definitions of 22 occupations based on 2010 Census occupation codes. The number of entrants refers to the number of individuals in the PSID who start their career in each occupation and meet the sample restrictions of having 10 years of positive labor income.

cupations systematically, then the average measure would bias downwards the return of occupations that have lower early returns and bias upwards the risk. One way to address this would be to weight individuals more heavily the longer they appear in the sample. Given the relatively small sample sizes within each occupation bin, this does not seem practical in the current framework. Thus, my baseline measure relies on the assumption that the

Table 2: Occupation sample description

	Mean	SD	p5	p50	p95	N
Individual						
High school	0.29	0.45	0	0	1	6,760
Some college	0.28	0.45	0	0	1	6,760
College	0.37	0.48	0	0	1	6,760
Women	0.46	0.50	0	0	1	6,760
White	0.87	0.34	0	1	1	6,760
Entry age	22.9	3.0	19	23	29	6,760
Birth year	1962	12.7	1943	1961	1983	6,760
Individual-year						
Age	38.3	10.5	23	37	57	141,053
Year	1998	12.3	1975	1999	2015	141,053
Real income	35,370	24,068	5,865	30,576	82,598	141,053

Note: The table reports mean, standard deviation, percentiles, and number of observations for the PSID sample used to characterize occupations. The individual statistics are weighted using the individual sample weight from the last year they appear in the PSID. The individual-year statistics are weighted using the individual sample weight. Real income is measured in 2000 dollars.

earnings profile is consistent across occupations.

2.3. Implementation

To implement these measures, I assume log earnings can be modeled as

$$\ln y_{ijt} = \beta X_{it} + \gamma_t + e_{ijt}, \tag{9}$$

where $\ln y_{ijt}$ is log real labor income for individual i in year t who started their career in occupation j; X_{it} includes race, age, age-squared, decade of birth, gender, availability of unemployment transfer data, four education bins, and interactions between gender and marital status and family size, and γ_t is a time fixed effect. To account for the sampling biases of the PSID, I weight observations using individuals' last non-zero weight in the sample.

In this framework, e_{ijt} is the portion of log earnings orthogonal to characteristics X_{it}

and time. I map these results back to equation 1 with the following transformation,[3]

$$\epsilon_{ijt} = \exp(\beta X_{it} + \gamma_t)(\exp(e_{ijt}) - 1) \tag{10}$$

and apply sample analogs of (5) and (6) to construct the measures of return and risk. I assume a discount rate of $R = 1.04$, consistent with Boar (2021).[4]

Other papers in the literature, such as Carroll & Samwick (1997) and Cubas & Silos (2017), focus more on the log income generating process. They decompose e_{ijt} into an occupation-specific premium and a shock process,

$$e_{ijt} = \alpha_j + \nu_{ijt}, \tag{11}$$

where the occupation premium is modeled as $\alpha_j = \mathbb{E}[\beta_j X_{ijt} - \beta X_{ijt}]$, with β_j as occupation-specific returns to observable characteristics and an intercept. They then decompose the error term e_{ijt} into permanent and transitory components. I choose to take a more flexible approach and focus on levels for several reasons. First, I want to study relatively granular occupations and I have a limited sample with which to do that. Decomposing variance into permanent and transitory processes would require estimating at least two if not more parameters for each occupation, which would likely lead to noisy estimates. Second, I have postulated that individuals consider the mean and variance of level lifetime earnings when choosing an occupation to enter. Thus there is a clear mapping between the mean and variance of ε_{ij} and the decision process that I consider. In particular, using the transformation in (10), return and risk are now measured in real US dollars, which is directly comparable to real earnings. Since the income generating process by occupation is not the primary focus of my paper, I choose to use this simpler framework to characterize occupations.

