The Impact of an Early Career Shock on Intergenerational Mobility*

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Abstract

Children's and parent's incomes are highly correlated, yet little is known about how early career shocks contribute to this correlation. This paper focuses on a consequential labor market shock: job loss. We document three new results. First, adult children born into the bottom 20% of the income distribution have double the unemployment following job loss compared with those from the top 20%, and 154% higher earnings losses. Second, this increases the rank-rank correlation 30% for those impacted. Third, richer parents provide career opportunities to their adult children after job loss, consistent with advantages from wealthy parents persisting well into adulthood.

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1 Introduction

Parents' and children's incomes are highly correlated (Martínez, 2021; Chetty *et al.*, 2014b; Black and Devereux, 2010; Björklund and Jäntti, 1997; Solon, 1992). The existing intergenerational mobility literature focuses on measuring this persistence and how much of it is explained by shocks in childhood. Yet parental influence may extend well beyond childhood. If those from lower- versus higher-income families experience early labor market shocks differently, then these shocks may also partly explain the measured persistence between child and parent incomes.

This paper uses Finnish administrative data to link the incomes of parents and their adult children and focuses on a consequential labor market shock: job loss. Prior research demonstrates large impacts of job loss on future employment and earnings (Couch and Placzek, 2010; Jacobson *et al.*, 1993). We find job loss imposes larger costs on those born poor, driving the correlation between parent and child incomes higher. These results demonstrate the importance of explicitly connecting the intergenerational mobility literature to what happens in the labor market once children are adults.

In the first part of this paper, we use an event study approach and exogenous separations from plant closures to show that adult children born to parents in the top 20% of the income distribution have almost half the unemployment and experience a faster earnings rebound following a layoff relative to adult children of parents in the bottom 20%. These effects are persistent and large. Significant differences persist at least six years following job loss for employment and three years for earnings. The net present discounted value (PDV) of earnings losses are 154% higher for adult children born into the bottom 20% relative to the top 20%. Large gaps in the impacts of job loss remain even conditional on similar pre-displacement incomes, conditional on education, and conditional on high and low-income adult children working in the same plant before the layoff.

We find that higher-income children do better after a layoff in part because their parents step in to help them; children of high-income parents are more likely to work in the same firm as their fathers following job loss. This result indicates that higher-income parents invest more in their children well into adulthood, helping their children retain their higher perches on the job ladder.

It is difficult to justify this sort of nepotism on efficiency grounds, and eradicating it could lead to greater mobility.

Second, we examine the extent to which these disparate impacts of job loss increase the correlation between parent and child incomes, reducing intergenerational mobility. We estimate an extension to the calculation of the correlation between the income rank of the parent and the income rank of the child (Chetty *et al.*, 2014a), where we allow the rank-rank regression coefficient to vary with job loss. We find the rank-rank coefficient in the six years following a layoff is 30% higher for those impacted. To put this magnitude in context, Pekkarinen *et al.* (2009) find that a major education reform in the 1970s in Finland reduced intergenerational income elasticity by 23%; Chetty and Hendren (2016) find that moving to a better neighborhood causes children's incomes to converge to those of their higher-income peers at a rate of 4% per year in the U.S.

To extend these results to country-level rank-rank correlation, we run a simulation where we take all individuals at age 30 and estimate how their earnings would change from age 30 to age 40 either with no job loss in the economy or with the impacts of job loss. We use ages 30 to 40 (as opposed to earlier ages) because in Nordic countries the rank-rank correlations do not tend to stabilize until the late 30s (Landersø and Heckman, 2017). We estimate one simulation that only incorporates disparate impacts of job loss, and another that includes both disparate impact and disparate incidence, as children born into the bottom income decile are about twice as likely to experience unemployment compared with children born to the top decile. We find that the population-level rank-rank correlation at age 40 is 3.7% higher due to the disparate impacts and incidence of job loss. This is substantial given that despite the prolific literature on the impacts of job loss, only 6% of adult children born to the bottom decile and 3.5% of adult children born to the top decile transition into unemployment.

These results provide prima facie evidence that early career labor market shocks play a substantial role in determining the magnitude of rank-rank correlations. Other labor market shocks such as recessions (Kahn, 2010; Oreopoulos *et al.*, 2012), trade shocks (David *et al.*, 2013), and disability (Kostol and Mogstad, 2014) could similarly contribute to the rank-rank correlation. Our results demonstrate that even after entering the labor force, adult children of low-income parents have a more precarious perch on the job ladder compared with children of high-income parents, with important implications for intergenerational mobility. Not only are they more likely to lose their jobs, but when they do lose their jobs they experience larger negative impacts. As a result, early labor market shocks widen the gap between those born poor versus rich, increasing the measured persistence of incomes between parents and their children.

These results contribute to our understanding of how inequality transmits across generations. As such, this paper is most closely related to the intergenerational mobility literature (Black and Devereux, 2010; Corak, 2013; Jäntti and Jenkins, 2015; Cholli and Durlauf, 2022). Much of this literature focuses on quantifying the amount of intergenerational mobility across time and space (Davis and Mazumder, 2022; Jäntti and Jenkins, 2015; Chetty *et al.*, 2014a; Corak *et al.*, 2014; Aaronson and Mazumder, 2008), and measurement issues (Jácome *et al.*, 2021; Ward, 2021; Deutscher and Mazumder, 2021; Nybom and Stuhler, 2017). Relative to these papers, it is worth noting that overall intergenerational mobility in Finland, as measured by the rank-rank correlation, is two-thirds the size of the same figure for the United States.[1] Thus even in Nordic countries where mobility is higher this is still an important phenomenon.

We show that the importance of parental background and parental investments follow children well into their careers. The impact of labor market shocks during adulthood is partly mediated by parental interventions, leading to lower mobility and fueling a negative cycle. These results have implications for the broader literature and how policy might increase intergenerational mobility. First, our results emphasize the importance of early career shocks in decreasing overall intergenerational mobility, while much of the prior literature focused on shocks in childhood. Our findings suggest policies that help reduce the impact of job loss on adult children from lower-income backgrounds – for example, by helping them expand their comparatively smaller job networks – might be effective at increasing intergenerational mobility.

Second, we contribute to a rich debate on when in the adult child's life to calculate intergenerational correlations and what one captures at different ages and with different measures. Our results suggest that while measuring intergenerational mobility correlations when children are in

[1] We find the rank-rank correlation is 0.191 in the full sample. For comparison, the equivalent estimate for the United States in Chetty *et al.* (2014a) is 0.287 (see Table 1 row 7 of that paper).

their twenties or early thirties is interesting[2], these measures will not fully capture lifetime mobility for substantive reasons, and not just due to measurement error. Specifically, because labor market shocks impact the rank-rank correlation as children experience the early labor market, the rank-rank correlation is likely to increase over the life cycle. More broadly, these results highlight the importance of income and resource uncertainty and how this varies over the child's lifetime, including well into adulthood (see also Eshaghnia *et al.* (2022) who highlights this point).

We also contribute to the job loss literature. Many papers have documented that layoffs lead to long-term losses in both employment and earnings (Lachowska *et al.*, 2020; Couch and Placzek, 2010; Jacobson *et al.*, 1993). We find job loss causes worse outcomes for those born to lower-income parents, and this remains true even conditional on similar pre-displacement earnings.[3] We go on to calculate the contribution of job loss to the rank-rank correlation, demonstrating that early career shocks like this one play an important role in shaping the amount of intergenerational persistence in incomes.

2 Data and Institutional Context

2.1 Data and Measurement of Income Ranks

We use Finnish linked employer-employee data (FLEED and FOLK) consisting of all Finnish residents between the ages of 16 and 70 years in the period 1988–2016. The unique person identification codes allow us to follow individuals over time and link to their parents' incomes. Unique firm and plant codes allow us to identify each worker's employer and observe job separations.

We restrict to those aged 25-35 at the time of job loss to form our "adult children" sample. We restrict to ages 25-35 for two reasons. First, since the earnings data is only available from 1988 onward and we need to calculate their parents' earnings before their parents reach retirement

[2]It is common not to use the child's (or the parents') lifetime incomes to measure intergenerational mobility due to data constraints. For example, Chetty *et al.* (2014a) measure child earnings primarily for ages 21-22 or 31-32.

[3]A related literature explores the reverse direction, i.e., the impacts of a parent losing their job on their child's outcomes (Willage and Willén, 2020; Huttunen and Riukula, 2019; Lindo, 2011; Rege *et al.*, 2011; Oreopoulos *et al.*, 2008). Another related literature examines who suffers the most from job loss. For example, Hoynes *et al.* (2012) show that men, Black and Hispanic workers, and low educated workers are more affected by job loss. East and Simon (2020) show that low-income workers are also less protected against the earnings costs of job loss.

age, we can only link to parent incomes for younger adult children. More substantively, we are interested in the differential impacts of early career shocks. We focus on the early career given that age-wage profiles show that wages increase rapidly in the beginning of the career, peaking in the forties, and thereafter decline (Johnson and Neumark, 1996). Moreover, rank-rank correlations tend to stabilize after the early career (in Nordic countries in the late 30s), suggesting that one's early career plays a disproportionate role in determining lifetime incomes.

Parental Ranks To divide the sample into adult children of low- or high-income parents, we calculate the total labor market earnings of both biological parents of the adult child. We are able to match biological parents to children using unique identifiers established at birth. We measure parental earnings by taking the average total labor market earnings of both parents from 1988 until the year of the displacement of their adult child. We choose this as our main measure of parental earnings as it captures a large number of observed earnings years for the parents. We rank the resulting average earnings to assign each child a parental income rank within the child's birth cohort, as is standard in this literature.[4] For the first set of results we focus on adult children in the bottom and top 20% in terms of parental income rank. We show our results are robust to including taxable benefits in addition to labor market earnings when defining parental income groups, are robust to only using the years 1988-1990 to calculate the average earnings of parents, are robust to using only the earnings of the father at age 55, and are robust to residualizing out the parent's age.

We can not show the robustness of our results to using lifetime earnings for the parents to calculate ranks because we do not observe lifetime earnings of parents in our data. However, our approach follows best practices in this literature which commonly do not observe the lifetime incomes of parents (and in some cases don't observe any incomes for parents and instead impute them): "the ideal data set should contain several years of income for both parents and children, preferably measured around the middle of their careers" (Mogstad and Torsvik, 2021, p. 13).

For adult children, we also do not observe lifetime earnings. However, one of the main ques-

[4]Parents may be at different ages when the child is born, but given we measure parental earnings over a long stretch of time this is unlikely to bias our estimates of parental ranks.

tions this paper seeks to answer is whether adult child ranks might change substantially in their early careers precisely because early life shocks have persistently different impacts on incomes of children of low- versus high-income parents. To capture the impact of early career shocks on rank-rank correlations as they happen, we estimate how an adult child's income rank within their own birth cohort changes over time before and after a shock. Generally, our approach in terms of measuring parent and child ranks is consistent with Chetty *et al.* (2014a), although we differ slightly in timing.[5]

Last, we note that in order to lose one's job, an individual must first have a job, meaning we condition on employment for our estimation sample. While this does not impact the internal validity of our estimates, this naturally leads to a selected sample. Inequality in initial labor market opportunities will potentially further contribute to intergenerational inequality on top of the heterogeneous effects of job loss. For just one example, Staiger (2020) finds that high-income parents helping their kids find their first jobs increases elasticity of child-parent earnings by 7.2%.

2.2 Job Loss and Plant Closures

We identify causal impacts of job loss on adult children by looking at workers displaced by plant closures from 1993-2010. Unlike other separations like being fired, a plant closure is likely an exogenous shock to a worker's career since it results in separation of all the plant's workers and is unlikely to be related to a single worker's performance. To define plant closures, we observe all private sector plants from 1988 to 2016. A plant is a production unit (for goods or services) A plant is defined as closing in year t if it is in the data in year t but is no longer there in year $t+1$ or in any of the years after $t+1$. Those plant closures for which 70% or more of the workforce is working in a single new plant in the following year are not included to rule out firm reclassification.

We label workers "displaced" if their plant closed down between t and $t+1$, or if they separated

[5] Chetty *et al.* (2014a) measure child earnings primarily for ages 21-22 or 31-32. According to Chetty *et al.* (2014a) earnings stabilize in the early 30s in the United States. We include up to age 40 (and do not stop in the early 30s) because people enter the labor market later and earnings stabilize at older ages in Nordic countries compared with the United States. Chetty *et al.* (2014a) measure parents' incomes as the mean income when the children are between the ages of 15 and 20. We calculate mean income for parents over a longer period and do not restrict to specific child ages. When we use father's income only at age 55 or just the years 1988-1990 we get similar results. We only include labor market earnings in the main specification, but results are unchanged if we also include benefits.

from a plant during t and $t+1$ that closed down the next year between $t+1$ and $t+2$ and that reduced its workforce by more than 30% between t and $t+1$ ("early leavers") (Huttunen and Kellokumpu, 2016; Huttunen *et al.*, 2018). We follow each displaced worker 5 years prior and 6 years after a layoff. This results in a panel of workers spanning the years 1988–2016. Consistent with previous papers in this literature, we restrict the plant size to more than 10 but fewer than 500 workers, and workers must have three or more years of tenure before the layoff. We relax this assumption to only 1 year of tenure in a robustness checks.

As with prior papers on job loss, our control group of non-displaced workers consists of all workers who were not displaced between years t and $t+1$ and meet the same tenure and plant size restrictions as the displaced workers. Importantly, we allow workers in the control group to separate for reasons other than displacement, including voluntary job changes and sickness. For robustness, we also use the matching procedure from Schmieder *et al.* (2018) to construct the control group and estimate a matched difference-in-difference design.

Our main analysis considers three primary outcomes. First, we look at an individual's employment status at the end of each calendar year. Second, we construct an individual's relative earnings by comparing that individual's labor and entrepreneurial earnings each year with his average annual labor and entrepreneur earnings in the 3 years before the layoff. For this measure all earnings are deflated to 2013 euros using the consumer price index. Third, we estimate impacts on the adult child's earnings rank. We construct the individual's yearly earnings rank by comparing an individual's labor earnings relative to the full population of individuals in Finland in the same birth cohort.

We present the main impacts on earnings using relative earnings as the outcome of interest for two reasons. First, if an individual starts with $20,000 and loses $10,000 then this 50% loss in relative earning is more consequential than an individual who starts with $100,000 and loses $10,000, i.e. 10% of pre-displacement earnings. Second, relative earnings give a reasonable interpretation of magnitudes while still allowing us to include those who have zero earnings. However, we also report results using absolute earnings as outcomes in Appendix Table D.12.

Note that in Finland, all workers are entitled to unemployment benefits. In addition, workers who have been working and contributing insurance payments to an unemployment fund are entitled to earnings-related allowances. The conditions for being entitled to these allowances vary slightly by year. In 2020, working at least 26 weeks during fund membership was required. The average salary replacement rate is 60%, and the maximum length of the earnings-related allowance varies from 300 to 500 days depending on the year, the worker's employment history, and the worker's age.

2.3 Intergenerational Mobility in Finland

Figure 1 graphs the rank-rank correlation as in Chetty *et al.* (2014a) for our estimation sample and the full population. The overall rank-rank correlation we estimate of 0.191 for the full population in Finland is two-thirds the size of the equivalent correlation in the United States of 0.287 (Chetty *et al.*, 2014a). The correlation between the rank of the parents and the rank of the child for the estimation sample of 0.121 indicates that parental income may still play an important role in determining the child's future income, even conditioning on children who obtain jobs.[6]

This graph indicates that by virtue of having a full-time job most people will leave the bottom of the income distribution which is largely made up of the unemployed. Thus, obtaining a job serves as something of an equalizer, although a strong correlation between parental and child incomes remains. This paper asks how precarious this success is: can children who were born poor, conditional on entering the labor market and thus leaving the bottom 20% and achieving some degree of career success, withstand a labor market shock in the same way as adult children of richer parents? If not, what are the implications for intergenerational mobility?

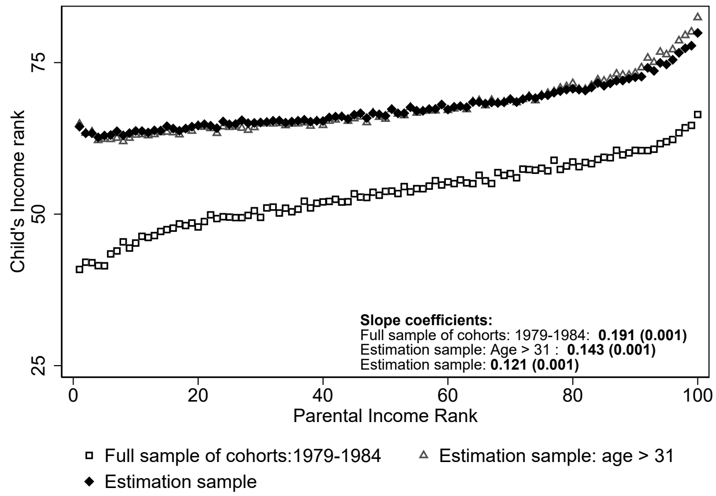
3 Impacts of Job Loss

3.1 Employment and Earnings

Descriptive Results Figure 2 presents earnings and employment trajectories before and after plant closures for adult children born to parents in the top 20% of the income distribution versus

[6]Halvorsen *et al.* (2021) find children of wealthier parents are more likely to pursue high-risk, high-reward jobs.

Figure 1: Intergenerational Mobility in Finland



Note: Figure plots the percentile income rank of the child (y-axis) versus the percentile rank of the parents (x-axis) for three groups: the entire population (grey squares) the sample analyzed in this paper (black diamonds) and our sample restricting to those over age 31 (grey triangles). Estimates from Equation (9) are reported in the bottom right for each group with standard errors in parentheses. Note that we use full taxable income to produce this graph, in contrast to results reported in Table 3

adult children born in the bottom 20%, along with employment and earnings trajectories for those who are not displaced. Plant closures are unlikely to be related to individual worker productivity and thus capture quasi-random job loss. The figure shows that adult children whose parents are in the bottom 20% of the income distribution experience much larger and longer-term decreases in employment and earnings following a displacement.

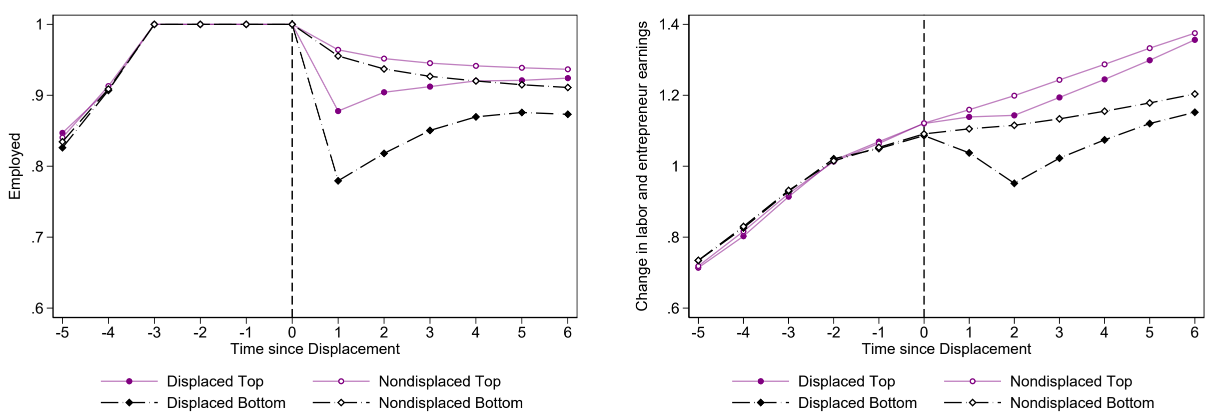
Event Study Specification Moving beyond descriptive results, to formally identify the labor market effects of job loss and how these might differ between children of low- and high-income parents, we use an event-study-style fixed effects regression:

$$Y_{ibt} = \alpha_{ib} + \beta' \mathbf{X}_{ibt} + \sum_{j=-5}^{6} \delta_j D_{b,t+j} + \pi_b + \gamma_t + \epsilon_{ibt}, \tag{1}$$

where Y_{ibt} is the outcome variable for worker i in base-year b at time t, where base year is the layoff year for the treated. The variables $D_{b,t+j}$ are dummies equal to 1 if an individual was displaced. The parameters of interest are the δ_js that measure, for example, the earnings dif-

Figure 2: Raw Patterns of Employment and Relative Earnings Before and After Job Loss by Parental Income Group, Bottom vs. Top 20%

(a) Employment (b) Relative Earnings



Note: Panel A (B) shows employment (relative earnings) of displaced and non-displaced individuals 5 years before and 6 years after a job loss by parental income group. Employment is measured at the end of the year. Relative earnings compare yearly earnings to the mean yearly earnings the 3 years before displacement.

ferentials of displaced workers relative to non-displaced workers in pre- and post-displacement years $j \in [-5, ..., 6]$. The period $t-1$ is used as the baseline and thus the displacement dummy for this year is dropped. To identify the impact for children of low- and high-income parents, equation 1 is estimated separately for individuals whose parents belong to the bottom and top 20% of the earnings distribution.