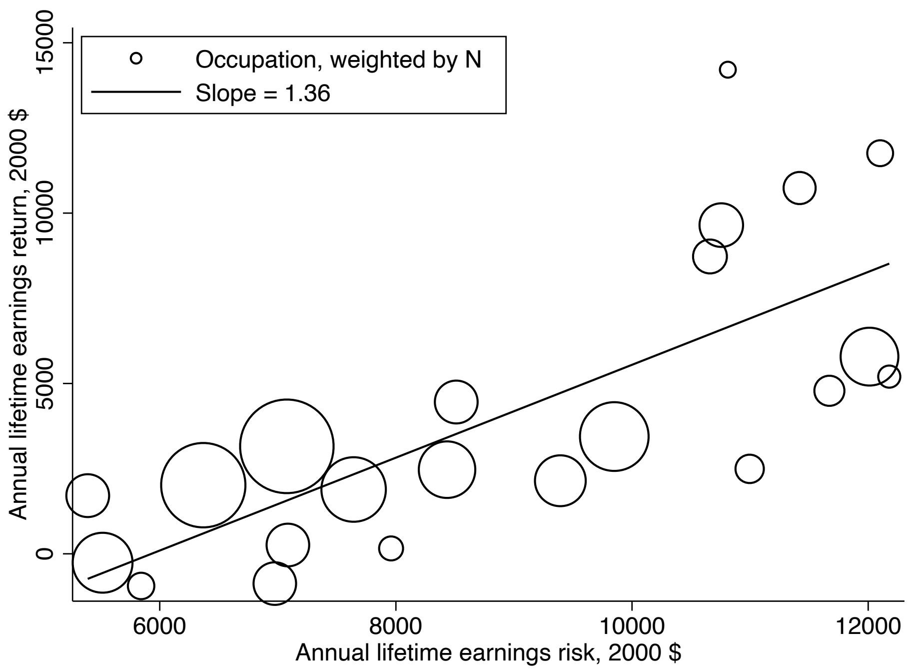
[3]If $y = \hat{y} + \epsilon$ and $\ln y = \ln \hat{y} + e$, then $\epsilon = y - \hat{y} = \exp(\ln y) - \exp(\ln \hat{y}) = \exp(\ln \hat{y} + e) - \exp(\ln \hat{y}) = \exp(\ln \hat{y})(\exp(e) - 1)$.

[4]The results are similar with $R = 1.03$ or $R = 1.05$.

2.4. Risk-return trade-off

Using the methodology described above, I estimate lifetime earnings return and risk for the 22 occupations detailed in Table 1. Figure 1 shows the relationship between average lifetime earnings return and risk as defined in equations 5 and 6. The upward sloping line suggests that occupations that have higher cross-sectional earnings in excess of demographics also tend to have greater cross-sectional volatility, which is consistent with a risk-return trade-off in starting occupations.

Figure 1: Risk-return trade-off



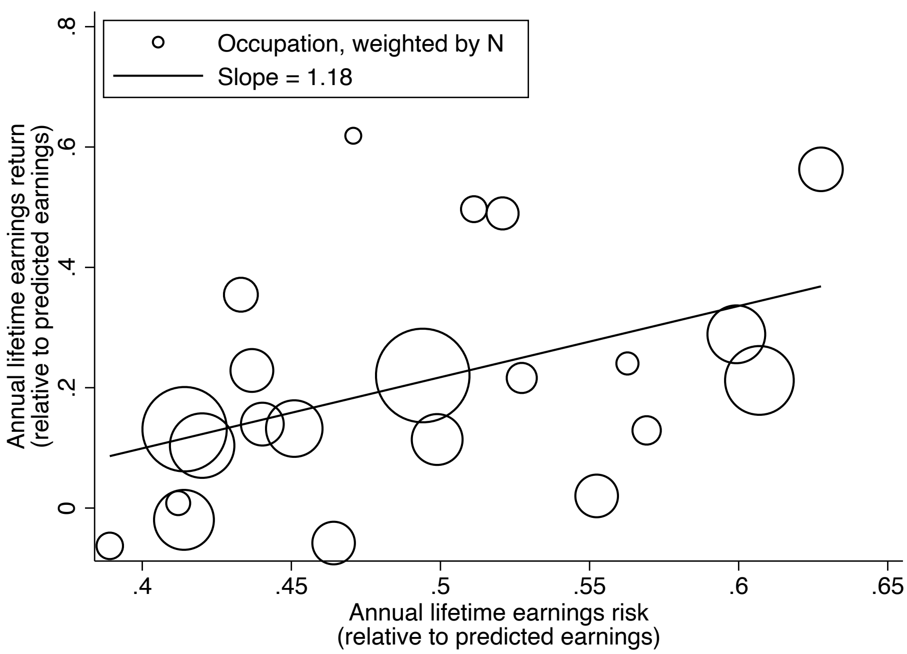
Note: The figure shows the annual lifetime earnings return and risk for 22 occupations, defined as the within-occupation cross-sectional mean and standard deviation of annual average lifetime earnings as defined in equation (4). The units are 2000 US dollars. The size of the circlles indicates the relative share of individuals in each occupation using the individual sample weight for the last wave in which a person appears in the PSID. Occupations are equally weighted in the line of best fit (slope would be 1.02 if weighted by occupation share).

The measures introduced so far are unit-dependent. Due to the mapping to levels in (10), both risk and return could be mechanically higher if individuals have higher expected earnings. To account for this, I provide a unitless measure where I scale lifetime earnings risk and lifetime earnings return by the average predicted lifetime earnings of individuals in that occupation, $\hat{Y}_j$, where

$$\hat{Y}_j = \mathbb{E}_j[\hat{Y}_{ij}], \tag{12}$$

with $\hat{Y}_{ij}$ defined as in equation (3). Figure 2 displays the rescaled version of Figure 1. The interpretation here is that after adjusting for differences in the demographic composition of entrants to different occupations, higher return occupations are associated with higher risk. This result is sensitive to the assumption that occupations follow the same age profile of earnings.

Figure 2: Risk-return trade-off in ratios



Note: The figure shows the annual lifetime earnings return and risk for 22 occupations, defined as the within-occupation cross-sectional mean and standard deviation of annual average lifetime earnings as defined in equation (4). Risk and return are scaled by predicted lifetime earnings, as defined in equation 12, so the units are ratios. The size of the circles indicates the relative share of individuals in each occupation using the individual sample weight for the last wave in which a person appears in the PSID. Occupations are equally weighted in the line of best fit (slope would be 1.05 if weighted by occupation share).

The measures of risk and return that I have proposed aggregate among individuals who sort into a given occupation. A better measure of occupation risk and return would be measures specific to individual i. For example, the expected return of architects might be higher than demographics alone would suggest, but if an individual knows that they do not have the spatial reasoning skills required, their expected return could be much lower than the observed return. If individuals self-select into occupations that they are best at, under the strong assumption that occupation-specific skills are independently distributed across occupations, the observed expected return of the occupation should be an upper bound of the expected return for any individual considering that occupation, and similarly the volatility of lifetime earnings should be a lower bound of the underlying volatility if there is more downside risk in the population as a whole. If this assumption does not hold then I cannot assume a bound in either direction.

I use the results from Figure 1 as my baseline measures of return and risk, as they have the clearest mapping back to the framework introduced earlier in this section and they have the interpretation that a \$1 increase in the risk of an occupation is associated with a \$1.36 increase in return. This relationship will be important for back-of-the-envelope estimates of the effects of occupation sorting on adult earnings in the interpretation of my empirical results.

3. Empirical framework

The goal of this paper is to evaluate whether children's occupational outcomes differ in terms of risk in response to parental labor market shocks. The ideal comparison would be the occupation choice of an individual whose parent experiences an economic shock compared to what that same individual would have chosen if the shock had not occurred. This thought experiment is of course impossible to carry out with data. As an alternative, I turn to the job displacement literature and compare the outcomes of individuals whose parents were laid off during their childhood to otherwise similar individuals whose parents maintained steady employment. In particular,

$$z_i = \gamma \cdot \text{layoff}_i + \beta_1 X_i^c + \beta_2 X_i^p + u_i, \tag{13}$$

where z_i is the adulthood outcome of individual i, X_i^c is a vector of the child's characteristics, X_i^p is a vector of the parent's characteristics, and layoff_i is an indicator for whether the individual's parent is laid off at any point during childhood. The exclusion restriction here is that after controlling for these parent and child characteristics we shouldn't expect any systematic differences between the two groups of children before the layoff occurred. This could be violated if the parent characteristics insufficiently control for parents' earning potential and likelihood of being laid off. To address these threats, I propose two sets of parental controls and I also include a robustness check focusing on the subset of parents who are displaced by firm or plant closure, as these are likely more exogenous to the household (after controlling for industry, etc.) than all layoffs.

The adult outcomes z_i I study are income in early adulthood and risk of first occupation choice, as defined in Section 2. Child characteristics, X_i^c, include the decade in which the child was born and race. In my baseline specification I do not include the child's education, though this clearly affects their labor market outcomes in adulthood. One of the key channels through which negative parental experiences may affect children's outcomes is through their human capital accumulation. If I control for the child's education, then I am shutting down this channel. I also do not include the age at which I observe the child as an adult in my baseline specification, as this could also be related to education decisions.

Parental characteristics, X_i^p, include the parent's education and modal industry and occupation. Because lower income or lower educated individuals tend to experience layoffs at a higher rate than their higher income or educated counterparts, these parental characteristics are important to ensure that this framework is not just picking up socioeconomic characteristics of the parent. Ideally, one would like to measure the family's financial resources as well to better capture the child's socioeconomic upbringing. However, using average family income over childhood will likely absorb some of the financial channel through which parental job loss affects adult outcomes. Additionally, children experience the parental layoff at different ages. Thus it is not clear which age range of parental income is relevant. To that end, my baseline specification uses education, occupation, and industry fixed effects in lieu of family income. As a robustness check, I follow Page *et al.* (2009) and use the distribution of ages at which parental job loss occurs to randomly assign reference ages for the children whose parents are not laid off. This allows me to control for family income two to four years prior to the job loss to better control for the child's socioeconomic background.

4. Data

Using the parent linkage files from the PSID, I identify over 4,600 parent-child pairs. I identify the birth mothers for nearly all of these children and the birth fathers for roughly 3,000 of them. To be included in my sample, a child must be observed living with at least one parent for at least one year before age 15 and they must be observed again as an adult in the labor force, after finishing school.[5] The parent must be working for at least one year in order to observe occupation and industry.