The specification also includes year dummies, γ_t, and base year fixed effects, π_b, to ensure a comparison between the earnings of displaced and non-displaced workers in the same base-year sample and with the same distance to the base year (-5 to 6 years). Both year effects and baseline year dummies are required due to tenure restrictions, see Schmieder *et al.* (2018). Finally, individual fixed effects, α_{ib}, are included to control for permanent differences in earnings between displaced and non-displaced workers. X_{ibt} includes current-year age fixed effects. Standard errors are clustered by individual i to allow for the correlation of the error terms, ϵ_{ibt}, across different time periods t and base years b for individual i.

The key identifying assumption is that displaced and non-displaced individuals' outcomes would have similar trends in the absence of plant closure. Figure 2 provides visual evidence that the outcomes for displaced and non-displaced groups were evolving very similarly before the displacement shock, suggesting that they would have followed similar trajectories had the plant closure not taken place. A recent literature suggests that event study estimates may be severely biased if the timing of the treatment is staggered and treatment effects are heterogeneous or evolve over time (Sun and Abraham, 2020; Goodman-Bacon, 2018). To ensure staggered treatment is not a problem in this application, the data is constructed so that comparisons always occur between treated and never-treated individuals.

Event Study Estimates Figure 3 reports estimates from equation 1. Those who are laid off experience immediate and large negative effects on employment and earnings. These effects are persistent, lasting at least six years. However, individuals with parents in the bottom 20% of the income distribution fare much worse compared to those in the top 20%. Individuals with low-income parents have almost double the non-employment compared with individuals with high-income parents. This result is not necessarily obvious a priori. A standard job search model where children of the top 20% and the bottom 20% are similar except that the top 20% have access to a stronger safety net could predict that the top 20% remain unemployed for longer, waiting for a better job to arrive. Individuals born to low-income parents also experience much larger earnings losses in the years post-layoff. These differences are significant in the first three years post-layoff for earnings and at least six years post-layoff for employment.

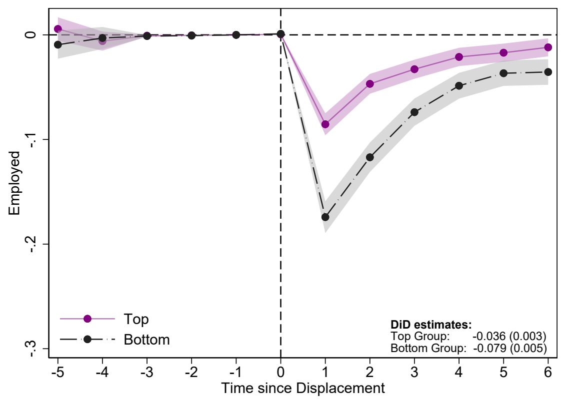
The impact is large in absolute terms. In the first year after the layoff, adult children of low-income parents are 17.4 percentage points less likely to be employed relative to the control group. The comparable number for adult children of high-income parents is 8.5 percentage points. In the second year post layoff, those with low-income parents have a 15.5% drop in earnings relative to their average earnings in the 3 years preceding the layoff compared with a 5.9% drop in earnings for those with high-income parents (see also Table D.11).

In Panel II, we implement the matched approach from Schmieder *et al.* (2018) and the results are very similar. The disparity in the impact is larger for employment, and a little smaller for relative earnings. Together, these results indicate a key way in which intergenerational mobility might be reduced. If adult children of lower-income parents have a looser grip on the job ladder leading to greater scarring following a labor market shock such as job loss, then this will exacerbate intergenerational inequality. We explore this in more detail in Section 4.

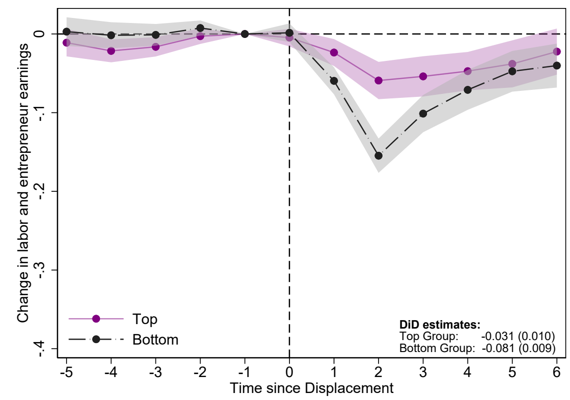
Figure 3: Impacts of Job Loss on Employment and Earnings by Parental Income Group

Panel I: Main Estimates

(a) Employment

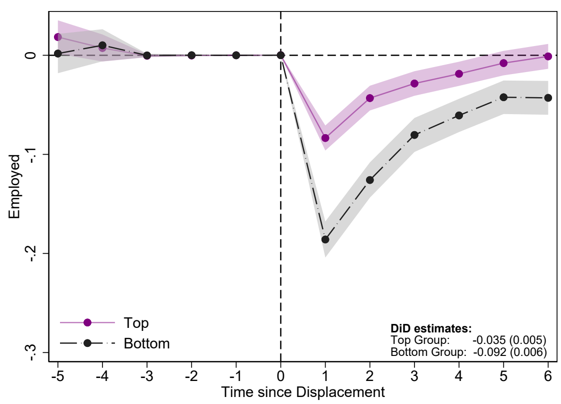


(b) Earnings Relative to Pre-mean

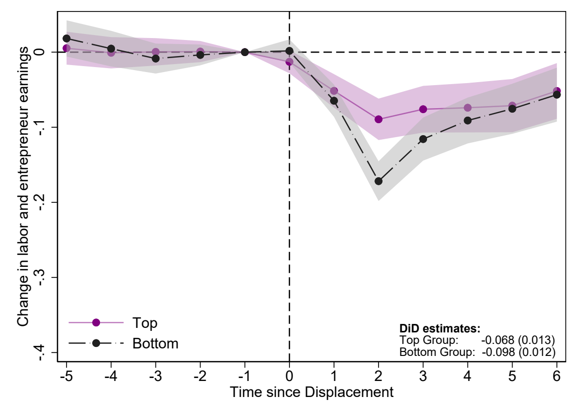


Panel II: Matched Estimates

(a) Employment



(b) Earnings Relative to Pre-mean



Note: Panel I plots the estimates of δ_t obtained using Equation (1) separately children born rich versus poor. In Panel A (B), the outcome is employment (relative earnings). Employment is measured at the end of the year. Relative earnings compare yearly labor and entrepreneurial earnings to the mean of yearly earnings in the 3 years before displacement. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level. DiD estimates are obtained using an alternative version of Equation (1) in which event study dummies are collapsed into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses. Panel II reports event studies and DiD estimates using a matched difference in differences strategy from Schmieder *et al.* (2018) where we extend to 5 years before and do not match on years -4 and -5.

DiD estimates for both groups appear in the bottom right corner of each graph. These are significant, and significantly different from each other. For employment, these estimates show that those with parents in the bottom 20% experienced a 7.9 percentage point average drop in employment (relative to the control group) versus a 3.6 percentage point average drop for the top 20%. This represents a 119% statistically significantly larger increase in non-employment for those with parents in the bottom versus the top group. The reduction in earnings in the six years post layoff is 161% higher for those whose parents are in the bottom versus the top income group, and again, this difference is statistically significant (Appendix Tables D.4–D.6 and D.10–D.12.) Results are even more pronounced with narrower parental income bands, such as the bottom 10% versus the top 10% (Appendix Figure E.3). In Appendix Figure E.4 we report the impacts on total income, where we also include benefits. Interestingly, while generous social support in Finland decreases the negative impacts of job loss for both groups, the stark gap between those born to richer versus poorer parents remains.

Table 1, column 1, summarizes these results by presenting estimates of the PDV for children of parents in the bottom versus the top 20%. In the 6 years post layoff, the estimates show that adult children with parents in the bottom 20% experience a PDV of job loss of €18,254 compared with a PDV of €7,193 for children with parents in the top 20%. Thus, the bottom 20% experiences 154% higher PDV earnings losses compared with the top 20%. As an alternative way to interpret the scale of these results, we next scale the PDV losses using average earnings for the two groups in the 3 years before the layoff. Column 2 shows that those with parents in the top 20% lose just under a fourth of a year's pre-layoff earnings, while those with parents in the bottom 20% lose over two-thirds of a year's pre-layoff earnings. These numbers correspond to PDV earnings losses that are 198% higher for adult children in the bottom 20% in terms of pre-layoff earnings. See Appendix A for additional details on this exercise.

Impacts Over the Business Cycle Motivated by papers showing impacts of job loss vary with economic conditions (Aaronson *et al.*, 2004; Farber, 2017; Davis and Von Wachter, 2011; Schmieder *et al.*, 2018), Appendix Figure E.6 documents an interesting pattern between the state of the economy when the layoff occurred and the disparate impact of job loss (yearly estimates reported in Appendix Figures E.7-E.8). For this exercise, we divide the sample into layoffs that occurred when GDP was growing versus shrinking. While pre- and post-years for growth years will in

Table 1: Present Discounted Value of Earnings Losses and Impacts on Earnings Inequality

	PDV_{Loss}	PDV_{Loss} in years of average pre-layoff earnings	$PDV_{Earnings}$ without job loss	$PDV_{Earnings}$ with job loss	Change in 80:20 inequality
	(1)	(2)	(3)	(4)	(5)
Top 20	€7,193	0.225	€219,683	€212,489	1.084
Bottom 20	€18,254	0.671	€169,867	€151,613	

Notes: Top 20 refers to adult children who were born into the top 20% based on their parent's income (equivalently for Bottom 20). Column 1 shows estimates of the PDV of job loss in the 6 years following the layoff derived by Equation (7) for adult children who lost their jobs but were born in the top 20% versus bottom 20%. Column 3 shows estimates of the PDV of earnings over 6 years for those not laid off, derived by Equation (8); and column 4 for those laid off, also derived by Equation (8). The column 3 and 4 estimates are used to calculate the change in inequality using Equation (9), shown in column 5. All estimates use the matching exercise adapted from Schmieder *et al.* (2018).

some cases overlap with recession years and vice versa, this heterogeneity analysis explores if losing one's job when the economy is currently growing versus shrinking results in different impacts and if these differences are more or less salient if you are born poor versus rich.

Unsurprisingly, the negative impacts of a layoff on earnings and employment are larger in recession years. However, the differences between adult children of low- versus high-income parents are more pronounced in growth years, as demonstrated by both the event study graphs and the DiD estimates. The DiD estimates show that the employment drop is 3 times larger for low-income children compared with high-income children in growth years. In contrast, in recession years the employment drop is 1.4 times higher for low-income children compared with high-income children. When it comes to earnings, the earnings drop is 4.7 times larger for low-income children in growth years, and 1.6 times larger for low-income children in recession years. These results are consistent with the possibility that in recession years it is much more difficult to find a new job compared with growth years, making, for example, family connections less advantageous.

Layoffs from the Same Plant Perhaps adult children born to wealthier parents sort into unobservably better firms, and this is why they experience smaller costs from job loss. To explore this possibility, we estimate the impacts of being laid off from the same firm for a child born in the top 20% relative to a child born in the bottom 20%, compared with their matched controls who also work in firms that employ adult children from both the top 20% and the bottom 20%. Formally, we estimate the following specification, which is similar in spirit to a triple difference framework.

$$Y_{ibt} = \alpha_{ib} + \beta'\mathbf{X}_{ibt} + \sum_{j=-5}^{6} \delta_{1,j} D_{b,t+j} B_i + \sum_{j=-5}^{6} \delta_{2,j} D_{b,t+j} + B_i + \pi_b + \gamma_t + \epsilon_{ibt}, \tag{2}$$

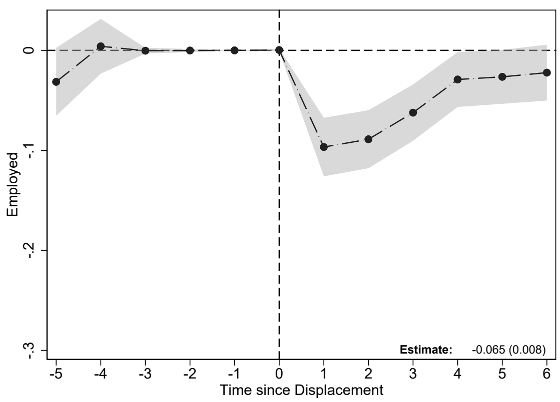
Terms are as defined in equation 1, except we now estimate the top 20% and bottom 20% together, restricting to those experiencing layoffs in the same plant. B_i is an indicator for whether the individual is in the bottom 20%. The coefficients of interest are $\delta_{1,j}$ which capture the impacts on employment and earnings of being in the bottom 20% and experiencing a layoff relative to a colleague in the same plant in the top 20% who also experiences a layoff.

We report results in Figure 4. We find that the significant differences between adult children born poor versus rich remain, even conditional on working in the same firm. Moreover, in Appendix Figure E.9 we compare effects across adult children born to the bottom 20% who work in plants that do not also hire adult children born in the top 20% to adult children born in the bottom 20% who work in firms that also hire adult children born in the top 20%. We find no statistically significant differences. We also do the same for adult children in the top 20% in Panel 1 of Appendix Figure E.9 (comparing their outcomes in plants that do not hire children from the bottom 20% to plants that hire both), and again find no statistically significant differences.

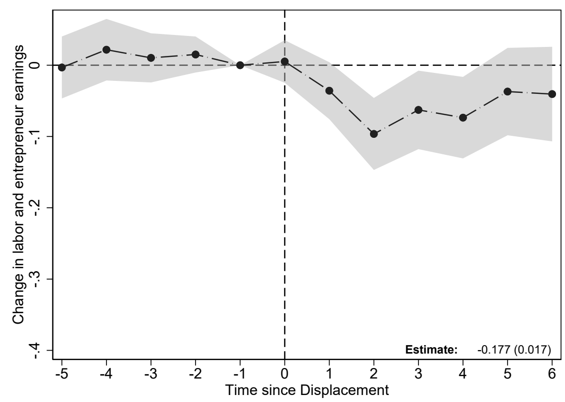
Is This Fully Explained by Education? Figure 5 Panel A (B) shows how the individual-level job loss scars in employment (earnings) vary with education level separately for those born in the top versus bottom 20%. Earnings and employment job scars are half to one-third as large for those with a tertiary degree compared with those who only have basic education. Yet even within the same educational groups, the impacts of job loss still differ for adult children of low- and high-

Figure 4: Impacts of Job Loss on Employment and Earnings Comparing Rich and Poor Kids from the Same Firm

(a) Employment



(b) Relative Earnings



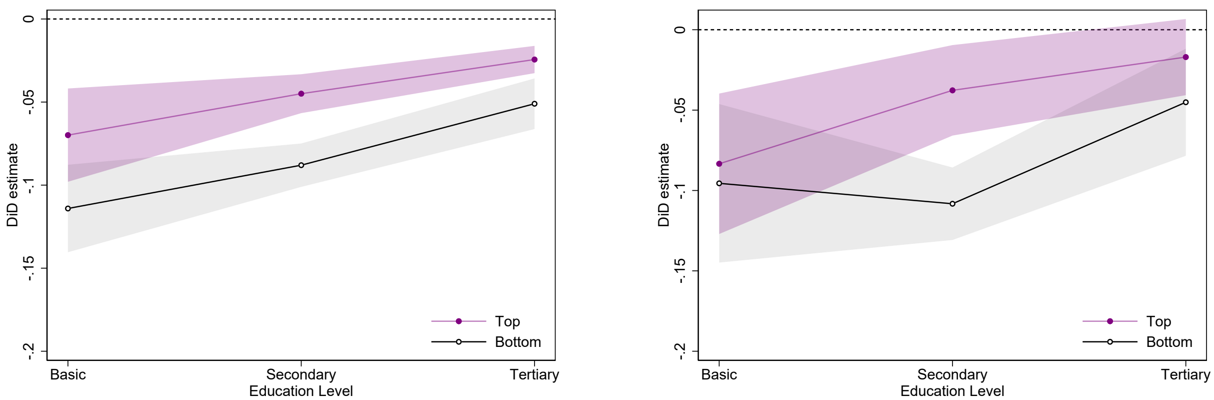
Notes: Figure plots the estimates obtained using Equation (2), comparing the impact of being laid off from the same plant for an adult child born to parents in the bottom 20% relative to an adult child born to parents in the top 20%, and relative to their counterfactuals who are not laid off but are in the top or bottom 20% and work in a plant that employs adult children from both low- and high-income parents. Employment is measured at the end of the year. Relative earnings compare yearly labor and entrepreneurial earnings to the mean of yearly earnings the 3 years before displacement. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level. DiD estimates obtained using an alternative version of Equation (2) in which event study dummies are collapsed into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses.

income parents. For employment, the two groups always experience significantly different job loss scars. For earnings, point estimates always suggest larger effects for the bottom 20%, and the difference is significant for those with secondary education. The majority (56%) of those in the bottom 20% have only a secondary education and 39% of those in the top 20% have only a secondary education (see Table D.1).

These figures suggest that education may play a role in reducing the impacts of job loss but differences on this margin alone cannot fully explain our main results. To formally estimate the role education plays, we decompose the percentage of the difference in job loss scars that can be attributed to observable differences in education versus that which is unexplained by education. We use the canonical Kitagawa-Blinder-Oaxaca decomposition, but introduce a methodological extension to complete this exercise in our setting to account for the fact that the object of interest is itself estimated. We provide more details and outline conditions under which this approach

Figure 5: Education Gradient in Employment and Earnings Job Loss Scars by Parental Income Group, Bottom vs. Top 20%

(a) Employment (b) Relative Earnings



Note: Figures show the education–job loss scar gradient in employment and earnings by parental earnings group. Results are based on DiD job scar estimates. Note that the majority (55%) of those in the bottom 20% have only a secondary education and 40% of those in the top 20% have only a secondary education (see Table D.1), so while these graphs do not account for the portion of the population in each education group, the reader should focus on the secondary school gaps as the largest education category.

is valid in Appendix B. This approach could easily be used in other settings to decompose an estimated object, such as a child penalties.

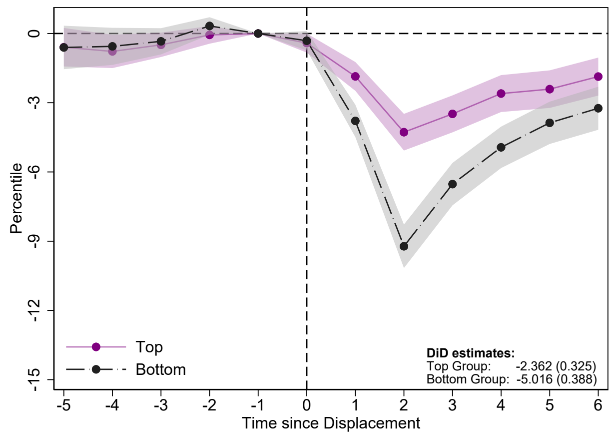
Appendix Table D.7 reports results. Observable differences in the education of adult children of low- versus high-income parents account for 22% of the employment and 78% of the earnings differences in the impacts of job loss. Thus, education gaps by parental income are important for intergenerational mobility (Chetty *et al.*, 2020; Davis and Mazumder, 2022) not only by determining the first job but also by making adult children more resilient to labor market shocks.

3.2 Ranks

Figure 6 reports how the percentile rank changes after a layoff for adult children of parents in the bottom versus top 20%. The percentile rank is defined as one's rank in the distribution of income for one's birth cohort. The figure shows that while both groups experience a drop in percentile rank following a layoff, the effects are larger for adult children of parents in the bottom 20%. This difference is statistically significant 4 years post-layoff.