In my baseline sample, I include all parent-child pairs that are observed at least once by the time the child is 15. There are several reasons a child-parent pair could appear for only part of the full childhood–if they are part of the original 1968 sample, if they move into a PSID family, if the family does not respond to the survey for some years but then returns, if the parents divorce and the child lives with just one of them after, if the child lives with a grandparent or other family member for part of childhood, etc. One might be concerned about censoring with including these pairs that we only observe for several years rather than the entirety of childhood. For example, in the PSID the parent might never be laid off but perhaps they were laid off before they entered the sample or during a period in which they did not respond to the survey. I choose to include all of these individuals because setting an ad-hoc minimum observation threshold could elimination important variation. For example,

[5]In order to observe the child's adult outcomes, they must be observed as the head or spouse of a split-off family unit. I also include young adults surveyed in the Transition to Adulthood Supplement for the 2005 to 2017 waves as long as they meet the criteria of being done with school and working.

divorce rates have been shown to rise following layoffs (Charles & Stephens, 2004). If I exclude partial observations, I could be missing some of the children most affected by parent layoffs. To alleviate concerns about censoring, I can repeat my analysis for the subsample of roughly 3,000 children I observe living with at least one parent for the entirety of childhood. However, these results should have the caveat that this sample likely has more stable family structure than the population as a whole.

Tables 3 and 4 show descriptive statistics for the parents and children in my matched sample. The incidence of parental layoff in my sample is about 14 percent for fathers and 13 percent for mothers. About one quarter of total layoffs are displacements due to plant or firm closure. In Table 3, I see that the parents who are laid off are generally less educated

Table 3: Matched parent data description

	Fathers		Mothers	
	Laid off	Others	Laid off	Others
Parent's highest education				
High school	.37	.29	.39	.35
	(.48)	(.45)	(.49)	(.48)
Some college	.24	.22	.35	.26
	(.43)	(.41)	(.48)	(.44)
College	.21	.38	.12	.29
	(.40)	(.49)	(.33)	(.46)
Parent's modal industry				
Manufacturing	.27	.26	.13	.11
	(.45)	(.44)	(.33)	(.31)
Public sector	.05	.08	.03	.05
	(.21)	(.27)	(.16)	(.21)
Observations	469	2,537	789	3,535

Note: The table reports mean education and industry of employment for the parents in the linked parent-child sample. Standard errors are reported in parenthesis. Statistics are weighted using individual survey weight in the last wave the child is observed in the PSID. The number of observations is at the child level (i.e. parents with multiple children will appear more than once).

than the others. I highlight two industries of employment– first, the displacement literature often focuses on plant closures in the manufacturing industry. Since I am including all layoffs rather than just displacements, the laid-off parents in my sample are only slightly more likely to work in manufacturing than the non-laid-off group. To the extent that public sector jobs tend to have more job security than private sector jobs, it is unsurprising that I see slightly fewer laid-off parents working in the public sector, but the size of the differences is relatively small.[6] These statistics illustrate the importance of including controls for parental education and other employment factors in my regressions.

Table 4 shows characteristics of the children in my matched sample. The sample is broadly balanced in age, gender, and birth cohort. The slight difference in birth year for the mothers' sample could reflect shifts in labor force participation over the sample period, which is one of the reasons I report both pooled results and results by parent gender. The children of laid-off parents are less white and go on to receive less education than their peers. Looking at the adulthood outcomes, the affected children earn less on average and start their careers in occupations that have lower risk and lower excess returns, as estimated in Section 2.

As a validation for my measure of occupation risk, I turn to survey questions from the Transition to Adulthood Supplement. This supplement was administered from 2005 to 2017 and asked young adults questions about their career plans and their priorities in job characteristics. I focus on one question in particular: "On a scale of 1 to 7, where 1 means not at all important and 7 means very important, how important is it to you to have a job that is steady, with very little chance of being laid off?" For young adults who were surveyed more than once, I look at the first response they gave. My sample includes 2,300 individuals who responded to this question and can be assigned to a starting occupation. The survey responses are highly skewed with about 54% of respondents saying that it is very important for them to have a steady job. This skewness could come from a lack of trade-off in the survey design–respondents were asked to rate the importance of each job quality separately, rather than prioritize among a set of job characteristics. Although this measure is not perfect, it is closely related to what I am trying to study. Since the variation appears to be at the highest

[6] These industries are measured as the mode over childhood, not the industry in which the parent was employed at the time of the layoff. The reason for this distinction is so that they are comparable to the non-laid-off parent measurement. It is unclear at what age to measure the industry for the parents who are not laid off, and comparing modes for one group to point-in-time measures for the other group does not seem appropriate.

Table 4: Matched child data description

	Fathers		Mothers	
	Laid off	Others	Laid off	Others
Demographics				
Age in adulthood (first)	22.6	22.9	22.1	22.9
	(3.1)	(2.9)	(3.0)	(3.0)
Woman	.51	.50	.53	.51
	(.50)	(.50)	(.50)	(.50)
White	.88	.87	.62	.83
	(.33)	(.34)	(.49)	(.37)
Birth year	1978	1981	1983	1978
	(9.9)	(11.2)	(8.6)	(11.0)
Highest education				
High school	.30	.19	.33	.21
	(.46)	(.41)	(.47)	(.41)
Some college	.27	.25	.35	.27
	(.45)	(.45)	(.48)	(.44)
College	.37	.53	.27	.48
	(.48)	(.5)	(.44)	(.50)
Adult outcomes				
Real earnings	17,907	19,648	14,496	18,710
	(13,111)	(12,637)	(10,558)	(12,794)
Occupation excess return	2,458	3,069	2,224	2,837
	(2,414)	(2,929)	(2,270)	(2,807)
Occupation risk	7,440	7,876	7,264	7,703
	(1,802)	(1,892)	(1,716)	(1,853)
Observations	469	2,537	789	3,535

Note: The table reports mean characteristics for the children in the linked parent-child sample. Real earnings are the average earnings in 2000 dollars in the first three years of work. Occupation excess return and risk are the estimates from Section 2 for the first occupation the child works in. Standard errors are reported in parenthesis. Statistics are weighted using individual survey weight in the last wave the child is observed in the PSID. The number of observations is at the child level.

response, I define prioritizing a steady job as a response of 7.

Using this indicator for prioritizing steady employment, I try two validation exercises. First, I regress children's occupation risk on the steady job indicator. I find a very small (0.6 percentage point) decrease in risk for individuals who respond that a steady job is very important to them, though the standard error is high. Next, I regress the steady job indicator

Table 5: Prioritizing steady employment

	Occupation risk	Prioritize steady job	
Priorize steady job	-0.006		
	(0.010)		
Parent laid off		0.049	0.026
		(0.031)	(0.031)
Parent controls			X
Observations	2,300	2,323	2,323
R-Squared	.000	.002	.054

Note: Column 1 reports the point estimate from regressing occupation risk on the indicator for prioritizing a steady job. Columns 2 and 3 show the point estimates from regressing the indicator for prioritizing a steady job on parental layoff. Column 3 includes controls for parents' education, occupation, industry, and race. Standard errors are reported in parenthesis. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight.

on parental layoff. I find that children whose parents are laid off are 3 to 5 percentage points more likely to respond that a steady job is very important, though again the difference is not statistically significant. Both of these exercises move in the direction I expect which is encouraging, though the limited variation in responses makes it difficult to use these data more robustly.

5. Results

5.1. Adult earnings

Before examining the effect of parental job loss on occupation choice, I first demonstrate that this parental experience is important for adult outcomes. I estimate equation (13) with the child's log mean real earnings over the first three years in the labor force as the outcome of interest. I only include children who are observed for at least three years as adults since young adult earnings are typically noisy in one given year. As described in Section 3, I include controls for parents' education, industry, and occupation. I use four education bins, six broad occupation groups described in table 1 and 15 industries.[7] I include controls for both

[7]The industries are 1. Agriculture, 2. Mining, 3. Construction, 4. Manufacturing, 5. Wholesale trade, 6. Retail trade, 7. Transportation, 8. Utilities, 9. Information and communication, 10. FIRE, 11. Professional,

parents when possible, and an indicator for not observing the second parent characteristics as necessary. For example, in a two-parent household I control for both parents' education, occupation, and industry. If the second parent is not working over the entirety of childhood, I still control for their education but I include indicators for missing industry and occupation. If I do not observe the second parent at all then I will have an additional indicator for missing education.[8]

12. Education, health and social services, 13. Arts, entertainment and food services, 14. Other services, and 15. Public administration.

[8]For the effect of fathers' layoffs on children's outcomes, the results are similar with and without controls for mothers' characteristics. For mothers it is more important to control for father characteristics, likely because there are more single mothers and mothers' layoffs will be more important for single parent families than families in which the mother is a secondary earner.

Table 6: Effect of parent's job loss on adult earnings

Father	-0.135^{***}			-0.0987^{*}		
	(0.0517)			(0.0539)		
Mother		-0.114^{**}			-0.0530	
		(0.0481)			(0.0478)	
Either parent			-0.120^{***}			-0.0869^{**}
			(0.0360)			(0.0367)
Family income				0.299^{***}	0.255^{***}	0.251^{***}
				(0.0383)	(0.0320)	(0.0290)
Mean ($)	18,121	16,803	16,864	17,456	16,656	16,765
Mean (log $)	9.56	9.47	9.47	9.52	9.46	9.46
Observations	2,477	3,516	3,852	2,035	3,001	3,424
R-Squared	.15	.15	.15	.14	.15	.15