Do these differences remain even conditional on similar pre-displacement income ranks? If

Figure 6: Impacts of Job Loss on Percentile Rank by Parental Earnings Group, Bottom vs. Top 20%



Note: Figure plots the estimates of δ_t obtained using Equation (1) separately for top and bottom parental income groups. The outcome is an individual's earnings rank within the birth cohort. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level. DiD estimates are obtained using an alternative version of Equation (1) in which event study dummies are collapsed into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses.

there were no differences conditional on pre-displacement rank, the overall impact in Figure 6 would primarily be a "composition" effect, i.e., it would be fully explained by observable differences in pre-displacement ranks across the two groups. While pre-layoff income rank is potentially a treatment effect of having higher-income parents so we do not control for it in Figure 6, it is informative to see if the costs of job loss differ even when we compare those with similar ranks themselves (but born to different parental income groups) prior to displacement.

To address this question, we again estimate the impact of job loss on income rank, but this time condition on income rank before job loss. Table 2 reports the results from this exercise. In the five columns are the parent's quintile of income from the bottom 20% to the top 20% for all quintiles (and not just the bottom and top 20%). Each row depicts a given adult child's pre-displacement income rank. For example, the top left entry is the DiD estimate for children born into the bottom 20% who themselves are in the bottom 20% prior to displacement, and the bottom left corner depicts impacts of job loss for children born into the bottom 20% who are themselves in the top 20% prior to displacement. Each entry in the table is a separate DiD estimate of the impact of job loss on the rank of the child within their birth cohort in the six years post layoff for the specified parental income group and child pre-displacement income group.

This table illustrates two main facts. First, within each column as we move down the column the impact of job loss generally (but not always) increases, meaning that conditional on parental income quintile, those who have higher-paying jobs prior to displacement tend to experience larger negative impacts on their ranks from a layoff. Second, within each row when we move from the left to the right the DiD estimates tend to decrease. In other words, even when keeping the child's pre-displacement income quintile fixed, as we move from children born to poorer parents to children born to richer parents the impacts of job loss generally decrease. Thus, our results are not simply capturing the fact that children who are born to lower-income parents are themselves more likely to obtain lower-paying jobs as adults, and anyone who is in a lower-paying job experiences larger impacts of job loss. Even conditional on similar pre-displacement incomes, we still see that those who are born to higher-income parents suffer less following job loss.

Table 2: Difference in Difference Estimates of the Impact of Job Loss on the Adult Child's Income Rank

		Parent Quintile				
		1	2	3	4	5
Child Quintile	1	-3.159	-4.088	-3.416	-2.685	-1.019
		(0.737)	(0.709)	(0.704)	(0.688)	(0.873)
	2	-5.413	-5.891	-4.039	-4.671	-3.904
		(0.719)	(0.725)	(0.669)	(0.736)	(0.932)
	3	-4.234	-4.857	-4.311	-4.195	-3.001
		(0.893)	(0.823)	(0.718)	(0.754)	(0.844)
	4	-6.318	-5.406	-4.715	-4.557	-2.478
		(0.910)	(0.817)	(0.744)	(0.703)	(0.667)
	5	-4.695	-4.660	-5.481	-3.821	-2.134
		(0.929)	(0.834)	(0.740)	(0.646)	(0.497)

Notes: Table reports DiD estimates from Equation (1). The outcome is the income rank of the adult child within their birth cohort. Columns indicate parental income quintile. Rows indicate the child's income quintile pre-displacement. For example, the top left indicates a child who was born into the bottom 20% in terms of parental income, and the child is also in the bottom 20% before they lose their job based on their own income.

3.3 Parental Investments After Job Loss

How are richer children able to bounce back quicker after job loss? Perhaps their parents directly intervene to help them recover. We test two possible interventions we can observe in the data. First, parents may let their children temporarily move in while the child searches for a new job. In Appendix Figure E.10 Panel A, we show that just under 8% of adult children of lower-income parents live with their parents prior to job loss, 4 percentage points higher than those born to higher-income parents. In Panel B we estimate the impact of job loss on whether the adult child lives with his or her parents. We find very small effects that are never statistically significantly different from each other for the top and bottom 20%, with point estimates slightly larger for the bottom 20%. When we restrict to parents 65 or younger at the time of job loss to address concerns of elderly parents moving in at the time of job loss in Panel C, the results are similar.

Second, high-income parents may employ their children in their own firms or use broader connections to obtain jobs in the same industry after their adult child is laid off. To explore this possibility, we identify all firms in which the father worked between 1988 and the layoff year t and estimate equation 1 with the outcome an indicator variable that takes the value 1 if a child's employer at the time t is among the set of his or her father's employers, and 0 otherwise.

In Figure 7 we present results separately for those who worked with their fathers prior to job loss versus those who did not.[7] We find that those whose parents are in the top 20% are more likely to work for one of their father's employers post-layoff in both cases. Amongst those who do not work with their father prior to job loss, richer kids are almost twice as likely to work with their fathers after job loss. The effect arises in the years immediately after job loss. For those who worked with their fathers prior to job loss, the shared plant closure means that both low- and high-income kids are mechanically less likely to work with their fathers after job loss. However, the negative effect is smaller for those born into the top 20%, and this gap is significant in the first year after job loss.

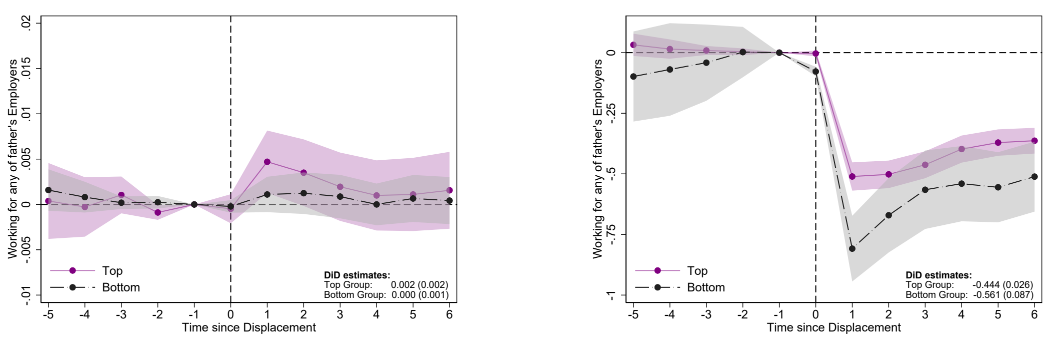
[7] We report results separately by whether the child worked with their father before job loss because Appendix Figure E.11 shows that high-income fathers are at least eight times more likely than low-income fathers to work in the same firm as their children prior to job loss. This will mechanically cause children of high-income parents to be less likely to work with their parents after a job loss, as these children will share the same firm closure with their fathers.

These results show that higher-income parents intervene directly after job loss by helping their kids get jobs in their own firms. This network effect is consistent with the models in Calvo-Armengol and Jackson (2004) and Jackson (2021). Conditional on working (not working) with one's father prior to job loss (92% of the top 20% and 99% of the bottom 20%), our estimates indicate a 0.5 percentage point significant increase in the probability of working in the same firm as one's father for the top 20% in the first year post layoff years and nonsignificant 0.1 percentage point impact for the bottom 20%. The overall employment gap 1 year after job loss is 8.9 percentage points from our main results, meaning this mechanism could explain just over 4% of the employment gaps we documented earlier if those who are employed by their fathers would otherwise remain unemployed. Furthermore, those born to higher-income parents likely benefit from better-connected siblings, aunts and uncles, school friends, and more, suggesting an even larger role for this mechanism.

Figure 7: Impacts of Job Loss on Working in the Same Firm as One's Father by Parental Earnings Group, Separately by Whether a Child and Their Father Were Working in the Same Firm Before Displacement

(a) Not working in the same firm as father at time 0

(b) Working in the same firm as father at time 0



Note: Figures show the estimated impacts of job loss on the probability of working for any of the father's employers since 1988. Estimates of δ_t obtained using Equation (1) separately for the top and bottom 20% parental income groups. Panel A consists of individuals not working in the same firm as their father at time 0. Panel B consists of those sharing the same employer with their father at time 0. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level.

3.4 Robustness

We perform several robustness checks of our results. In Columns 3 and 4 of Appendix Tables D.4-D.9, we add base-year characteristics X_{ibt} such as gender, tenure, education level, and industry, and individual fixed effects are removed. Appendix Figure E.14 shows that the results are robust to alternative measures of earnings for the adult child such as real earnings as opposed to relative earnings. Appendix Figure E.15 shows that our results hold if we use alternative approaches to assign parental income ranks. Results also look similar when we take out the effects of parents' ages when constructing parental income ranks (Appendix Figure E.16) or when we only require 1 year of tenure before the layoff as opposed to the restriction of 3 years required in the main results (Appendix Figure Figure E.17). While 3 years is standard in the job loss literature, relaxing this assumption is particularly relevant in this context where there might be less attachment to the labor force among adult children from low-income backgrounds. Together, these robustness checks suggest that no matter how we approach the data, we always find similarly sized gaps in the impacts of job loss on employment and earnings between adult children of low- versus high-income parents.

4 Intergenerational Mobility

4.1 Impacts of Job Loss on the Rank-Rank Correlation

To understand the implications of our estimates for intergenerational mobility we estimate the impact of job loss on the rank-rank correlation and expand to all income groups (and not just the top and bottom 20%). Consider the traditional rank-rank regression:

$$R_C = a + \beta R_P + \epsilon_i, \tag{3}$$

where R_C is the income percentile rank of the child and R_P is that of the parents. To capture if the coefficient on parental income percentile rank, β, varies with job loss we can write the coefficient as:

$$\beta = \beta_1 + \beta_2 D_C Post + \beta_3 D_c + \beta_4 Post, \tag{4}$$

where D_c is a dummy equal to 1 if the adult child is eventually laid off. Post is equal to 1 in the 6 years after a displacement has occurred both for those who are actually displaced as well as those in the same event year who are not displaced. Thus, $D_C Post$ is the "treatment" of job loss, and the parameter β_2 measures the effect of job loss on intergenerational mobility.

Plugging into equation 3 with the addition of the main effects of job loss ($D_c Post$), the post layoff period ($Post$), and ever being laid off at all (D_c), we estimate the following regression:

$$R_C = \alpha + \beta_1 R_P + \beta_2 R_P D_C Post + \beta_3 R_P D_C + \beta_4 R_P Post + \beta_5 D_C + \beta_6 Post + \beta_7 D_C Post + \varepsilon_i. \tag{5}$$

This exercise is similar to the approach in Pekkarinen *et al.* (2009) to estimate the impact of a major education reform on the intergenerational income correlation, although we use ranks instead of income to address issues with zero earnings (particularly relevant in the context of job loss).[8]

Table 3 reports results from this exercise. The income ranks of parents and children are correlated, as captured by β_1 which is equal to 0.087. Recall that the full population estimate of 0.191 as seen in Figure 1 is two-thirds the size of the equivalent estimate in the United States (0.287 according to Table 1 row 7 of Chetty *et al.* (2014a)). Our estimate here is smaller because our estimation sample is restricted to those who work (a necessary pre-condition to experience job loss) and we focus on labor market earnings only. If we instead include all income the coefficient increases to 0.121 for our estimation sample (see Figure 1).

Unsurprisingly, negative labor market shocks reduce everyone's upward mobility. We find that a layoff leads to large, negative, and significant impacts on the adult child's rank, captured by β_7. Turning to the main regression coefficient of interest, we find that β_2 is 0.033 and is statistically significant. The fact that it is positive means that layoffs are experienced differently by adult children of low- and high-income parents, and as a result, there is an increase in the correlation between the percentile income rank of the parents and the percentile rank of the

[8]Rank-rank correlations are also a better measure if parental and child earnings are not measured at the same age, as is this case in this context (Nybom and Stuhler, 2017).

child. Conceptually, this effect is equivalent to job loss causing the slope of the line representing the relationship between parent and child ranks to grow steeper. Compared to the overall rank-rank correlation of 0.087, our results suggest that intergenerational mobility decreases by 38% as a result of job loss (as in Pekkarinen *et al.* (2009), this is calculated as $0.033/0.087 = 0.38$). A more conservative comparison is the impact relative to those who are not displaced, which indicates that intergenerational mobility decreases by 30% as a result of job loss ($0.033/(0.064 + 0.046) = 0.3$).

Table 3: Impacts of Job Loss on Intergenerational Mobility

Independent Variable	(1)	(2)	(3)	(4)	(5) Plus Benefits
Family rank (β_1)	0.087	0.087	0.087	0.064	0.078
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Displaced (β_5)		-1.300	0.653	0.364	0.478
		(0.133)	(0.127)	(0.273)	(0.286)
Post (β_6)			-6.211	-8.577	-8.339
			(0.024)	(0.049)	(0.045)
Displaced $\times$ Post (β_7)			-3.915	-5.771	-4.463
			(0.154)	(0.331)	(0.286)
Family rank $\times$ Displaced $\times$ Post (β_2)				0.033	0.030
				(0.005)	(0.005)
Family rank $\times$ Displaced (β_3)				0.006	0.008
				(0.005)	(0.005)
Family rank $\times$ Post (β_4)				0.046	0.057
				(0.001)	(0.001)
Observations	16,646,230	16,646,230	16,646,230	16,646,230	16,646,230

Notes: The table shows the impact of displacement on the rank-rank regression coefficient. The dependent variable is the child's yearly earnings percentile rank in the earnings distribution of children in the same birth cohort. Each of the columns shows a different regression specification. Column 1 regresses the child's earnings rank on the parents' earnings rank and so shows the traditional rank-rank regression from the intergenerational mobility literature. We rank the parents by comparing their earnings relative to other parents of the child's birth cohort. Column 2 adds a displacement indicator and so shows the effect of being displaced conditional on parents' rank. Column 3 shows the results when we include a post-period dummy and interaction between displacement and post-period indicators, and so in this specification displaced captures the effect on rank of ever being displaced and displaced x post captures the effect of the job loss itself on rank. Column 4 presents results from the full specification depicted in Equation (1), interacting parents' earnings rank together and separately with displacement and a post-period indicator. Column 5 replicates column 4 with total income including benefits. The interaction between parents' earnings rank, the post-period indicator, and the displacement indicator captures the impact of displacement on the intergenerational earnings rank-rank relationship.

We also estimate yearly effects to get a sense of whether we are capturing permanent or transitory impacts on ranks. Formally, we estimate the following regression:

$$R_{C,t} = \alpha + \beta_1 R_P + \sum_{j=-5}^{6} \beta_{2,t} D_{b,t-j} R_P + \sum_{j=-5}^{6} \beta_{3,t} D_{b,t-j} \tag{6}$$
$$+\beta_4 R_P D_C + \beta_5 R_P Year + \beta_6 Year + \beta_7 D_C + \varepsilon_{i,t},$$

Figure 8 Panel (a) reports estimates of $\beta_{2,t}$. There are no pre-trends, consistent with quasi-random job loss. Immediately following the layoff there is a large jump in the Displacement x Rank x Time coefficient $\beta_{2,t}$, which increases to 0.06 by the second year after the layoff. The coefficient then decreases over time and is 0.02 six years after the layoff but is still statistically significant.

Several recent studies (Deutscher and Mazumder, 2020; Landersø and Heckman, 2017) show that mobility estimates are affected when examining post-redistribution income, and this could be especially relevant in the context of Finland, which has an especially generous social welfare system. To investigate possible implications for our results, we report estimates using post-redistribution income in Table 3 in column (5) (for a full replication of Table 3 using total income including benefits, see Appendix Table D.16) and in Figure 8 Panel (b). We find that including benefits in addition to labor market earnings yields almost identical results.

In summary, the cumulative effects of exposure to unemployment shocks increases the correlation between child and parent income ranks after a cohort enters the labor market, since adult children from low- and high-income backgrounds experience job loss differently. This insight is a key takeaway from this paper.

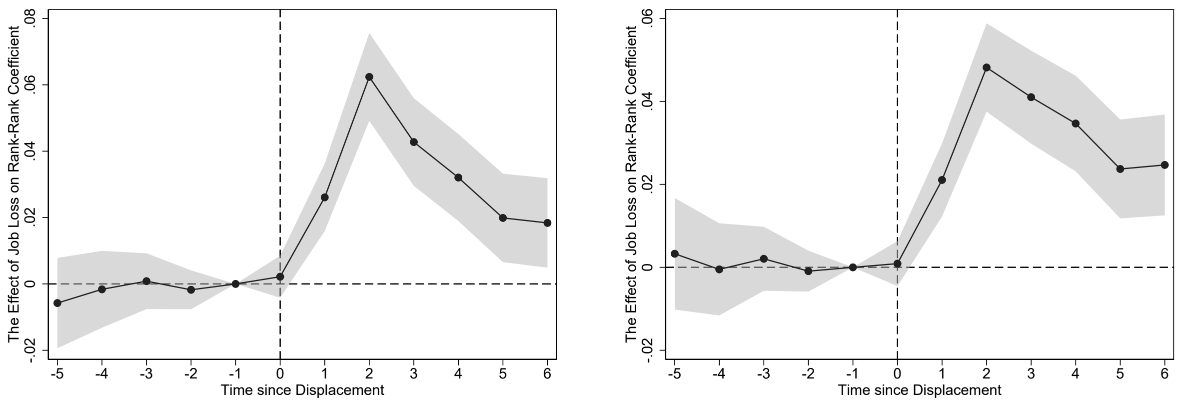
4.2 Contribution of Job Loss to Overall Intergenerational Mobility

To what extent does job loss contribute to overall rank-rank correlations in the full population? To answer this question we introduce a simulation where we allow people to either fall into unemployment at similar rates to the data or remain employed and estimate how their earnings evolve from age 30 to 40 with and without the possibility of such unemployment shocks. We

Figure 8: Estimated Impacts of Job Loss on Intergenerational Mobility

(a) Ranks Excluding Benefits

(b) Ranks Including Benefits



Note: Figure plots the estimates of β_{2t} obtained using equation (6) using all income groups. The outcome in subfigure (a) is a child's earnings rank within the birth cohort using only labor market earnings and in subfigure (b) is a child's earnings rank calculated with earnings plus taxable benefits. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level.

then use these simulated earnings to estimate how much job loss contributes to the population rank-rank correlation.

To construct the simulation, we start with the earnings of all individuals aged 30 in 2000-2019. We divide individuals into deciles according to their parents' earnings. We assign the starting earnings at age 30 to be equal to each person's actual earnings in the data. For each person we then draw a number from a uniform distribution. If the resulting number is greater than the unemployment transition probability for that decile (Table D.15), we assign the person to remain employed and add to their previous year's earnings the age-decile-specific wage growth absent job loss in the data (Figure E.19).

Alternatively, if the individual becomes unemployed, they receive the same earnings growth but also incur the job loss penalty. The job loss penalty is calculated separately for each decile using equation 1 for the six years post-layoff. After six years, the person becomes employed and we assign them the earnings they would have received absent job loss. This is conservative and will likely understate the true contribution of job loss to overall rank-rank correlations.

Decile-specific probabilities of unemployment in Appendix Table D.15 are calculated from the data. These probabilities include fires and quits, in addition to layoffs, since we cannot distinguish between the three in the data. However, if individuals quit and immediately start a new job they will not enter our unemployment transition probabilities. We find that the risk of falling into unemployment is highest for those born to parents in the bottom income decile, at 5.98%. This unemployment probability decreases monotonically moving up the deciles, with the top decile 59.2% less likely to experience unemployment than the bottom decile. These estimates demonstrate the disparate incidence of job loss by parental background. We continue this process for each age until the full population is 40. We then take the simulated earnings at each age and convert them into ranks to estimate the rank-rank correlation. This is our "Job Loss: Incidence and Impact" Simulation.

We present two alternative simulations. In the second alternative, we restrict to only disparate impacts of job loss, in which case we assign all deciles the same probability of unemployment as the bottom decile but the simulation is otherwise identical. In the third alternative, we do not allow for any unemployment as a point of comparison. We call this the "Baseline Simulation".