Note: All columns include controls for child's decade of birth and race and parents' education. In columns (1)-(3), parent employment controls include dummies for 15 industries and 6 broad occupation categories, measured as mode over career. In columns (4)-(6), parent employment controls are replaced with the log of average real household income over the 2-4 years prior to child's reference age, defined as the age at which their parent was laid off or a randomly assigned age based on the distribution of ages at parent layoff. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight. Mean outcome variables in both levels and logs are reported.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Columns (1)-(3) of Table 6 show the results of my baseline specification. Children whose parents are laid off go on to earn 12 percentage points less as young adults than their peers. Columns (4)-(6) show the results using family income instead of occupation and industry characteristics and show that parent's job loss leads to 9 percentage points lower income as adults. Overall, these estimates are broadly consistent with the finding of Page *et al.* (2009), who find that parental job loss results in 10 to 11 percentage points lower earnings using an earlier sample from the PSID.

5.2. Occupation choices

Now that I have shown that parental job loss negatively affects earnings, I want to explore whether there is a difference in the riskiness of their occupation choices. I assign the children in my sample a level of occupation risk based on the measures estimated in Section 2 and the first occupation these children work in. Table 7 shows the results of regressing occupation risk measured in log dollars on the indicator for parental layoff and the same controls as Table 6. These results indicate that children whose parents are laid off tend to sort into occupations with about 2 percentage points lower risk, though the estimate varies by parent and attenuates with the inclusion of pre-layoff income controls.

Table 7: Effect of parent's job loss on occupation risk

Father	-0.0364^{**}			-0.0116		
	(0.0155)			(0.0160)		
Mother		-0.00630			0.0147	
		(0.0130)			(0.0134)	
Either parent			-0.0233^{**}			-0.00432
			(0.0104)			(0.0107)
Family income				0.0656^{***}	0.0534^{***}	0.0557^{***}
				(0.0115)	(0.00846)	(0.00811)
Mean ($)	8133	7936	7921	8063	7908	7907
Mean (log $)	8.97	8.95	8.95	8.96	8.95	8.95
Observations	3006	4324	4662	2484	3723	4162
R-Squared	.11	.12	.12	.11	.12	.12

Note: All columns include controls for child's decade of birth and race and parents' education. In columns (1)-(3), parent employment controls include dummies for 15 industries and 6 broad occupation categories, measured as mode over career. In columns (4)-(6), parent employment controls are replaced with the log of average real household income over the 2-4 years prior to child's reference age, defined as the age at which their parent was laid off or a randomly assigned age based on the distribution of ages at parent layoff. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight. Mean outcome variables in both levels and logs are reported.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In order to evaluate the importance of this difference, I use the trade-off estimated in section 2 between occupation risk and return. A \$1 increase in occupation risk was associated with a \$1.4 increase in expected return. Using the means in Tables 6 and 7, the estimated elasticities, and this relationship, I find that sorting into less risky occupations can explain up to 13% of the earnings loss for either parent being laid off (3% under the specification with alternative controls) or up to 17% of the earnings loss for fathers being laid off.[9]

5.3. Robustness and discussion

My results presented so far provide evidence that negative parent experiences lead children to sort into less risky occupations, explaining some of the earnings gap in adulthood. However, the magnitude varies with the two sets of parent controls. Another concern could be that even with both sets of controls, layoffs are correlated with unobservable factors that could affect children's earnings potential. I repeat the same specifications for children whose parents are displaced by plant or firm closure. These children still sort into less risky occupations, as seen in Table A.2, but the estimated effects on earnings are imprecisely estimated and close to zero, as seen in Table A.1. Since the number of displacements is quite small, it is hard to draw strong conclusions from these results.

Overall, I interpret these results to suggest that occupation risk choices are affected by negative parental experiences. Given the sensitivity to choice of controls and layoffs versus displacements, I complement this exercise with a second parent experience, described in Section 6.

6. Macroeconomic exposure

The goal of this section is to explore how children's exposure to negative macroeconomic conditions through parental employment affects the occupation choices they make. If I naively

[9]For example, the earnings loss following fathers' layoffs is $0.135 \times \$18,121 = \$2,446$ on average, from column (1) of Table 6. The average decrease in occupation risk is $0.364 \times \$8,133 = \$296$, from column (1) of Table 7. Using the trade-off from Section 2, this deccrease in risk would map to a $1.4 \times \$296 = \$414$ decrease in return, which accounts for 17% of the average decrease in earnings.

look at children who grew up during recessions or booms, I will simply be measuring cohort effects. To the extent that cohorts face different job markets, I may be mistaking different occupation vacancies on the labor demand side for different occupation choices on the labor supply side. Instead, I use variation in both birth year and parent's primary industry of employment to construct a measure of relative exposure to macroeconomic growth. By using within-cohort variation, I can take a cohort's labor demand as fixed and focus on differences in supply decisions.

In particular, I define $\tilde{g}_{kt} = g_{kt} - \bar{g}_t$ as the growth rate of output in industry k in year t relative to the aggregate growth rate of output. I define

$$\eta_{knt} = -\frac{1}{n}\sum_{l=0}^{n-1} \tilde{g}_{k,t-l}, \tag{14}$$

where k is the parent's primary industry of employment, n is the number of years considered, and t is the ending year. I use the negative sign to allow the interpretation that η_{knt} is exposure to relatively worse macroeconomic conditions. In my baseline specification, I choose $n = 18$ and t as the year in which the child turns 18. η_{knt} is thus the average relative macroeconomic growth from birth to age 18 in the parent's industry of employment. I measure growth using percent growth in chain-type quantity indexes for gross output by industry from the BEA, which is available from 1943-2019.

There are two main benefits of using parent's modal industry rather than letting it change over time. The first practical reason is that I do not observe all parents over the entire childhood so I would have to impute missing years for some children or focus on a stable panel. As argued in the previous section, I believe this would eliminate some important variation if macroeconomic exposure leads to changes in family structure. The second benefit of using modal industry is that I will capture fewer endogenous industry changes. If there is a downturn in one industry, some workers may shift to a different industry in response. I may still capture some of these shifts if they end up working in the new industry for a longer period of time, but I shouldn't have year-to-year switching.

I use this measure to study the effect of exposure to negative macroeconomic conditions

Table 8: Macroeconomic conditions and adult outcomes

	Income		Occupation risk	
Father	-0.066^{*}		-0.116^{***}	
	(0.034)		(0.029)	
Mother		-0.127^{***}		-0.110^{***}
		(0.033)		(0.028)
Mean($)	18,121	16,803	8,133	7,936
Obs.	2,455	3,413	2,976	4,174
R-Squared	.08	.08	.04	.04

Note: Regressions include fixed effects for child's birth year. Coefficients reported are on average relative macroeconomic growth of parent's industry from birth to age 18. Outcome variables and macroeconomic exposure are standardized so the estimated coefficients can be interpreted as the standard deviation increase in income or risk associated with a one standard deviation decrease in relative macroeconomic conditions. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

on the riskiness of children's occupation choice. I estimate the reduced form model,

$$z_i = \gamma \eta_{knt} + \iota_t + u_i, \tag{15}$$

where η_{knt} is constructed as above, ι_t are birth cohort fixed effects, and z_i is either average real earnings in adulthood or occupation risk. I standardize z_i and η_{knt} so that γ may be interpreted as the standard deviation increase in outcome z_i associated with one-standard-deviation decrease in relative macroeconomic growth. My prior is that γ will be negative for both outcomes, meaning that children with more negative exposure earn less as adults and sort into less risky occupations. I include birth cohort fixed effects so that γ reflects within-cohort effects, holding fixed labor market conditions when these children reach adulthood.

Table 8 reports the results of estimating (15) for income and occupation risk. A one standard deviation decrease in relative economic performance of the father's industry is associated with a .07 standard deviation decrease in adult earnings and .12 standard deviation decrease in occupation risk. For mother's exposure, the estimated effect on earnings is larger. The relative magnitude of the effect on risk is larger for this shock than the parent's layoff. Using the relationship between risk and return, the decrease in occupation risk accounts for

Table 9: Macroeconomic conditions and adult outcomes, conditional on parent education

	Income		Occupation risk	
Father	-0.0118		-0.0395	
	(0.0349)		(0.0291)	
Mother		-0.0734^{**}		-0.0443
		(0.0327)		(0.0280)
Mean($)	18121	16803	8133	7936
Obs.	2455	3413	2976	4174
R-Squared	.11	.11	.10	.10

Note: Regressions include fixed effects for child's birth year and parent's education. Coefficients reported are on average relative macroeconomic growth of parent's industry from birth to age 18. Outcome variables and macroeconomic exposure are standardized so the estimated coefficients can be interpreted as the standard deviation increase in income or risk associated with a one standard deviation decrease in relative macroeconomic conditions. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

40% of the decrease in earnings through father's exposure and 20% of the decrease through mother's exposure.

One concern with this specification is that relative performance of a parent's industry is not truly random within cohorts. There could be simultaneity bias, in which parents with more education and higher skills are able to sort into high-performing industries, and this is what causes the difference in children's adult outcomes. To address this possibility, I modify the regression framework in (15) to include controls for the parent's education. The results are reported in Table 9. Though the magnitudes of both effects are smaller, they are both still negative. The magnitude of the decrease in occupation risk is still larger than the decrease in earnings for father's exposure.