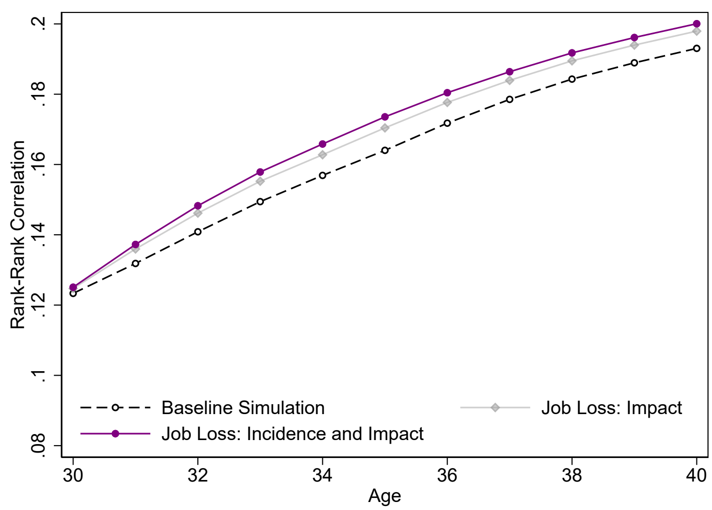
We can characterize this process through a series of labor market earnings equations:

$$y_{t+1} = \begin{cases} y_t + growth_{age,decile} + losses_{decile,t} & \text{if job loss in period t-5 to t} \\ y_t + growth_{age,decile} & \text{otherwise.} \end{cases}$$

Where y_t refers to earnings in period t and y_{t+1} is earnings the following year. "$losses_{decile,t}$" are the estimated earnings losses experienced by an individual each year in each of the six years following a job loss. These earnings losses are estimated as described in the previous sections, separately for each parental income decile. "$growth_{age,decile}$" refers to the age- and parental-income-decile-specific earnings growth accumulated between year t and $t+1$ in the absence of job loss. Last, we calculate the resulting rank-rank correlations for each age within birth cohorts. We capture uncertainty in the simulation by repeating the exercise 1000 times and taking the mean rank-rank correlation for each age.

We graph the rank-rank correlation for each age as the shocks accumulate according to this process in Figure 9 (see also Appendix Table D.18). We find that the rank-rank correlation increases as the child ages, but that the increase is larger when there is job loss included. Based on our estimates, absent job loss the rank-rank correlation would grow from 0.1233 at age 30 to 0.1930 at age 40. With job loss, the rank-rank correlation grows from 0.1251 at age 30 to 0.2001 at age 40. The simulation results imply that the increase in the intergenerational rank-rank correlation from age 30 to age 40 is 8.0% ($\frac{(0.2001-0.1251)}{(0.1930-0.1233)} = 1.080$, see also Appendix Table D.18) higher due to the disparate incidence and impacts of job loss. An alternative way to frame these results is in terms of the rank-rank correlation at age 40. We find that the rank-rank correlation is 3.7%[9] higher at age 40 when we take into account the disparate incidence and impact of job loss. The light gray line reports the simulation excluding disparate incidence and focusing only on disparate impact. It shows that almost the entire difference is explained by disparate impact.

Figure 9: Simulation of the Contribution of Disparate Impacts of Job Loss to Overall Intergenerational Mobility



Note: Figure plots the estimates from the three simulations. The black dashed line represents the trajectory of the rank-rank correlation calculated separately for each age where the earnings at age 30 are equal to the earnings in the data, and the earnings from age 31 to age 40 are simulated using the age-decile-specific wage growth calculations represented in Figure E.19. We call this simulation the "Baseline Simulation". The solid purple line adds to this calculation the possibility of job loss, and is called the "Job Loss: Incidence and Impact". For this simulation we additionally allow individuals to fall into unemployment, using the decile-specific unemployment rates calculated from the data and reported in Table D.15. The solid light gray line removes the disparate incidence of employment, focusing only on disparate impact. For point estimates, see Appendix Table D.18.

In Appendix C we adapt the approach from Jácome *et al.* (2021) to provide an alternative estimate of the impact of job loss on overall rank-rank correlations, as well as intergenerational

[9] 0.2001/0.1930=1.0367. Note that .0053 ((0.2001-0.1251)-(0.1930-0.1233)), or 2.6%, of the overall 0.2001 rank-rank correlation at age 40 is explained by the disparate incidence and impact of job loss.

income elasticity (IGE) estimates. We again find job loss materially changes intergenerational mobility, with rank-rank (IGE) correlations 6% (19%) higher due to job loss, driven primarily by the unequal impacts of job loss by parental background.

Is this 3.7% contribution of job loss to the country-level rank-rank correlation large or small? It would be implausible for the number to be much larger. Despite the large literature on job loss, it is still relatively rare, even for adult children of lower-income parents who experience job loss more often. However, there are two reasons we view this as a substantive number. First, it is unlikely that any one thing explains the majority of country-level rank-rank correlations. Rather, rank-rank correlations are explained by a multitude of different factors that research must uncover one by one. Second, there are many other shocks to early careers that could also contribute to a country's rank-rank correlation, such as recessions (Kahn, 2010; Oreopoulos *et al.*, 2012), trade shocks (David *et al.*, 2013), disability (Kostol and Mogstad, 2014), and more. The fact that job loss alone causes the country's rank-rank correlation to be 3.7% higher suggests that the combined impacts of all early career shocks might explain quite a bit of overall rank-rank correlations.

5 Conclusion

This paper documents two new findings. First, while getting a first job can be a great source of upward mobility, those born into lower-income families have a more precarious perch on the job ladder. Adult children of low-income parents experience persistently larger employment (and to a lesser extent, earnings) job loss scars. These gaps remain conditional on similar pre-displacement incomes, education, and working in the same plant pre-layoff. One reason for these differences is that wealthier parents continue to invest more in their children well into adulthood, partly insulating their children from negative labor market shocks. This result demonstrates important heterogeneity in the resilience to shocks by parental background. While some prior work has shown such heterogeneity in childhood (Goldhaber *et al.*, 2022), our paper shows that differential resiliency can extend well into adulthood.

These disparate impacts of job loss contribute non-negligibly to intergenerational mobility.

Job loss causes a 30% increase in the rank-rank correlation, and the impact on intergenerational mobility is still significant 6 years post job loss. The overall rank-rank correlation at age 40 is 3.7% higher due to the disparate impacts and incidence of job loss in the preceding decade.

These results deepen our understanding of the many ways parental poverty leads to intergenerational impacts. While much of the previous literature on intergenerational mobility has focused on quantifying the amount of mobility, and early life causes, this paper demonstrates the importance of differential impacts of labor market shocks.

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Online Appendix

A PDV of Earnings Losses and Earnings Inequality

To capture the total impact on earnings, we calculate the PDV of job loss as in Von Wachter and Davis (2011). The PDV is calculated using the following equation:

$$PDV_{Loss} = \sum_{s=1}^{6} \bar{\delta}_s \frac{1}{(1+r)^{s-1}}, \tag{7}$$

where r is the real interest rate that we assume to be 5% and $\bar{\delta}_s$ is the average estimated earnings loss in year s after displacement.

For these results we use a slightly different estimation strategy. We match each displaced individual to a counterfactual non-displaced individual following a two-step matching estimator, similar to Schmieder *et al.* (2018). In the first step, we restrict the pool of potential matches to be consistent with the main analysis–for example, they must have 3 years of tenure in a private sector firm and be in the same parental income quintile. In the second step, within this pool we estimate the propensity of being displaced using plant size; wages 3 years, 2 years, and 1 year before the event year; education; tenure; and age. We select the observation with the closest propensity score as the match for the displaced person. We then estimate event-study or DiD results using the displaced individual and their counterfactual matched control. This alternative matching approach yields identical results, but is necessary if we want to recover counterfactual earnings streams which we use below and are reported in column 3 of Table 1.

Table 1, column 1, presents estimates of the PDV for children of parents in the bottom versus the top 20%. In the 6 years post layoff, the estimates show that adult children with parents in the bottom 20% experience a PDV of job loss of €18,254 compared with a PDV of €7,193 for children with parents in the top 20%. Thus, the bottom 20% experiences 154% higher PDV earnings losses compared with the top 20%. As an alternative way to interpret the scale of these results, we next scale the PDV losses using average earnings for the two groups in the 3 years before the layoff. Column 2 shows that those with parents in the top 20% lose just under a fourth of a year's pre-layoff earnings, while those with parents in the bottom 20% lose over two-thirds of a year's pre-layoff earnings. These numbers correspond to PDV earnings losses that are 198% higher for adult children in the bottom 20% in terms of pre-layoff earnings.

Next, we estimate the impact on earnings inequality. First, we estimate equation 8 for those who lose their jobs. Then we use the matched counterfactual earnings (Schmieder *et al.*, 2018) and estimate equation 8 had each person not lost their job. Formally, we estimate:

$$PDV_{Earnings} = \sum_{s=1}^{6} \bar{Y}_s \frac{1}{(1+r)^{s-1}}, \tag{8}$$

where $\bar{Y}_s$ is the average earnings either for those who lost their jobs or for the matched counterfactual individual in year s after the displacement. These estimates are reported in columns 3 and 4 of Table 1. We use these estimates to characterize the percentage change in our version of the S80:S20 ratio in the following equation:

$$\Delta inequality = \frac{PDV_{Earnings}^{Top\,20} / PDV_{Earnings}^{Bottom\,20}}{PDV_{Earnings,counterfactual}^{Top\,20} / PDV_{Earnings,counterfactual}^{Bottom\,20}}. \tag{9}$$

The S80:S20 is a common approach to measuring inequality that normally reflects the income held by the wealthiest 20% relative to the income held by the poorest 20%. In our version we change this measure to the earnings held by children born to the wealthiest 20% of parents relative to the earnings held by children born to the poorest 20% of parents. We find that inequality defined in this way increases by 8% following job loss for those effected (see Table 1 column 5).

B Decomposition Details

Formally, let $\Delta_t = E\left[\hat{Y}_{it}^{No\,Layoff,H} - Y_{it}^{Layoff,H}\right] - E\left[\hat{Y}_{it}^{No\,Layoff,L} - Y_{it}^{Layoff,L}\right]$ represent the mean difference in the employment or earnings job loss scars at event time t between adult children of parents in the top 20%, $E\left[\hat{Y}_{it}^{No\,Layoff,H} - Y_{it}^{Layoff,H}\right]$, and adult children of parents in the bottom 20%, $E\left[\hat{Y}_{it}^{No\,Layoff,L} - Y_{it}^{Layoff,L}\right]$. This exercise is made complicated by the fact that unlike mean earnings, which are usually the objects of interest in a Kitagawa-Blinder-Oaxaca decomposition and are observed directly, the job loss scar is itself an estimated object and not directly observed at the individual level. For the purpose of this exercise, we must estimate the job loss scar at the individual level, and the job loss scar must be allowed to vary in a general way. While we directly observe realized earnings post layoff, to estimate the job loss scar at the individual level we must estimate counterfactual earnings for each individual.

We do so by using the matched counterfactual from Schmieder *et al.* (2018) and described in detail in Section A. We then estimate the following regression to decompose the overall job loss scar into the explained and unexplained portions:

$$\hat{\Delta}_t = \underbrace{\Sigma_k \left(\hat{\beta}_k^H - \hat{\beta}_k^*\right) E\left[X_{kit}^H\right] + \Sigma_k \left(\hat{\beta}_k^* - \hat{\beta}_k^L\right) E\left[X_{kit}^L\right]}_{\text{Unexplained}} + \underbrace{\Sigma_k \hat{\beta}_k^* \left(E\left[X_{kit}^H\right] - E\left[X_{kit}^L\right]\right)}_{\text{Explained by difference in pre-determined endowments}}, \tag{10}$$

where i refers to individual i and k refers to the specific endowment being considered, in our case education. The first term on the right-hand side of equation 10 is the "unexplained" part, while the second term is the "explained" part (Fortin *et al.*, 2011).[10]

For this exercise to be valid, given that we estimate the individual job loss scar, the following must be true:

$$\begin{aligned} &E\left[\hat{\beta}_k^H, \hat{\beta}_k^L, \hat{\beta}_k^* | \hat{Y}_{it}^{No\,Layoff,H} - Y_{it}^{Layoff,H}, \hat{Y}_{it}^{No\,Layoff,L} - Y_{it}^{Layoff,L}\right] \\ -&E\left[\hat{\beta}_k^H, \hat{\beta}_k^L, \hat{\beta}_k^* | Y_{it}^{No\,Layoff,H} - Y_{it}^{Layoff,H}, Y_{it}^{No\,Layoff,L} - Y_{it}^{Layoff,L}\right] = 0, \end{aligned} \tag{11}$$

namely that conditional on all of the observables included in the matching exercise to obtain the counterfactual earnings for the displaced individual had he or she not been displaced, we get the same estimate for the βs as we would if we had actually observed counterfactual earnings. This would be the case if $\hat{Y}_{it}^{No\,Layoff} - Y_{it}^{Layoff}$ were exactly equal to the true job loss scar for each individual. This is unlikely to be true given that there are surely unobserved variables that

[10]We use the approach from Neumark (1988) and Oaxaca and Ransom (1994), given that there is no a priori reason to assume that one of our two groups is the "no discrimination" group, so this approach allows for estimation of $\hat{\beta}_k^*$ from pooled regressions over both groups (as opposed to assuming that $\hat{\beta}_k^* = \hat{\beta}_k^L$, for example). The trade-off is that it can inadvertently put a bit too much weight on the explained portion.

determine counterfactual earnings that we do not include in the matching exercise.

However, a weaker condition will also make this assumption hold:

$$E\left[\hat{\beta}_k^H | \left(\left(\hat{Y}_{it}^{No\,Layoff,H} - Y_{it}^{Layoff,H}\right) |X_{kit}\right)\right] - E\left[\hat{\beta}_k^H | Y_{it}^{No\,Layoff,H} - Y_{it}^{Layoff,H}\right] = 0. \quad (12)$$

In other words, this amounts to requiring that conditional on the observables included in the decomposition and also included when finding the counterfactual matched earnings, the predicted βs are identical. This is more likely to hold, but is fundamentally an untestable assumption. However, under this assumption, the decomposition exercise correctly identifies the parameters we are interested in, namely $\hat{\beta}_k^H$, $\hat{\beta}_k^L$, and $\hat{\beta}_k^*$, and the overall decomposition is valid for what we wish to do in this context. Panel II of Figure 3 shows that the estimated job loss scars when estimating counterfactual earnings in this way are almost identical to the main results, which is consistent with the underlying identification assumptions for this exercise.

C Alternative Simulation

This section explains the details behind our alternative simulation, which builds on the work of Hertz (2008) and Jácome *et al.* (2021). We employ this simulation to investigate how unemployment shocks potentially affect intergenerational mobility. Further, using the simulation, we can decompose the decline in mobility due to labor market shock into parts explained by changes in within-group mobility and between-group mobility.

Data and Variable Definitions In the alternative simulation, we consider cohorts born between 1979-1984. We calculate parents' annual average income between the years 1995-1999. We calculate adult children's annual average income using the years 2011-2018 when they are between the ages 32-39. As in the main results, to construct income percentile ranks, we rank adult children based on their average annual income compared to other adult children within the same birth cohort. We do the same for the parents but rank them among other parents whose children belong to the same birth cohort. We supplement the rank-rank comparisons in this simulation with an additional simulation using parents' and adult children's log incomes. Finally, we track whether the adult children experienced an observable unemployment spell within the same period we use to calculate their average annual income. We categorize individuals who have experienced an unemployment shock as "displaced individuals". Their share of the sample is equal to p_D. We refer to the rest of the sample as "non-displaced individuals". Their share of the sample is equal to $1 - p_D$.

Measuring Intergenerational Mobility in the Alternative Simulation In this alternative simulation, we measure intergenerational mobility in two ways. First, we use the rank-rank regression as in the main text:

$$r_i = \alpha + \beta^R r_i^p + e_i \tag{13}$$

where r_i is individual i's income percentile in the cohort and r_i^p is the individual i's parents' income percentile. The coefficient β^R measures the correlation between children's and parents' income ranks.

However, in addition to using ranks, in order to conduct a similar counterfactual exercise as Jácome *et al.* (2021), we also use the intergenerational elasticity regression

$$y_i = \alpha + \beta^{IGE} y_i^p + v_i \tag{14}$$

where y is the logarithm of adult children's average income, and y^p is the logarithm of average parental income. The coefficient β^{IGE} captures the intergenerational elasticity between children's and parents' incomes.

Decomposing Both the IGE and Rank-Rank Correlation As Jácome *et al.* (2021) shows, we can use the OLS formula and the law of total covariance to decompose the population IGE as follows:

$$\beta^{IGE} = p_D \frac{Var(y^p|D)}{Var(y^p)} \beta^{IGE}_D + (1 - p_{ND}) \frac{Var(y^p|ND)}{Var(y^p)} \beta^{IGE}_{ND} \tag{15}$$

$$+ \frac{p_D E[y^p|D] \cdot E[y|D] + (1 - p_{ND}) E[y^p|ND] \cdot E[y|ND] - E[y^p]E[y]}{Var(y^p)}, \tag{16}$$

where $Var(y)$ and $Var(y^p)$ represent the variances of children's and parents' incomes. Equation 17 says that the population level IGE coefficient is equal to the weighted average of subgroup slopes and between-group covariance of subgroup averages. To put it differently, the coefficients β^{IGE}_D and β^{IGE}_{ND} refer to within-group mobility, whereas the last term stands for between-group mobility.

The decomposition shows that adult children's job loss shocks may affect IGE in two ways. First, mobility among displaced individuals decreases if the adult children of poor parents suffer a larger shock than children of rich parents. In other words, heterogeneous effects of job loss make β^{IGE}_D steeper, which affects the full population IGE. This effect is proportional to the size of the group p_D.

Second, the decomposition indicates that job loss can affect β^{IGE} even if the effect of the job loss does not vary by parental income, but there are between-group differences in children's (y) and parents' (y^p) incomes. To illustrate this channel, assume that parents of displaced and non-displaced individuals have, on average, similar incomes. In such a situation, the last term in equation 17 is zero, implying that the population IGE is equivalent to the weighted average of subgroup IGE slopes. Nonetheless, if differences in sub-population averages exist, then between-group covariances of subgroup averages also shape the population IGE. For example, suppose displaced individuals have lower average income and less affluent parents than other individuals in the sample. If this is the case, then a negative but homogeneous shock that only hits displaced individuals increases β^{IGE}. Note that this homogeneous shock does not impact within-group mobility β^{IGE}_D but increases the last term in equation 17, which increases β^{IGE}.

We can also decompose the rank-rank correlation. Under the assumption that both parent's and adult children's ranks have a uniform distribution, the rank-rank coefficient is equal to

$$\beta^R = 12 \times \Big(p_D Var(r^p|D)\beta^R_D + (1 - p_{ND})Var(r^p|ND)\beta^R_{ND} \tag{17}$$

$$+ p_D E[r^p|D] \cdot E[r|D] + (1 - p_{ND})E[r^p|ND] \cdot E[r|ND] - 0.25\Big). \tag{18}$$

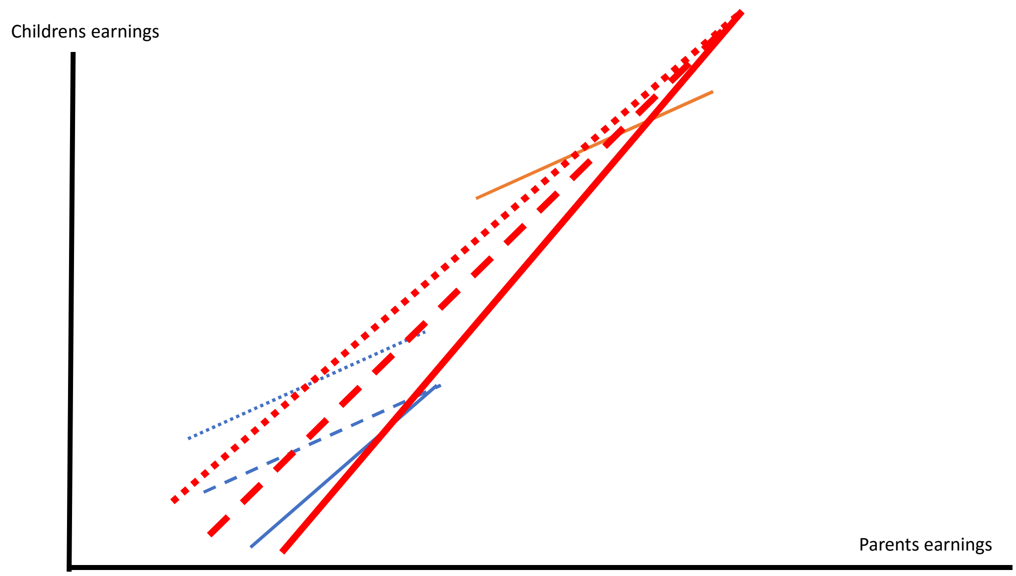
To illustrate what we will capture with this alternative simulation, consider Figure C.1 below. The orange solid line in the top right measures intergenerational mobility for the non-displaced individuals. The solid blue line in the bottom left measures intergenerational mobility for displaced individuals. The red solid line shows the relationship between parents' and children's income in the full population and is equal to a weighted average of the solid blue and orange lines.

We will examine three different estimates of intergenerational mobility. The first approach will have no shock. In this scenario, the dotted blue line shows the relationship between parents' and children's income among displaced people in the absence of the shock. The red dotted line illustrates the intergenerational mobility of the full population in this scenario. The red dotted line's slope is equal to a weighted average of the slopes of the solid orange and dotted blue lines plus the between-group correlation.

In our second scenario, an "equal shock", the size of the displacement shock does not vary by parental income, implying that within-group mobility remains constant. This case is illustrated by the blue and red dashed lines. We see that the red dashed line measuring the correlation between parents' and children's incomes at the population level has a steeper slope compared to the "no shock" situation. So, even though within-mobility has not changed, the homogeneous shock by parental income changes the between-group correlation, which makes the slope of the red dashed line steeper.

Last, we can consider the possibility that the unemployment shock reduces the incomes of displaced individuals from lower-income backgrounds more than displaced individuals from higher-income backgrounds, as we find in our main results. This will result in both a level shift in the dotted blue line, but also a slope change, as indicated by the solid blue line. This is the "full shock" case where we include both the unemployment shock and allow it to vary by parental background. The resulting population intergenerational mobility is given by the solid red line, and we can see that this mechanically results in the largest correlation given our main results.

Figure C.1: Illustrative Example of Alternative Simulation



How Much Does Job Loss Affect Intergenerational Mobility? We use the FLEED/FOLK data, our job loss estimates arising from plant closure from the main text, and the decomposition explained above to study how the disparate impacts of job loss affect intergenerational mobility at the population level. Figure C.2 shows the results of this exercise. The first bars show the baseline intergenerational mobility estimates. These estimates capture the full impact of the shock that has already materialized in this sample.

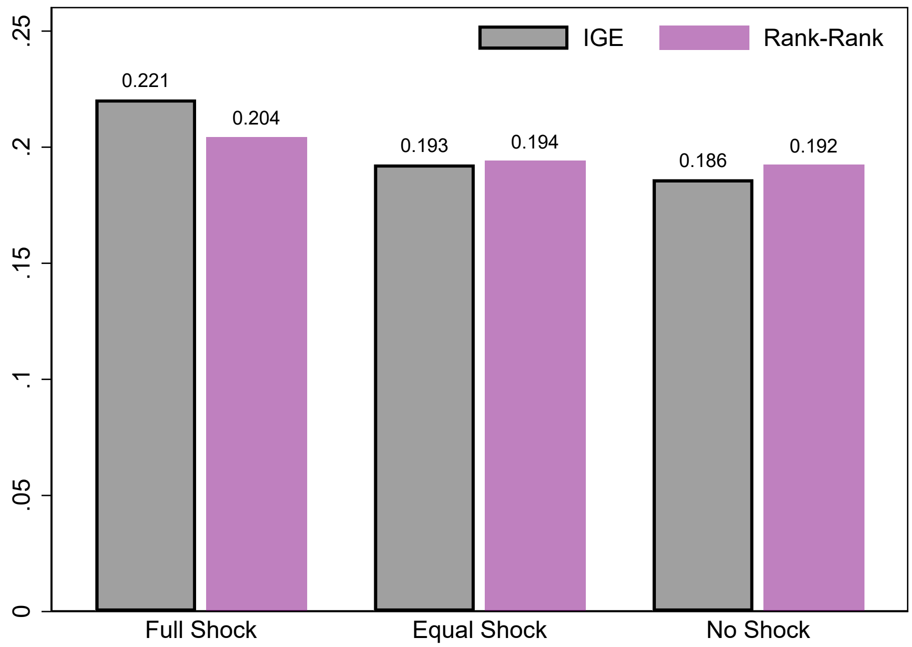
To understand how job market shocks impact intergenerational mobility, we undertake two counterfactual exercises. First, we create a counterfactual in which we "fully undo" the effects of job loss by assigning positive income shocks to the displaced group. We determine the sizes of these shocks using our main plant closure estimates, allowing the shock size to vary by parental income. The third set of bars on the right in Figure C.2 show how fully undoing the effects of the job loss shock affects intergenerational mobility at the population level. We find that moving from the full shock (left-most bars) to no shock (right-most bars) decreases the IGE (rank-rank correlation) from 0.221 (0.204) down to 0.186 (0.192). This means that there is much less persistence between child and parent incomes without the shock compared to when the unequal shock is fully realized. Note that in this exercise, both within-group and between-group mobility changes.

The second set of bars in Figure C.2 shows the results from the second counterfactual exercise. In this "equal shock" scenario, we assign an identical positive income shock to all displaced individuals but still allow everyone to fall into unemployment as they experience it in the data. The size of this shock is "equal" in that we assign to all displaced people a loss equal to the income individuals from high-income families lose following plant closures. In other words, we keep the within mobility estimates constant ($\beta_D^{IGE}, \beta_{ND}^{IGE}$) but let the last term of equation 17 vary. We find that when we compare the equal shock scenario (middle bars) to the no shock scenario (right-most bars) the IGE marginally decreases from 0.193 to 0.186 and the rank-rank correlation decreases from 0.194 to 0.192. This implies marginally less persistence between parent and child incomes without the shock compared to when there are equal job loss shocks.

To summarize, we find in this alternative simulation from Jácome *et al.* (2021) that the persistence between child and parent incomes as measured by IGE at the population level is 19% ($0.1881 = (0.221 - 0.186)/0.186$) higher and as measured by the rank-rank correlation at the population level is 6% ($0.0625 = (0.204 - 0.192)/0.192$) higher because of the unequal impacts of job loss. If we instead constrain the shock to be equal, then the persistence between child and parent incomes as measured by IGE at the population level is 3.8% ($0.0376 = (0.193 - 0.186)/0.186$) higher and the rank-rank correlation at the population level is 1% ($0.0104 = (0.194 - 0.192)/0.192$) higher compared with a world where there is no job loss shock.

Together, these results align with our main simulation results shown in Section 4 that suggest rank-rank correlations by age 40 are 3.8% higher due to the unequal impacts of job loss. Furthermore, our decomposition exercise uncovers that both reductions in within-group and between-group mobility may contribute to the overall decline in intergenerational mobility arising from labor market shocks and that effects remain if we instead examine IGE instead of rank-ranks.

Figure C.2: Contribution of Job Loss to Overall Intergenerational Mobility



Note: Figure reports estimates from the simulation adapted from Jácome *et al.* (2021) described in this section capturing how much job loss contributes to intergenerational mobility as measured by rank-rank correlations (purple bars on the right) versus IGE correlations (gray bars on the left).

D Additional Tables

Table D.1: Characteristics of Workers 1 Year Prior to Layoff

	Displaced	Not displaced	P-value
Panel A: Adult Children Whose Parents Are in the Bottom 20%			
Age	30.777	30.700	0.172
Female	0.355	0.358	0.728
Number of children	0.890	0.909	0.370
Tenure, years	5.026	5.432	0.000
Plant size	96.173	102.886	0.001
Primary education only	0.151	0.144	0.339
Secondary education only	0.556	0.570	0.135
Tertiary education	0.291	0.282	0.306
Experience, years	10.268	10.386	0.287
Married	0.381	0.405	0.009
Real earnings in 1000s (€)	31.860	30.560	0.000
Real income in 1000s (€)	33.394	31.825	0.000
Observations	2,870	238,922	
Panel B: Adult Children Whose Parents Are in the Top 20%			
Age	30.975	30.964	0.806
Female	0.358	0.371	0.094
Number of children	0.791	0.840	0.004
Tenure, years	4.778	5.174	0.000
Plant size	102.091	116.099	0.000
Primary education only	0.097	0.086	0.016
Secondary education only	0.388	0.408	0.013
Tertiary education	0.513	0.502	0.181
Experience, years	9.213	9.120	0.383
Married	0.442	0.456	0.089
Real earnings in 1000s (€)	39.642	37.388	0.000
Real income in 1000s (€)	41.263	38.952	0.000
Observations	3,755	257,450	

Notes: The table shows the pre-layoff characteristics of displaced and non-displaced individuals aged 25–35 one year before displacement.

Table D.2: Characteristics of Workers 1 Year Prior to Layoff for Growth Years

	Displaced	Not displaced	P-value
Panel A: Bottom 20%			
Age	30.788	30.741	0.477
Female	0.357	0.350	0.529
Number of children	0.863	0.909	0.066
Tenure, years	5.143	5.519	0.000
Plant size	103.861	104.541	0.787
Primary education only	0.159	0.149	0.240
Secondary education only	0.550	0.569	0.083
Tertiary education	0.289	0.279	0.335
Experience, years	10.423	10.442	0.837
Married	0.368	0.407	0.000
Real earnings in 1000s (€)	31.569	30.202	0.000
Real income in 1000s (€)	32.976	31.355	0.000
Observations	2,037	180,728	
Panel B: Adult Children Whose Parents Are in the Top 20%			
Age	30.993	31.024	0.581
Female	0.358	0.363	0.593
Number of children	0.784	0.856	0.000
Tenure, years	4.830	5.286	0.000
Plant size	103.516	117.056	0.000
Primary education only	0.099	0.092	0.239
Secondary education only	0.392	0.417	0.007
Tertiary education	0.508	0.488	0.038
Experience, years	9.086	9.166	0.327
Married	0.444	0.459	0.116
Real earnings in 1000s (€)	39.781	37.054	0.000
Real income in 1000s (€)	41.214	38.521	0.000
Observations	2,757	191,922	

Notes: The table shows the pre-layoff characteristics of displaced and non-displaced individuals aged 25–35 one year before displacement during growth years.

Table D.3: Characteristics of Workers 1 Year Prior to Layoff for Recession Years

	Displaced	Not displaced	P-value
Panel A: Bottom 20%			
Age	30.750	30.575	0.096
Female	0.349	0.382	0.057
Number of children	0.956	0.908	0.240
Tenure, years	4.742	5.160	0.000
Plant size	77.373	97.746	0.000
Primary education only	0.131	0.129	0.849
Secondary education only	0.571	0.573	0.924
Tertiary education	0.295	0.291	0.786
Experience, years	9.888	10.210	0.322
Married	0.414	0.401	0.428
Real earnings in 1000s (€)	32.569	31.673	0.061
Real income in 1000s (€)	34.417	33.285	0.012
Observations	833	58,194	
Panel B: Adult Children Whose Parents Are in the Top 20%			
Age	30.925	30.787	0.137
Female	0.360	0.398	0.015
Number of children	0.811	0.795	0.644
Tenure, years	4.634	4.846	0.001
Plant size	98.153	113.298	0.000
Primary education only	0.093	0.069	0.002
Secondary education only	0.379	0.383	0.785
Tertiary education	0.527	0.543	0.314
Experience, years	9.565	8.985	0.088
Married	0.437	0.447	0.510
Real earnings in 1000s (€)	39.258	38.366	0.186
Real income in 1000s (€)	41.398	40.214	0.076
Observations	998	65,528	

Notes: The table shows the pre-layoff characteristics of displaced and non-displaced individuals aged 25–35 one year before displacement during recession years.

Table D.4: The Effect of Job Loss on Employment

	(1)	(2)	(3)	(4)
Panel A: Top 20				
DiD Estimate	-0.036	-0.036	-0.036	-0.036
	(0.003)	(0.003)	(0.003)	(0.003)
Panel B: Bottom 20				
DiD Estimate	-0.079	-0.079	-0.079	-0.080
	(0.005)	(0.005)	(0.005)	(0.005)
Individual fixed effects	✓			
Base year fixed effects	✓	✓	✓	
Year fixed effects	✓	✓	✓	
Displaced fixed effects		✓	✓	✓
Controls			✓	✓
Base year × time fixed effects				✓
N Top 20	3,122,612	3,122,612	3,122,612	3,122,612
N Bottom 20	2,895,761	2,895,761	2,895,7 61	2,895,761
Non-displaced mean Top 20	0.953	0.953	0.953	0.953
Non-displaced mean Bottom 20	0.942	0.942	0.942	0.942

Notes: The table shows the impact of displacement on an individual's employment over 6 years after the displacement. Employment is always measured at the end of the calendar year. Panel A (B) shows the impact on the children whose parents belong to the earnings distribution's top (bottom) quintile. We obtain the estimates using an adjusted version of Equation (1), in which we collapse the event study dummies into a single displacement indicator. Column 1 controls for individual fixed effects, age fixed effects, and base year fixed effects. Column 2 controls for displacement group fixed effects, age fixed effects, and base year fixed effects. Column 3 controls for displacement group fixed effects, age fixed effects, year fixed effects and removes individual fixed effects in order to replace them with base-year controls: gender, tenure, education level, and industry. Column 4 replicates column 3 but replaces year fixed effects with base year × time fixed effects. Standard errors clustered at the individual level appear in parentheses.

Table D.5: The Effect of Job Loss on Relative Earnings

	(1)	(2)	(3)	(4)
Panel A: Top 20				
DiD Estimate	-0.031	-0.032	-0.032	-0.032
	(0.010)	(0.010)	(0.010)	(0.010)
Panel B: Bottom 20				
DiD Estimate	-0.081	-0.081	-0.081	-0.082
	(0.009)	(0.009)	(0.009)	(0.010)
Individual fixed effects	✓			
Base year fixed effects	✓	✓	✓	
Year fixed effects	✓	✓	✓	
Displaced fixed effects		✓	✓	✓
Controls			✓	✓
Base year $\times$ time fixed effects				✓
N Top 20	3,122,612	3,122,612	3,122,612	3,122,612
N Bottom 20	2,895,761	2,895,761	2,895,761	2,895,761
Non-displaced mean Top 20	1.104	1.104	1.104	1.104
Non-displaced mean Bottom 20	1.045	1.045	1.045	1.045

Notes: The table shows the impact of displacement on an individual's relative earnings over 6 years after the displacement. The relative earnings are defined as earnings relative to mean of pre-displacement earnings. Panel A (B) shows the impact on the children whose parents belong to the earnings distribution's top (bottom) quintile. We obtain the estimates using an adjusted version of Equation (1), in which we collapse the event study dummies into a single displacement indicator. Column 1 controls for individual fixed effects, age fixed effects, and base year fixed effects. Column 2 controls for displacement group fixed effects, age fixed effects, and base year fixed effects. Column 3 controls for displacement group fixed effects, age fixed effects, year fixed effects and removes individual fixed effects in order to replace them with base-year controls: gender, tenure, education level, and industry. Column 4 replicates column 3 but replaces year fixed effects with base year $\times$ time fixed effects. Standard errors clustered at the individual level appear in parentheses.

Table D.6: The Effect of Job Loss on Real Earnings in Thousands

	(1)	(2)	(3)	(4)
Panel A: Top 20				
DiD Estimate	-1.038	-0.984	-0.997	-1.034
	(0.304)	(0.307)	(0.306)	(0.307)
Panel B: Bottom 20				
DiD Estimate	-2.638	-2.671	-2.679	-2.707
	(0.247)	(0.248)	(0.248)	(0.248)
Individual fixed effects	✓			
Base year fixed effects	✓	✓	✓	
Year fixed effects	✓	✓	✓	
Displaced fixed effects		✓	✓	✓
Controls			✓	✓
Base year $\times$ time fixed effects				✓
N Top 20	3,122,612	3,122,612	3,122,612	3,122,612
N Bottom 20	2,895,761	2,895,761	2,895,761	2,895,761
Non-displaced mean Top 20	36.344	36.344	36.344	36.344
Non-displaced mean Bottom 20	29.031	29.031	29.031	29.031

Notes: The table shows the impact of displacement on an individual's real earnings over 6 years after the displacement. The real earnings are reported in thousands euros. Panel A (B) shows the impact on the children whose parents belong to the earnings distribution's top (bottom) quintile. We obtain the estimates using an adjusted version of Equation (1), in which we collapse the event study dummies into a single displacement indicator. Column 1 controls for individual fixed effects, age fixed effects, and base year fixed effects. Column 2 controls for displacement group fixed effects, age fixed effects, and base year fixed effects. Column 3 controls for displacement group fixed effects, age fixed effects, year fixed effects and removes individual fixed effects in order to replace them with base-year controls: gender, tenure, education level, and industry. Column 4 replicates column 3 but replaces year fixed effects with base year $\times$ time fixed effects. Standard errors clustered at the individual level appear in parentheses.

Table D.7: Decomposition of Differences in Employment and Earnings Job Loss Scars

	Differences in Job Loss Scar	Percentage Explained by Education
Employment:	0.079	22 %
Earnings	0.040	78 %

Notes: Table shows the decomposition of the differences in employment and earnings job loss scars between children of parents in the bottom 20% of the income distribution versus the top 20% into the explained and unexplained parts. Estimates are based on Equation (10) for all years.

Table D.8: The Effect of Job Loss on Working for Any of Father's Prior Firms

	(1)	(2)	(3)	(4)
Panel A: Top 20				
DiD Estimate	-0.029	-0.029	-0.029	-0.029
	(0.004)	(0.004)	(0.004)	(0.004)
Panel B: Bottom 20				
DiD Estimate	-0.005	-0.005	-0.005	-0.005
	(0.002)	(0.002)	(0.002)	(0.002)
Individual fixed effects	✓			
Base year fixed effects	✓	✓	✓	
Year fixed effects	✓	✓	✓	
Displaced fixed effects		✓	✓	✓
Controls			✓	✓
Base year $\times$ time fixed effects				✓
N Top 20	3,122,612	3,122,612	3,122,612	3,122,612
N Bottom 20	2,895,761	2,895,761	2,895,761	2,895,761
Non-displaced mean Top 20	0.085	0.085	0.085	0.085
Non-displaced mean Bottom 20	0.009	0.009	0.009	0.009

Notes: The table shows the impact of displacement on whether an individual works for one of his father's prior firms over 6 years after the displacement. Panel A (B) shows the impact on the children whose parents belong to the earnings distribution's top (bottom) quintile. We obtain the estimates using an adjusted version of Equation (1), in which we collapse the event study dummies into a single displacement indicator. Column 1 controls for individual fixed effects, age fixed effects, and base year fixed effects. Column 2 controls for displacement group fixed effects, age fixed effects, and base year fixed effects. Column 3 controls for displacement group fixed effects, age fixed effects, year fixed effects and removes individual fixed effects in order to replace them with base-year controls: gender, tenure, education level, and industry. Column 4 replicates column 3 but replaces year fixed effects with base year $\times$ time fixed effects. Standard errors clustered at the individual level appear in parentheses.

Table D.9: The Effect of Job Loss on Working for Any of Father's Prior Industries

	(1)	(2)	(3)	(4)
Panel A: Top 20				
DiD Estimate	-0.004	-0.004	-0.004	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)
Panel B: Bottom 20				
DiD Estimate	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Individual fixed effects	✓			
Base year fixed effects	✓	✓	✓	
Year fixed effects	✓	✓	✓	
Displaced fixed effects		✓	✓	✓
Controls			✓	✓
Base year $\times$ time fixed effects				✓
N Top 20	3,122,612	3,122,612	3,122,612	3,122,612
N Bottom 20	2,895,761	2,895,761	2,895,761	2,895,761
Non-displaced mean Top 20	0.090	0.090	0.090	0.090
Non-displaced mean Bottom 20	0.015	0.015	0.015	0.015

Notes: The table shows the impact of displacement on whether an individual works for one of his father's prior industries over 6 years after the displacement. Panel A (B) shows the impact on the children whose parents belong to the earnings distribution's top (bottom) quintile. We obtain the estimates using an adjusted version of Equation (1), in which we collapse the event study dummies into a single displacement indicator. Column 1 controls for individual fixed effects, age fixed effects, and base year fixed effects. Column 2 controls for displacement group fixed effects, age fixed effects, and base year fixed effects. Column 3 controls for displacement group fixed effects, age fixed effects, year fixed effects and removes individual fixed effects in order to replace them with base-year controls: gender, tenure, education level, and industry. Column 4 replicates column 3 but replaces year fixed effects with base year $\times$ time fixed effects. Standard errors clustered at the individual level appear in parentheses.