Previous research has shown that experiences before age five can have substantial long-term impacts on children's long-term outcomes (Currie & Almond (2011)). To that end, I construct a second measure of childhood exposure with n and t corresponding to age five rather than age eighteen. The results are reported in Appendix Tables A.3 and A.4. I still see a negative effect of early childhood exposure on earnings and occupation risk, though smaller in magnitude than over full childhood. The difference in risk accounts for about

23% of the earnings gap for fathers and 5-9% of the gap for mothers. The smaller effect of shocks during early childhood could suggest that the influence on children's decision-making is important. If the entire mechanism were operating through loss of income or parental investment, then we might expect to see more of an effect in early childhood than later. If the mechanism depends on children internalizing their parents' experiences, then it would make sense that the experiences are more influential when they are older.

7. Conclusion

This paper studies the effect of childhood experiences on the riskiness of career paths that children choose in early adulthood. I focus on the choice of first occupation after completing school, which I argue can be characterized by return and risk relative to predicted lifetime earnings. Using parental layoffs and parent's exposure to relative macroeconomic growth as two childhood experiences, I find that children with negative parental experiences go on to earn less as adults and sort into less-risky starting occupations.

Understanding this transmission mechanism is important because it has implications for the pass-through of social policies to the next generation. Even if there is perfect unemployment insurance and parents recover the full amount of lost income during unemployment spells, this experience could still have scarring effects on children's future labor market outcomes if it shifts their decision-making. The welfare implications are unclear from this empirical study, but it will be important to understand how the transmission occurs in order to design policies that can effectively mitigate the consequences.

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A. Additional Empirical Results

Table A.1: Effect of parent's displacement on adult earnings

Father	0.021			−0.006		
	(0.088)			(0.097)		
Mother		-0.111^{*}			−0.009	
		(0.067)			(0.071)	
Either parent			−0.029			0.006
			(0.053)			(0.056)
Family income				0.275^{***}	0.259^{***}	0.254^{***}
				(0.038)	(0.032)	(0.030)
Mean ($)	18,121	16,803	16,864	17,412	16,656	16,756
Mean (log $)	9.56	9.47	9.47	9.51	9.46	9.46
Observations	2,477	3,516	3,852	2,009	3,001	3,406
R-Squared	.15	.15	.15	.13	.15	.14

Note: All columns include controls for child's decade of birth and race and parents' education. In columns (1)-(3), parent employment controls include dummies for 15 industries and 6 broad occupation categories, measured as mode over career. In columns (4)-(6), parent employment controls are replaced with the log of average real household income over the 2-4 years prior to child's reference age, defined as the age at which their parent was laid off or a randomly assigned age based on the distribution of ages at parent layoff. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Effect of parent's displacement on occupation risk

Father	-0.044^{*}			-0.040		
	(0.026)			(0.028)		
Mother		-0.005			0.010	
		(0.021)			(0.021)	
Either parent			-0.023			-0.014
			(0.016)			(0.017)
Family income				0.066^{***}	0.053^{***}	0.056^{***}
				(0.012)	(0.008)	(0.008)
Mean (\$)	8,133	7,936	7,921	8,063	7,908	7,907
Mean (log \$)	8.97	8.95	8.95	8.96	8.95	8.95
Observations	3,006	4,324	4,662	2,484	3,723	4,162
R-Squared	.11	.12	.11	.11	.12	.12

Note: All columns include controls for child's decade of birth and race and parents' education. In columns (1)-(3), parent employment controls include dummies for 15 industries and 6 broad occupation categories, measured as mode over career. In columns (4)-(6), parent employment controls are replaced with the log of average real household income over the 2-4 years prior to child's reference age, defined as the age at which their parent was laid off or a randomly assigned age based on the distribution of ages at parent layoff. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Early childhood macro conditions and adult outcomes

	Income		Occupation risk	
Father	-0.048^{*}		-0.047^{*}	
	(0.028)		(0.025)	
Mother		-0.127^{***}		-0.051^{*}
		(0.031)		(0.026)
Mean($)	18,121	16,803	8,133	7,936
Observations	2,455	3,413	2,976	4,174
R-Squared	.08	.08	.03	.02

Note: Regressions include fixed effects for child's birth year. Coefficients reported are on average relative macroeconomic growth of parent's industry from birth to age 5. Outcome variables and macroeconomic exposure are standardized so the estimated coefficients can be interpreted as the standard deviation increase in income or risk associated with a one standard deviation decrease in relative macroeconomic conditions. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Early childhood macro conditions and adult outcomes, conditional on parent education

	Income		Occupation risk	
Father	-0.015		-0.016	
	(0.029)		(0.026)	
Mother		-0.095^{***}		-0.022
		(0.030)		(0.026)
Mean($)	18,121	16,803	8,133	7,936
Obs.	2,455	3,413	2,976	4,174
R-Squared	.11	.11	.06	.05

Note: Regressions include fixed effects for child's birth year and parent's education. Coefficients reported are on average relative macroeconomic growth of parent's industry from birth to age 5. Outcome variables and macroeconomic exposure are standardized so the estimated coefficients can be interpreted as the standard deviation increase in income or risk associated with a one standard deviation decrease in relative macroeconomic conditions. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$