Table D.10: The Effect of Job Loss on Employment

Dependent variable: P(Employed)

	All		Recession		Growth	
Time (1)	Bottom (2)	Top (3)	Bottom (4)	Top (5)	Bottom (6)	Top (7)
-5	-0.009	0.006	-0.010	0.010	-0.009	0.004
	(0.007)	(0.006)	(0.012)	(0.011)	(0.008)	(0.007)
-4	-0.003	-0.006	-0.001	0.001	-0.003	-0.009
	(0.005)	(0.005)	(0.009)	(0.009)	(0.007)	(0.006)
-3	-0.001	-0.001	-0.001	-0.000	-0.000	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
-2	-0.001	-0.000	-0.000	-0.000	-0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
-1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0	0.001	0.001	0.001	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1	-0.174	-0.085	-0.218	-0.140	-0.157	-0.066
	(0.008)	(0.005)	(0.015)	(0.012)	(0.009)	(0.006)
2	-0.117	-0.047	-0.131	-0.079	-0.111	-0.035
	(0.007)	(0.005)	(0.014)	(0.011)	(0.008)	(0.005)
3	-0.074	-0.033	-0.091	-0.061	-0.067	-0.023
	(0.007)	(0.005)	(0.013)	(0.010)	(0.008)	(0.005)
4	-0.049	-0.021	-0.054	-0.046	-0.046	-0.012
	(0.006)	(0.004)	(0.012)	(0.010)	(0.007)	(0.005)
5	-0.037	-0.017	-0.056	-0.046	-0.029	-0.007
	(0.006)	(0.004)	(0.013)	(0.010)	(0.007)	(0.005)
6	-0.036	-0.012	-0.040	-0.032	-0.034	-0.005
	(0.006)	(0.004)	(0.012)	(0.010)	(0.007)	(0.005)
N	2,895,761	3,122,612	706,825	795,023	2,188,936	2,327,589

Notes: The table shows event time coefficients underlying Figure 3 A, E.6 A, and E.6 C. We obtain the estimates from Equation (1) for adult children of top and bottom 20% separately. The outcome variable is a binary variable which takes value one if an individual was employed at the end of the year. Each regression controls for base year fixed effects, year fixed effects, year fixed effects, age fixed effects, and individual fixed effects. Standard errors clustered at the individual level appear in parentheses.

Table D.11: The Effect of Job Loss on Relative Earnings

Dependent variable: Earnings relative to pre-displacement mean

	All		**Recession**		**Growth**	
Time (1)	Bottom (2)	Top (3)	Bottom (4)	Top (5)	Bottom (6)	Top (7)
-5	0.003	-0.011	0.004	0.004	0.002	-0.017
	(0.009)	(0.009)	(0.020)	(0.022)	(0.010)	(0.009)
-4	-0.002	-0.021	0.001	-0.012	-0.003	-0.026
	(0.008)	(0.007)	(0.017)	(0.016)	(0.010)	(0.008)
-3	-0.001	-0.016	-0.017	-0.017	0.005	-0.017
	(0.007)	(0.006)	(0.014)	(0.013)	(0.008)	(0.007)
-2	0.008	-0.003	0.010	-0.008	0.007	-0.001
	(0.005)	(0.005)	(0.010)	(0.011)	(0.006)	(0.006)
-1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0	0.001	-0.005	0.004	0.003	-0.000	-0.008
	(0.006)	(0.006)	(0.014)	(0.012)	(0.007)	(0.006)
1	-0.060	-0.024	-0.100	-0.054	-0.045	-0.013
	(0.009)	(0.009)	(0.019)	(0.021)	(0.010)	(0.009)
2	-0.155	-0.059	-0.206	-0.116	-0.135	-0.039
	(0.011)	(0.012)	(0.022)	(0.032)	(0.013)	(0.012)
3	-0.101	-0.054	-0.138	-0.104	-0.087	-0.036
	(0.012)	(0.013)	(0.022)	(0.034)	(0.014)	(0.013)
4	-0.071	-0.047	-0.120	-0.104	-0.052	-0.027
	(0.013)	(0.012)	(0.023)	(0.027)	(0.016)	(0.014)
5	-0.047	-0.038	-0.109	-0.070	-0.023	-0.027
	(0.013)	(0.015)	(0.022)	(0.040)	(0.016)	(0.015)
6	-0.040	-0.022	-0.110	-0.075	-0.013	-0.005
	(0.014)	(0.015)	(0.027)	(0.034)	(0.017)	(0.016)
N	2,895,761	3,122,612	706,825	795,023	2,188,936	2,327,589

Notes: The table shows event time coefficients underlying Figure 3 B, E.6 B, and E.6 D. We obtain the estimates from Equation (1) for adult children of top and bottom 20% separately. The outcome variable is the earning relative to pre-displacement mean. Each regression controls for base year fixed effects, year fixed effects, age fixed effects, and individual fixed effects. Standard errors clustered at the individual level appear in parentheses.

Table D.12: The Effect of Job Loss on Real Earnings

Dependent variable: Real earnings in thousands

	All		Recession		Growth	
Time (1)	Bottom (2)	Top (3)	Bottom (4)	Top (5)	Bottom (6)	Top (7)
-5	-0.466	-1.274	-0.476	0.215	-0.449	-1.834
	(0.228)	(0.362)	(0.421)	(0.543)	(0.271)	(0.451)
-4	-0.463	-1.213	-0.343	0.009	-0.495	-1.679
	(0.207)	(0.332)	(0.398)	(0.500)	(0.241)	(0.414)
-3	-0.302	-1.130	-0.615	-0.521	-0.165	-1.370
	(0.164)	(0.322)	(0.325)	(0.457)	(0.189)	(0.407)
-2	0.085	-0.352	0.118	-0.464	0.081	-0.320
	(0.112)	(0.365)	(0.225)	(0.383)	(0.129)	(0.478)
-1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0	-0.101	0.106	-0.242	-0.303	-0.060	0.242
	(0.137)	(0.453)	(0.262)	(0.397)	(0.161)	(0.600)
1	-1.821	-0.902	-3.049	-2.222	-1.356	-0.443
	(0.221)	(0.345)	(0.436)	(0.554)	(0.255)	(0.425)
2	-4.854	-2.142	-6.567	-4.854	-4.182	-1.179
	(0.291)	(0.340)	(0.558)	(0.658)	(0.340)	(0.397)
3	-3.460	-2.270	-4.701	-4.609	-2.973	-1.450
	(0.296)	(0.430)	(0.541)	(0.633)	(0.353)	(0.537)
4	-2.753	-1.949	-4.072	-4.288	-2.241	-1.135
	(0.299)	(0.433)	(0.574)	(0.677)	(0.350)	(0.535)
5	-2.247	-1.698	-3.798	-4.055	-1.635	-0.878
	(0.310)	(0.499)	(0.581)	(0.758)	(0.366)	(0.621)
6	-1.938	-1.131	-3.782	-3.746	-1.232	-0.226
	(0.331)	(0.538)	(0.685)	(0.872)	(0.379)	(0.662)
N	2,895,761	3,122,612	706,825	795,023	2,188,936	2,327,589

Notes: The table shows event time coefficients underlying Figure E.14. We obtain the estimates from Equation (1) for adult children of top and bottom 20% separately. The outcome variable is the real earnings in thousands. Each regression controls for base year fixed effects, age fixed effects, and individual fixed effects. Standard errors clustered at the individual level appear in parentheses.

Table D.13: The Effect of Job Loss on Working for Any of Father's Prior Employers

Dependent variable: Working for any of father's prior employers

	All		Recession		Growth	
Time	Bottom	Top	Bottom	Top	Bottom	Top
(1)	(2)	(3)	(4)	(5)	(6)	(7)
-5	0.001	0.007	0.001	0.008	0.001	0.007
	(0.002)	(0.003)	(0.004)	(0.006)	(0.002)	(0.003)
-4	0.001	0.004	0.000	0.004	0.001	0.003
	(0.001)	(0.002)	(0.003)	(0.004)	(0.001)	(0.003)
-3	0.000	0.002	0.001	0.003	-0.000	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
-2	0.000	-0.000	-0.000	0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
-1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0	-0.001	-0.001	-0.000	-0.002	-0.001	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
1	-0.006	-0.033	-0.009	-0.049	-0.005	-0.027
	(0.002)	(0.004)	(0.004)	(0.008)	(0.002)	(0.004)
2	-0.005	-0.032	-0.009	-0.046	-0.003	-0.028
	(0.002)	(0.004)	(0.004)	(0.008)	(0.002)	(0.005)
3	-0.004	-0.030	-0.008	-0.042	-0.002	-0.025
	(0.002)	(0.004)	(0.003)	(0.008)	(0.002)	(0.005)
4	-0.005	-0.025	-0.009	-0.035	-0.003	-0.021
	(0.002)	(0.004)	(0.003)	(0.008)	(0.002)	(0.005)
5	-0.004	-0.022	-0.005	-0.032	-0.004	-0.018
	(0.002)	(0.004)	(0.004)	(0.008)	(0.002)	(0.005)
6	-0.004	-0.020	-0.004	-0.029	-0.004	-0.017
	(0.002)	(0.004)	(0.004)	(0.009)	(0.002)	(0.005)
N	2,895,761	3,122,612	706,825	795,023	2,188,936	2,327,589

Notes: The table shows event time coefficients underlying Figure E.11 Panel B (which shows results from columns 2 and 3). We obtain the estimates from Equation (1) for adult children of top and bottom 20% separately. The outcome variable is whether the child works in one of the father's previous firms post layoff. Each regression controls for base year fixed effects, age fixed effects, and individual fixed effects. Standard errors clustered at the individual level appear in parentheses.

Table D.14: Effect of Job Loss on Working for Father's Industry at Time t

Dependent variable: Working for father's industry at time t

	All		**Recession**		**Growth**	
Time	Bottom	Top	Bottom	Top	Bottom	Top
(1)	(2)	(3)	(4)	(5)	(6)	(7)
-5	-0.002	0.009	-0.002	0.002	-0.002	0.012
	(0.002)	(0.004)	(0.004)	(0.009)	(0.003)	(0.005)
-4	-0.002	0.005	0.002	-0.003	-0.003	0.008
	(0.002)	(0.004)	(0.004)	(0.008)	(0.003)	(0.004)
-3	-0.000	0.006	0.005	0.003	-0.002	0.007
	(0.002)	(0.003)	(0.004)	(0.006)	(0.002)	(0.003)
-2	-0.001	0.004	-0.001	0.003	-0.001	0.004
	(0.001)	(0.002)	(0.002)	(0.005)	(0.001)	(0.003)
-1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0	-0.001	-0.003	-0.001	-0.005	-0.002	-0.003
	(0.001)	(0.002)	(0.002)	(0.004)	(0.001)	(0.003)
1	-0.004	-0.014	-0.003	-0.024	-0.004	-0.010
	(0.002)	(0.004)	(0.003)	(0.008)	(0.002)	(0.005)
2	-0.001	-0.010	-0.002	-0.019	-0.001	-0.006
	(0.002)	(0.004)	(0.003)	(0.008)	(0.003)	(0.005)
3	-0.000	-0.004	0.001	-0.014	-0.001	-0.001
	(0.002)	(0.004)	(0.003)	(0.008)	(0.003)	(0.005)
4	0.000	0.004	0.001	-0.007	0.000	0.009
	(0.002)	(0.004)	(0.003)	(0.008)	(0.003)	(0.005)
5	0.001	0.009	0.008	-0.004	-0.001	0.013
	(0.002)	(0.005)	(0.004)	(0.009)	(0.003)	(0.005)
6	0.004	0.012	0.009	-0.002	0.002	0.017
	(0.002)	(0.005)	(0.004)	(0.008)	(0.003)	(0.005)
N	2,895,761	3,122,612	706,825	795,023	2,188,936	2,327,589

Notes: The table shows event time coefficients underlying Figure E.11 Panel D (which shows results from columns 2 and 3). We obtain the estimates from Equation (1) for adult children of top and bottom 20% separately. The outcome variable is whether the child works in the father's industry. Each regression controls for base year fixed effects, age fixed effects, and individual fixed effects. Standard errors clustered at the individual level appear in parentheses.

Table D.15: Unemployment Transition Probabilities

Parental Income Decile (1)	**P(Unemployed$_{t+1}$| Employed$_t$)** (2)
1 (Bottom Decile)	5.98%
2	5.68%
3	5.49%
4	5.27%
5	5.01%
6	4.76%
7	4.56%
8	4.31%
9	3.99%
10 (Top Decile)	3.54%

Notes: This table displays the probability of transitioning from employment to unemployment, with separate estimates reported for the adult children of parents in each parental earnings decile. Calculations include all possible forms of unemployment the adult children might experience, including firings and quits in addition to plant closings. These estimates are used to produce the simulations described in Section 4.2 and shown in Figure 9 and Appendix Table D.18.

Table D.16: Impacts of Job Loss on Intergenerational Mobility When Ranks Are Defined Using Income

Independent Variable	(1)	(2)	(3)	(4)
Family rank (β_1)	0.107	0.107	0.107	0.078
	(0.001)	(0.001)	(0.001)	(0.001)
Displaced (β_5)		-0.529	0.864	0.478
		(0.134)	(0.134)	(0.286)
Post (β_6)			-5.455	-8.339
			(0.022)	(0.045)
Displaced $\times$ Post (β_7)			-2.792	-4.463
			(0.137)	(0.286)
Family rank $\times$ Displaced $\times$ Post (β_2)				0.030
				(0.005)
Family rank $\times$ Displaced (β_3)				0.008
				(0.005)
Family rank $\times$ Post (β_4)				0.057
				(0.001)
Observations	16,646,230	16,646,230	16,646,230	16,646,230

Notes: The table shows the impact of displacement on the rank-rank regression coefficient. The dependent variable is the child's yearly income percentile rank in the income distribution of children in the same birth cohort. Each of the columns show a different regression specification. Column 1 regresses the child's income rank on the parents' income rank and so shows the traditional rank-rank regression from the intergenerational mobility literature. We rank the parents by comparing their income relative to other parents of the child's birth cohort. For more details, see Section 2.1. Column 2 adds a displacement indicator and so shows the effect of being displaced conditional on parents' rank. Column 3 shows the results when we include a post-period dummy and interaction between displacement and post-period indicators, and so in this specification displaced captures the effect on rank of ever being displaced and displaced x post captures the effect of the job loss itself on rank. Finally, Column 4 presents results from the full specification depicted in Equation (1), and so interacts parents' income rank together and separately with displacement and a post-period indicator. The interaction between parents' income rank, the post-period indicator, and the displacement indicator captures the impact of displacement on the intergenerational income rank-rank relationship.

Table D.17: Impacts of Job Loss on Intergenerational Mobility Measured Using Log Incomes

Independent Variable	(1)	(2)	(3)	(4)
Family log income (β_1)	0.061	0.061	0.062	0.045
	(0.001)	(0.001)	(0.001)	(0.001)
Displaced (β_5)		-0.014	0.025	-0.055
		(0.004)	(0.003)	(0.060)
Post (β_6)			0.190	-0.151
			(0.001)	(0.012)
Displaced $\times$ Post (β_7)			-0.077	-0.250
			(0.005)	(0.075)
Family log income $\times$ Displaced $\times$ Post (β_2)				0.016
				(0.007)
Family log income $\times$ Displaced (β_3)				0.007
				(0.006)
Family log income $\times$ Post (β_4)				0.032
				(0.001)
Observations	16,646,230	16,646,230	16,646,230	16,646,230

Notes: The table shows the impact of displacement on the log income - log income regression coefficient. The dependent variable is the child's yearly log income. Each of the columns show a different regression specification. Column 1 regresses the child's log income on the parents' log income and so shows the traditional IGE regression from the intergenerational mobility literature. Column 2 adds a displacement indicator and so shows the effect of being displaced conditional on parents' rank. Column 3 shows the results when we include a post-period dummy and interaction between displacement and post-period indicators, and so in this specification displaced captures the effect on log income of ever being displaced and displaced x post captures the effect of the job loss itself on log income. Finally, Column 4 presents results from the full specification depicted in Equation (1), and so interacts parents' log income together and separately with displacement and a post-period indicator. The interaction between parents' income log income, the post-period indicator, and the displacement indicator captures the impact of displacement on the intergenerational log income-log income relationship.

Table D.18: Simulation Results

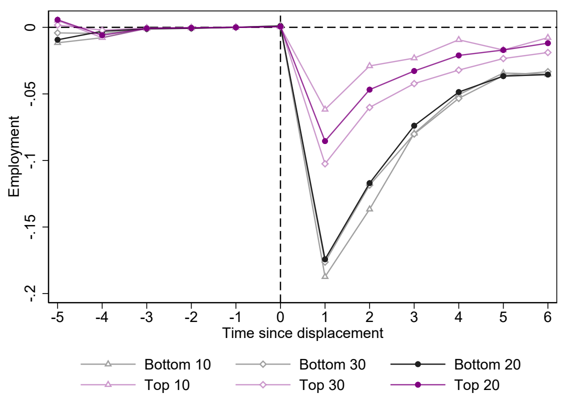
	Baseline Simulation	Job Loss: Incidence and Impact	Job Loss: Impact
Age	Rank-Rank Correlation	Rank-Rank Correlation	Rank-Rank Correlation
(1)	(2)	(3)	(4)
30	0.1233	0.1251	0.1247
		(0.0000)	(0.0000)
31	0.1318	0.1373	0.1360
		(0.0001)	(0.0001)
32	0.1409	0.1483	0.1462
		(0.0001)	(0.0001)
33	0.1494	0.1579	0.1552
		(0.0001)	(0.0001)
34	0.1569	0.1658	0.1628
		(0.0001)	(0.0001)
35	0.1640	0.1736	0.1704
		(0.0001)	(0.0001)
36	0.1718	0.1804	0.1777
		(0.0001)	(0.0001)
37	0.1785	0.1864	0.1839
		(0.0001)	(0.0001)
38	0.1843	0.1918	0.1895
		(0.0001)	(0.0001)
39	0.1889	0.1961	0.1940
		(0.0001)	(0.0001)
40	0.1930	0.2001	0.1979
		(0.0001)	(0.0001)

Notes: This table displays the estimates from the simulation exercise described in Section 4.2 and shown in Figure 9. Column 1 reports the age at which the rank-rank correlation is calculated. Column 2 reports results from a simulation where the earnings of the adult children at age 30 are equal to the earnings in the data, and the earnings from age 31 to age 40 are simulated using the age-decile-specific wage growth calculations represented in Appendix Figure E.19. We call this simulation the "Baseline Simulation". Column 3 reports results when we add to the simulation from Column 2 the possibility of job loss, and is called the "Job Loss: Incidence and Impact" simulation. For this simulation we additionally allow individuals to fall into unemployment (with some uncertainty), using the decile-specific unemployment rates calculated from the data and reported in Appendix Table D.15. Column 4 reports results identical to Column (3) but where we do not allow the incidence of unemployment to vary across deciles. Column 2 results are without any uncertainty so we simply report the estimates. To capture the uncertainty of job loss in Columns 3 and 4, we estimate the simulation 1000 times and report the mean of the simulations as the estimates and report the standard deviation of the 1000 simulations in parentheses below.

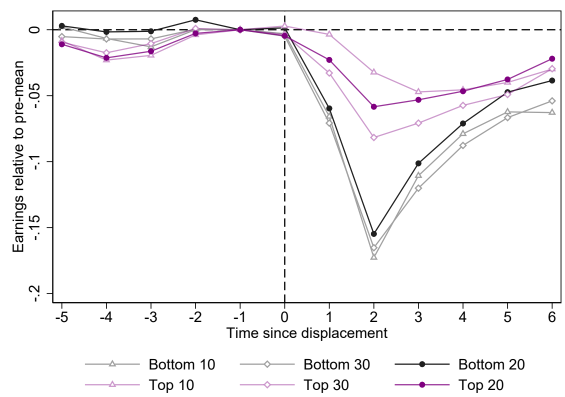
E Additional Figures

Figure E.3: Impacts of Job Loss on Employment and Earnings by Parental Income Group, Bottom vs. Top 10%, 20%, and 30%

(a) Employment

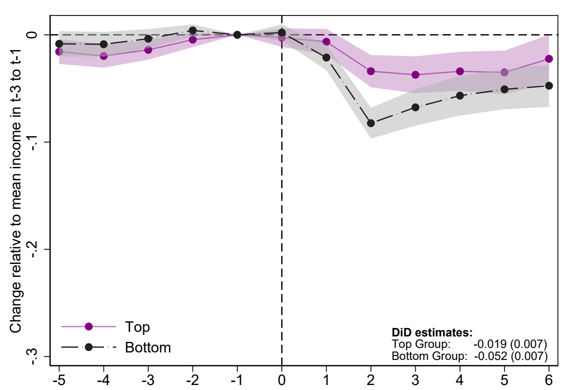


(b) Earnings Relative to Pre-mean



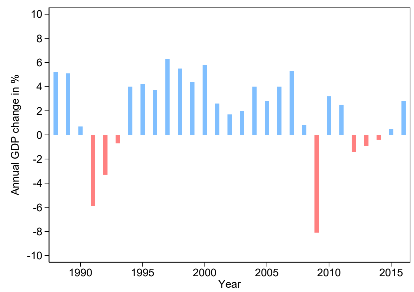
Note: Figures plot the estimates of δ_t obtained using Equation (1) separately for three pairs of top and bottom parental income groups. In Panel A (B), the outcome is employment (relative earnings). Employment is measured at the end of the year. Relative earnings compare yearly labor and entrepreneurial earnings to the mean of yearly earnings 1–3 years before displacement.

Figure E.4: Impacts of Job Loss on Total Income Including Benefits by Parental Income Group, Bottom vs. Top 20%



Note: Figures plot the estimates of δ_t obtained using Equation (1) separately for top versus bottom 20% in terms of their parents' incomes. Outcome is relative total income of the adult child, which includes labor market earnings, capital earnings, and benefits. Relative total income compares yearly total income to the mean of yearly total income 1–3 years before displacement.

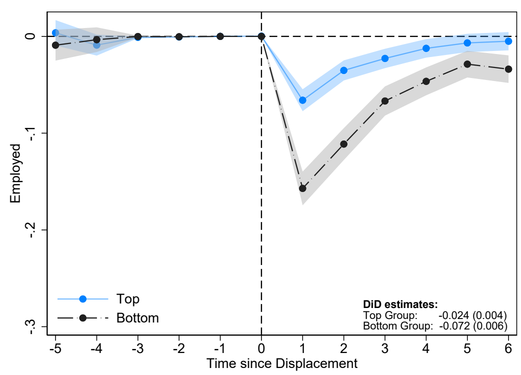
Figure E.5: GDP Growth in Finland, 1988–2017



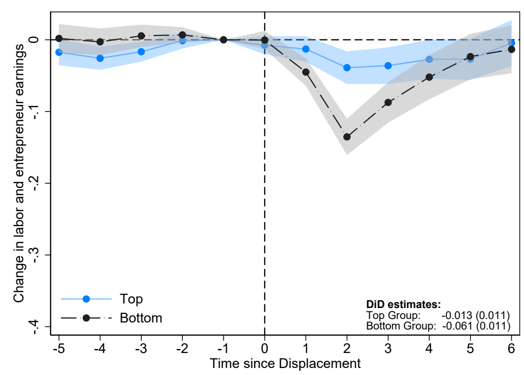
Note: The figure depicts years of growth (in blue) and recession (in red) in Finland used for the analysis.

Figure E.6: Impacts of Job Loss on Employment and Earnings by State of the Economy

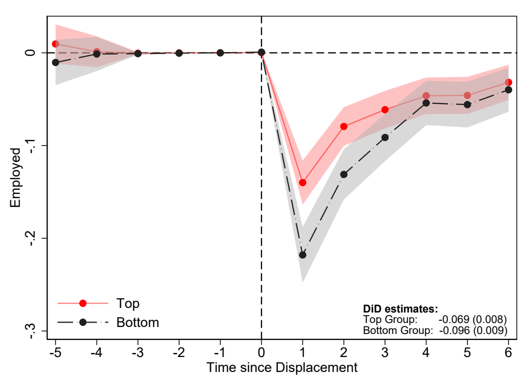
(a) Economy Growing: Employment



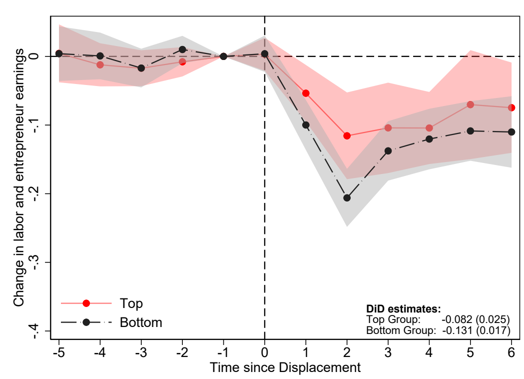
(b) Economy Growing: Relative Earnings



(c) Economy Shrinking: Employment



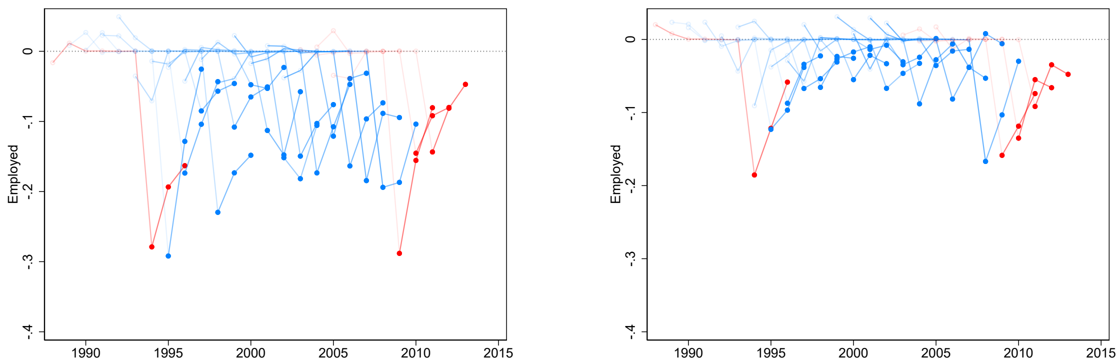
(d) Economy Shrinking: Relative Earnings



Note: Figures plot the estimates of δ_t obtained using Equation (1) separately for top and bottom 20% parental income groups. Panel A (C) depicts impact of job loss on employment when the economy is growing (shrinking). Panel B and D report results for relative earnings. Employment is measured at the end of the year. Relative earnings compare yearly labor and entrepreneurial earnings to the mean of yearly earnings 1–3 years before displacement. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level.

Figure E.7: Impact of Job Loss on Employment for Adult Children with Parents in the Bottom 20% vs. Top 20%, by Year of Job Loss

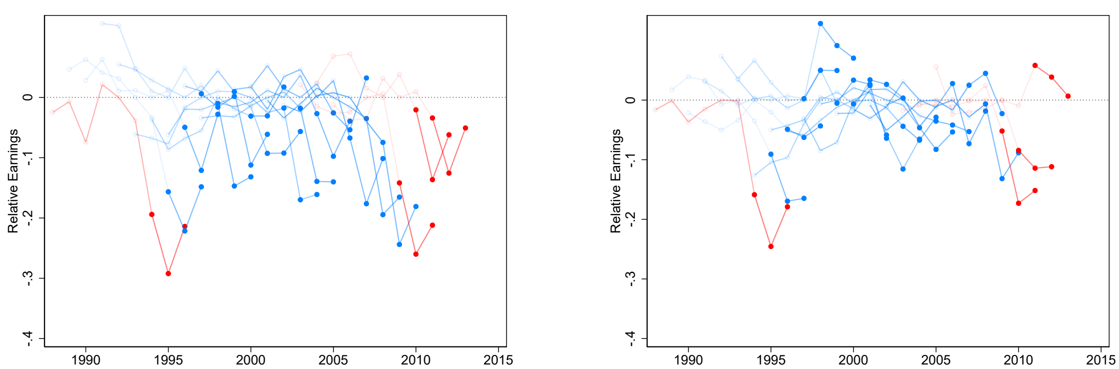
(a) Bottom 20% (b) Top 20%



Note: Figures plot the estimates of δ_t obtained using equation 1 separately for different treatment waves. For presentation purposes, we only show the first three years after layoff. Panel A (B) shows the impact for individuals whose parents belong to the bottom (top) 20% of the income distribution. The dependent variable is employment at the end of the year.

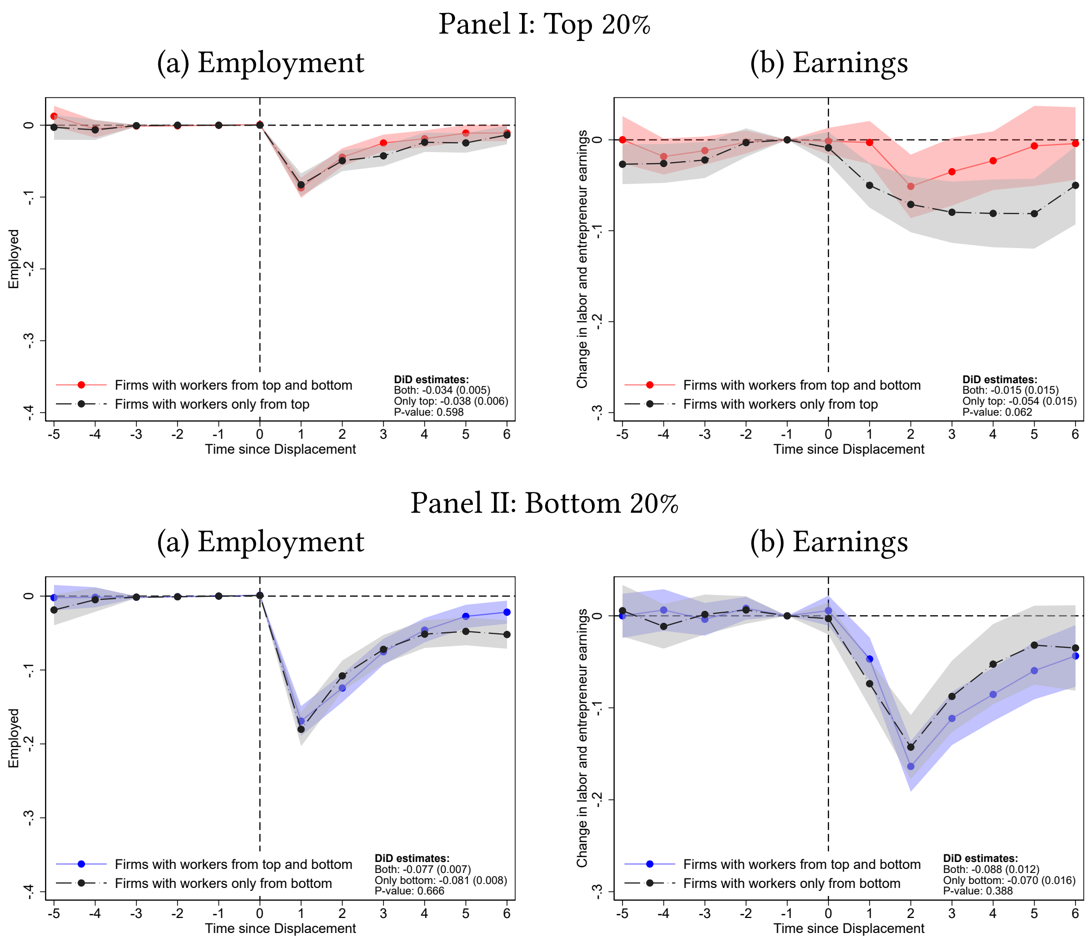
Figure E.8: Impact of Job Loss on Relative Earnings for Adult Children with Parents in the Bottom 20% vs. Top 20%, by Year of Job Loss

(a) Bottom 20% (b) Top 20%



Note: Figures plot the estimates of δ_t obtained using equation 1 separately for different treatment waves. For presentation purposes, we only show the first three years after layoff. Panel A (B) shows the impact for individuals whose parents belong to the bottom (top) 20% of the income distribution. The dependent variable is labor and entrepreneurial earnings relative to the mean of yearly earnings 1–3 years before displacement.

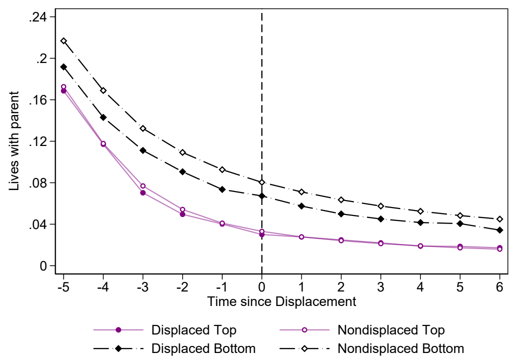
Figure E.9: Impacts of Job Loss on Employment and Earnings Plant Sorting Results



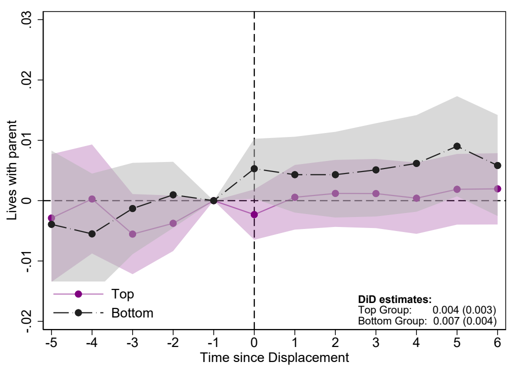
Note: Figure Panel I A (Panel II A) depicts the impact of job loss on employment comparing those in the top 20% (bottom 20%) who work in plants that only hire those in the top 20% versus plants that hire people from the top and bottom 20%. Panel I B (Panel II B) depicts the same but for relative earnings. Employment is measured at the end of the year. Relative earnings compare yearly labor and entrepreneurial earnings to the mean of yearly earnings 1–3 years before displacement. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level.

Figure E.10: Impacts of Job Loss on Living in the Same Address as Parents, Bottom 20% vs. Top 20%

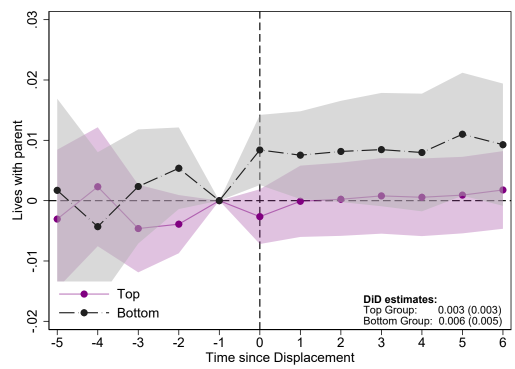
(a) Lives in the same address as parents



(b) Lives in the same address as parents



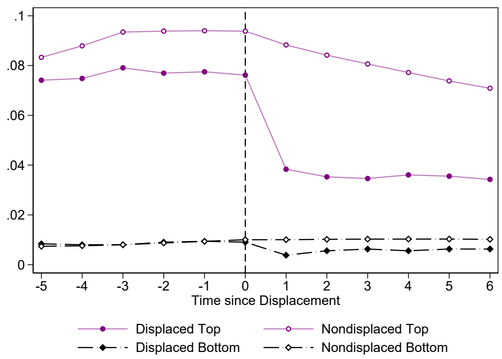
(c) Lives in the same address as parents, Under 65



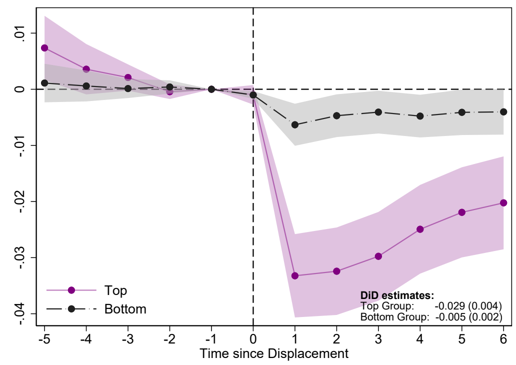
Note: Panel A shows the yearly probability of living in the same address as one of the parents. Panel B shows the estimates of δ_t obtained using Equation (1) separately for the top and bottom parental income groups. Panel C replicates Panel B but restricting to parents who are under the age of 65 at the time of the job loss. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level. DiD estimates are obtained using an alternative version of Equation (1) in which event study dummies are collapsed into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses.

Figure E.11: Impacts of Job Loss on Working in the Same Firm as One's Father by Parental Income Group, Bottom vs. Top 20%

(a) Working for Any of Father's Employers



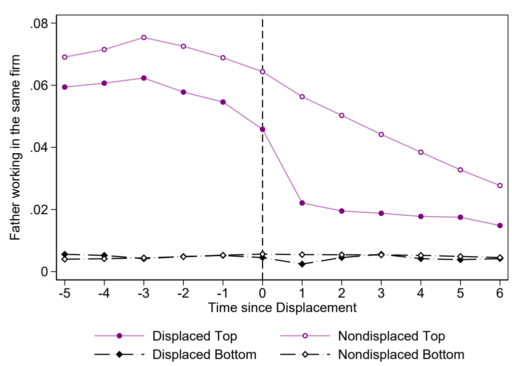
(b) Working for Any of Father's Employers



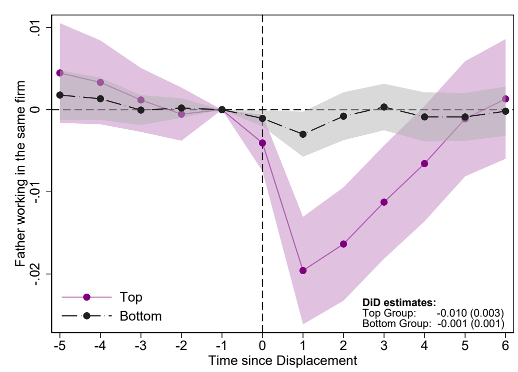
Note: Panel A shows the yearly probability of working for any of the father's employers for displaced and non-displaced individuals 5 years before and 6 years after the layoff by parental income group. The set of father's employers at year t contains all employers the father has had between years 1988 and t. Panel B shows the estimates of δ_t obtained using Equation (1) separately for the top and bottom parental income groups. Ninety-five percent confidence intervals appear in shaded bands around point estimates. Standard errors are clustered at the individual level. DiD estimates are obtained using an alternative version of Equation (1) in which event study dummies are collapsed into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses.

Figure E.12: Impacts of Job Loss on Working in the Same Firm Where the Father Worked in the Year Before the Job Loss by Parental Earnings Group, Bottom 20% vs. Top 20%

(a) Working in the Same Firm as Father



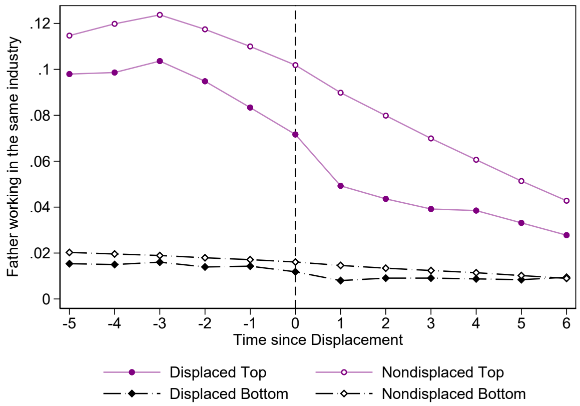
(b) Working in the Same Firm as Father



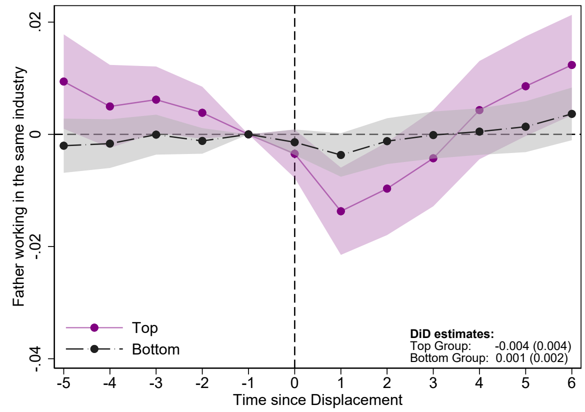
Note: Panel A shows the yearly probability of working in the same firm as the father. Panel B shows the estimates of δ_t obtained using Equation (1) separately for the top and bottom parental income groups. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level. DiD estimates are obtained using an alternative version of Equation (1) in which event study dummies are collapsed into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses.

Figure E.13: Impacts of Job Loss on Working in the Same Industry as One's Father by Parental Income Group, Bottom vs. Top 20%

(a) Working in the same Industry as Father



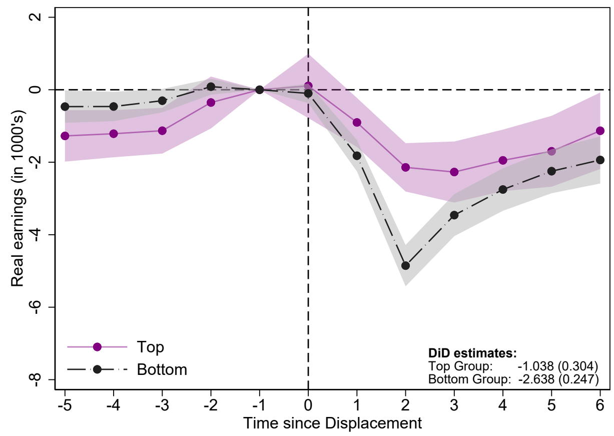
(b) Working in the same Industry as Father



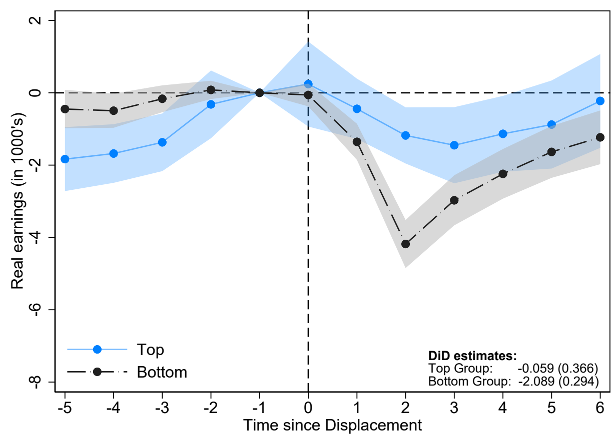
Note: Panel A shows the yearly probability of working for any of the father's industries for displaced and non-displaced individuals 5 years before and 6 years after the layoff by parental income group. The set of father's industries at year t contains all industries the father has had between years 1988 and t. Panel B shows the estimates of δ_t obtained using Equation (1) separately for the top and bottom parental income groups. Ninety-five percent confidence intervals appear in shaded bands around point estimates. Standard errors are clustered at the individual level. DiD estimates are obtained using an alternative version of Equation (1) in which event study dummies are collapsed into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses.

Figure E.14: Impacts of Job Loss on Real Earnings by Parental Earnings Groups, Bottom vs. Top 20%

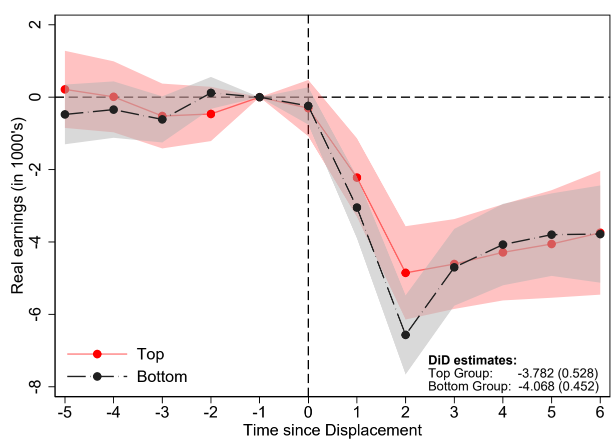
(a) All Years



(b) Growth Years



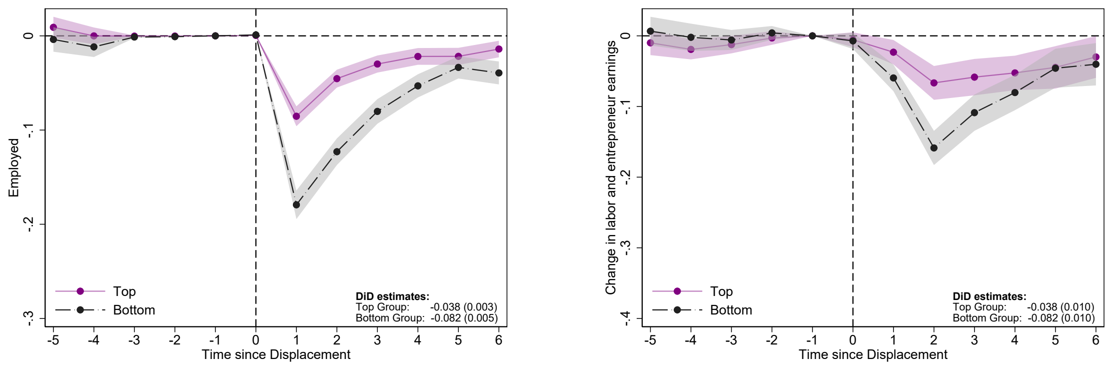
(c) Recession Years



Note: Figures show that our results are robust to measuring child earnings in raw earnings as opposed to relative earnings. Figures plot the estimates of δ_t obtained using Equation (1) separately for bottom and top 20% parental income groups. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level. DiD estimates are obtained using an alternative version of Equation (1) in which event study dummies are collapsed into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses.

Figure E.15: Impacts of Job Loss on Employment (Left) and Earnings (Right) by Parental Earnings Groups Using Labor Market Earnings Plus Benefits to Assign Parental Income Quintiles

(a) Employment (b) Earnings Relative to Pre-mean

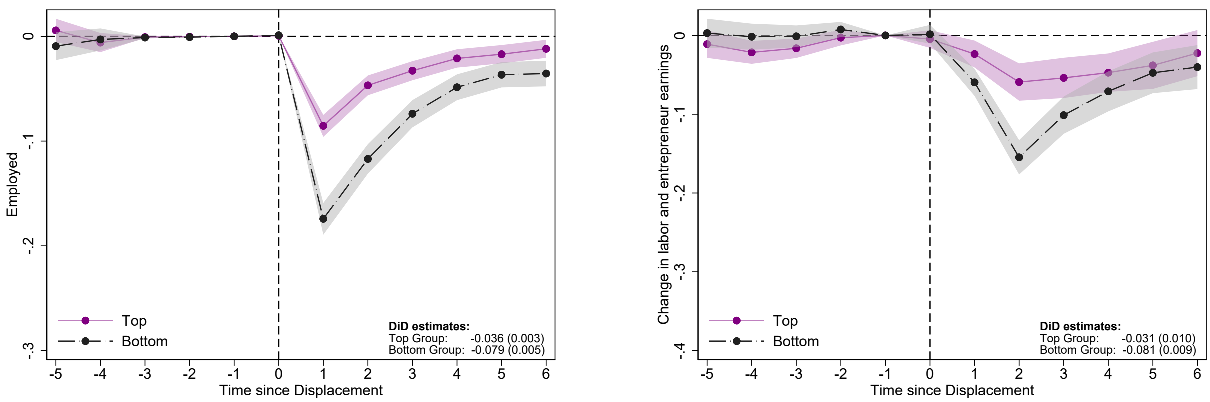


Note: Figures plot the estimated impacts of job loss on future employment and earnings and show that these results are robust to alternative approaches to defining parental income. Figures plot the estimates of δ_t obtained using Equation (1) separately for bottom and top parental income quintiles. In Panel A (B), the outcome is employment (relative earnings). Employment is measured at the end of the year. Relative earnings compare yearly labor and entrepreneurial earnings to the mean of yearly earnings 1–3 years before layoff. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level. DiD estimates are obtained using an alternative version of Equation (1) in which event study dummies are collapsed into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses.

Figure E.16: Impacts of Job Loss on Employment and Earnings by Parental Income Group, Bottom vs. Top 20%, Removing Parent Age Effects

(a) Employment

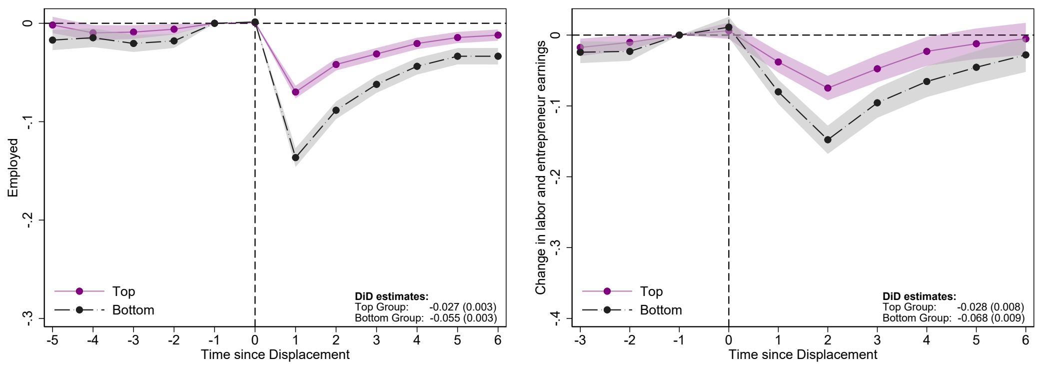
(b) Earnings Relative to Pre-mean



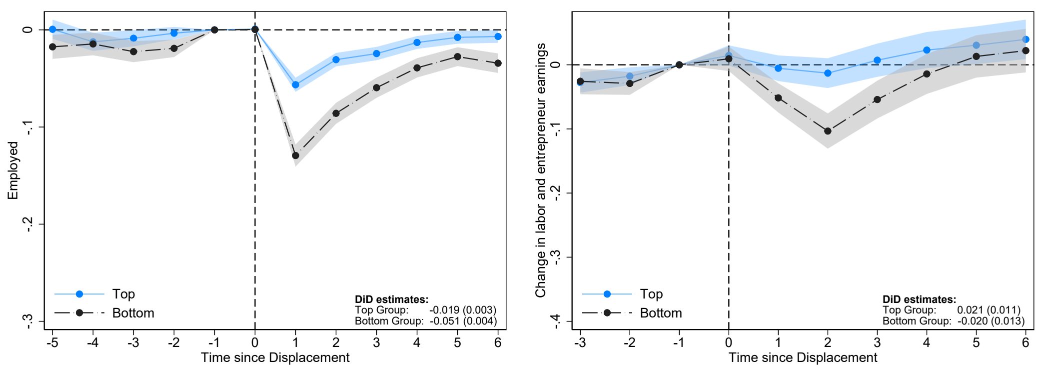
Note: Figures plot the estimates of δ_t obtained using Equation (1) separately for top and bottom parental income groups. For this specification, when assigning adult children to parental income groups, we resiedualize out parent age when calculating parental incomes. In Panel A (B), the outcome is employment (relative earnings). Employment is measured at the end of the year. Relative earnings compare yearly labor and entrepreneurial earnings to the mean of yearly earnings 1–3 years before displacement. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level. DiD estimates are obtained using an alternative version of Equation (1) in which event study dummies are collapsed into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses. Sample construction and data as defined in Section 2.1.

Figure E.17: Impacts of Job Loss by Parental Earnings Groups With Only 1 Year Tenure Required Instead of 3

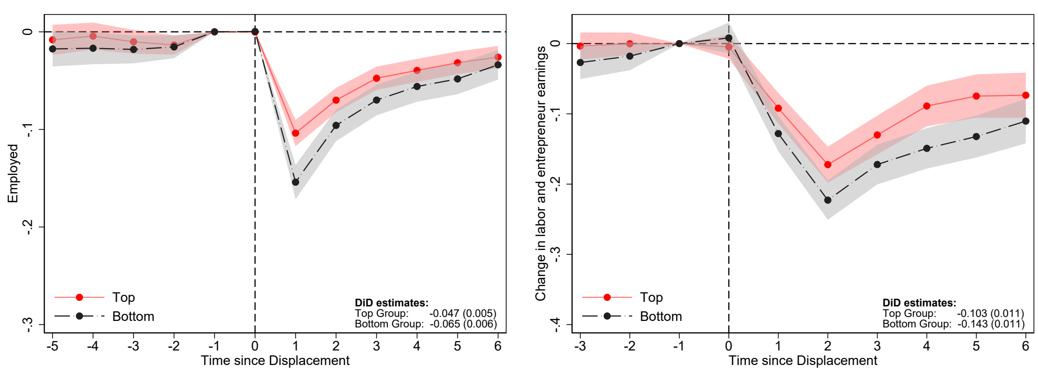
(a) Effects on Employment (Left) and Earnings (Right) for All Years



(b) Effects on Employment (Left) and Earnings (Right) for Growth Years



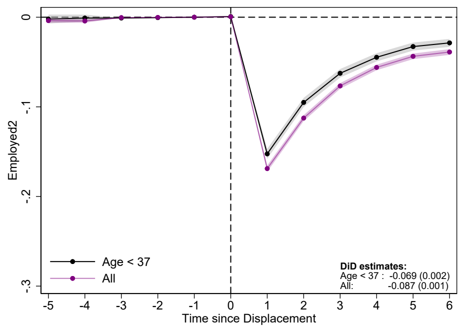
(c) Effects on Employment (Left) and Earnings (Right) for Recession Years



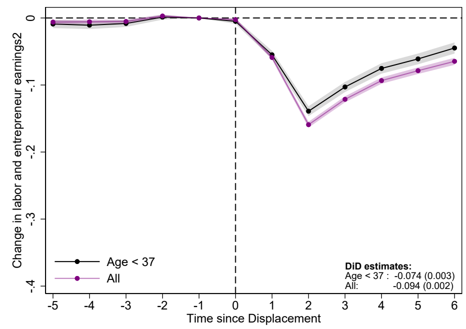
Note: Figures plot the estimated impacts of job loss on employment and earnings, and show that that these results are robust to only including 1 year of tenure before layoff as opposed to the 3 years in the main analysis. Figures plot the estimates of δ_t obtained using Equation (1) separately for bottom and top 20% parental income groups. Panel A reports results for all years. Panel B reports results for growth years, while Panel C reports results for recession years. Employment (left hand graphs) is measured at the end of the year. Relative earnings (right hand graphs) compare yearly labor and entrepreneurial earnings to the mean of yearly earnings 1–3 years before layoff. DiD estimates are obtained using an alternative version of Equation (1) in which event study dummies are collapsed into a single displacement indicator. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors for the DiD estimates are shown in parentheses.

Figure E.18: Impacts of Job Loss on Employment (Left) and Earnings (Right) for the Full Population Aged 25–55 vs Those Aged 25–36

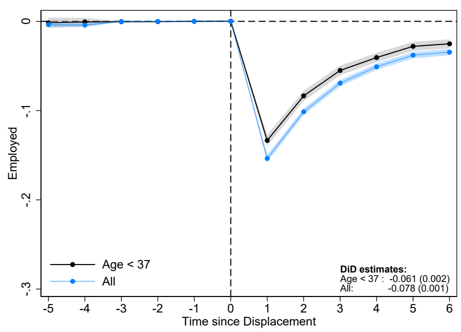
(a) Employment - All Years



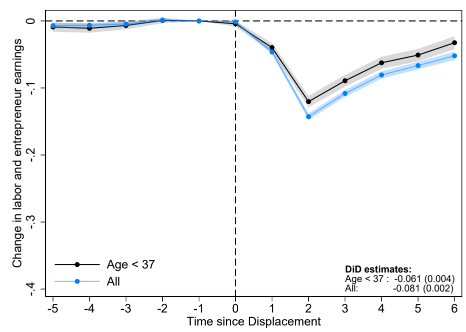
(b) Earnings - All Years



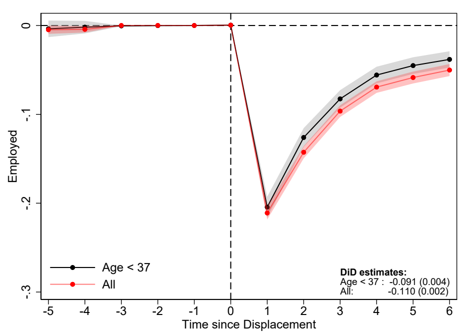
(c) Employment - Growth Years



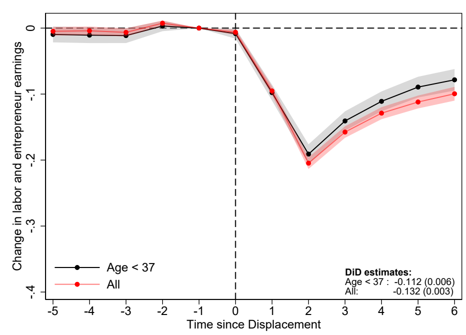
(d) Earnings - Growth Years



(e) Employment - Recession Years

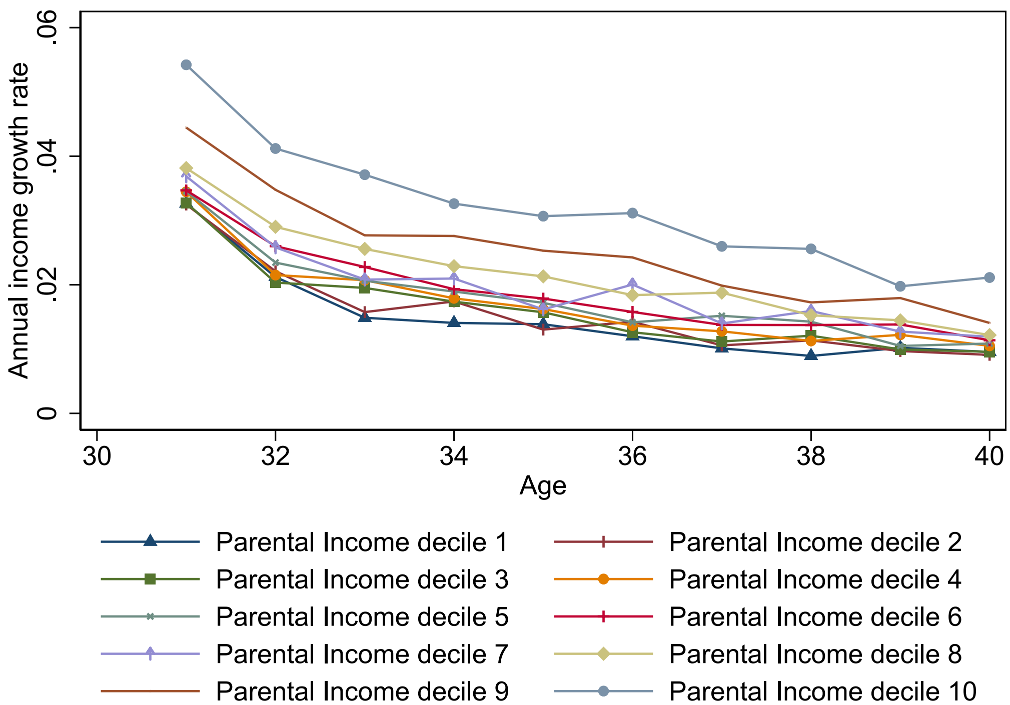


(f) Earnings - Recession Years



Note: Figure shows estimated impacts of job loss on future employment and earnings for the full population with all income groups for those aged 25–36 vs those aged 25–55. Panels A and B show results for layoffs in all years, Panels C and D for layoffs that occurs in growth years, and Panels E and F for recession years. Estimates derived using Equation (1). Ninety-five percent confidence intervals appear in shaded bands around point estimates. Standard errors are clustered at the individual level. DiD estimates are obtained using an alternative version of equation 1 in which event study dummies are collapsed into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses.

Figure E.19: Income Growth Rates by Parental Income Groups



Note: This figure displays the age-decile-specific earnings growth rates. Earnings growth within each age and within each decile is calculated using the entire population. These estimated growth rates are used to produce the simulations described in Section 4.2, with results reported in Figure 9 and Appendix Table D.18.