Disparate Impacts of Job Loss by Parental Income and Implications for Intergenerational Mobility*

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Abstract

Does job loss cause less economic damage if your parents are richer, and what are the implications for intergenerational mobility? We show that following a layoff, adult children born to parents in the bottom 20% of the income distribution have double the unemployment compared with those born to parents in the top 20%, with 118% higher present discounted value losses in earnings. Next, we show that these disparate impacts of job loss increase our version of the S80:S20 income inequality ratio by 8% and increase the rank-rank correlation by 34% for those impacted, implying large reductions in intergenerational mobility. We find that the age 40 rank-rank correlation is 3.9% higher due to the disparate impact and incidence of job loss over the preceding decade. In the last part of the paper we explore mechanisms and show that early education investments play an important role in explaining these differences.

Keywords: Intergenerational Mobility, Job Loss

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1 Introduction

Children born into disadvantaged families experience many more challenges on the road to economic success compared with children who are born advantaged (Black and Devereux, 2010). A large literature demonstrates a strong intergenerational relationship between parents' and children's incomes (Carneiro *et al.*, 2021; Corak, 2020; Modalsli, 2017; Chetty *et al.*, 2014b; Björklund and Jäntti, 1997; Solon, 1992). Yet we know little about how being born poor versus rich impacts people's labor market interactions upon reaching adulthood and after obtaining a job. A separate literature shows that labor market shocks, and in particular job loss, can have large and long-term impacts on people's future employment and earnings (Couch and Placzek, 2010; Jacobson *et al.*, 1993). However, this literature has not focused on how the response to labor market shocks might be shaped by and impact intergenerational mobility and inequality. In this paper we bring together these two seminal literatures and show that parental income inequality has important implications for how labor market shocks affect career trajectories, which in turn has substantial impacts on earnings inequality and intergenerational mobility.

Investigating how responses to labor market shocks might vary by parental income and impact intergenerational mobility is a challenge because it requires data that allows you to link the parents' and the adult child's incomes, as well as a source of exogenous variation in labor market shocks. To overcome these data challenges, we use Finish administrative data and an event study approach estimating the impact of layoffs following plant closures on future employment and earnings. The Finnish data uniquely allows us to connect the intergenerational mobility literature to what happens within firms once the children are adults. We estimate the impacts of job loss separately for children of low- and high-income parents. Note that there are many possible ways high-income parents could provide advantages to their children that might impact how they respond to labor market shocks, from investments in childhood (for example, in education) to direct interventions in adulthood at the time of job loss. While controlling for these possible ways high-income parents might advantage their children leading to different impacts of job loss would miss the full effects and be incorrect, we will explore possible underlying mechanisms at the end of the paper.

We use our data to present two new findings. First, we show that after children of low-income parents enter the labor force, they experience much larger costs from job loss compared with children of high-income parents. Those with parents in the top 20% of the income distribution bounce back significantly faster than those with parents in the bottom 20%. Specifically, they have almost half the unemployment and their earnings rebound faster following the layoff. These effects are persistent, with significant differences remaining in all 6 years following the layoff for employment and 3 years following the layoff for earnings. To better understand the magnitude of these estimates, we estimate the net present discounted value (PDV) of earnings losses and find that the PDV of earnings losses are 118% higher for adult children in the bottom 20% relative to the losses experienced by those with parents in the top 20%.[1][2]

Motivated by the cyclical impacts of job loss that have been shown in many papers (Schmieder *et al.*, 2018; Farber, 2017; Davis and Von Wachter, 2011; Aaronson *et al.*, 2004), which find larger impacts in recessions years, we examine whether the size of the disparity by parental income group varies depending on underlying economic conditions. We find that during recession years, the gaps in post-layoff employment and earnings effects between adult children of low- versus high-income parents are much smaller when compared with the same gaps for growth years. Thus while the overall size of job loss scars is cyclical, the size of the disparities between children of low- and high-income parents is countercyclical.

Second, we examine the extent to which the disparate impacts of job loss exacerbate earnings inequality and reduce intergenerational mobility. We define the change in earnings inequality as the percentage change in our version of the S80:S20 ratio, which we define as the change in the earnings held by adult children born to parents in the bottom 20% of the parental income distribution relative to the earnings held by those born to parents in the top 20%. Using our estimates of the PDV of job loss for the two groups we find that the disparate impact of job loss increases

[1] When we consider the PDV of earnings losses as a fraction of pre-layoff earnings, the gap is even larger with 159% higher losses for those in the bottom 20% versus the top 20%.

[2] These results are also not specific to our cutoffs. We show a consistent pattern with alternative cutoffs: differences are even larger between the bottom 10% and top 10%, and slightly smaller between the bottom 30% and top 30%.

earnings inequality by 8% for those affected. Next, we estimate the impact our main results have for intergenerational mobility. We estimate a simple extension to the calculation of the rank-rank coefficient from Chetty *et al.* (2014a).[3] To capture how job loss impacts intergenerational mobility, we allow the rank-rank regression coefficient to vary with job loss.[4] Using this approach we find that the rank-rank coefficient in the 6 years following the layoff is 34% higher for those impacted when accounting for the disparate impacts of job loss. When we disaggregate the overall effect into yearly effects of the disparate impacts of job loss on the rank-rank correlation, we find that there is a large initial increase in the rank-rank correlation. While the effect size decreases over time, the impact on the rank-rank correlation is still significant 6 years after the job loss, suggesting long term reductions in intergenerational mobility due to the disparate impacts of job loss.

To extend these results to country level rank-rank measures, 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 possibility of job loss. Our simulation includes not only our estimates of the disparate impacts of job loss, described above, but also the disparate incidence of job loss, as we incorporate the fact that the risk of unemployment is greater for children of lower-income parents. Based on this simulation, we find that the overall rank-rank correlation at age 40 is 3.9% higher due to the disparate impacts and incidence of job loss.

Together, these results show 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. While our main findings are striking, it is useful to explore the possible mechanisms behind the differences in outcomes. Parents could provide transfers to their children that mitigate the impacts of job loss in two time periods. Which of these two periods is most salient would change the optimal policy

[3]We use the rank-rank measure of intergenerational mobility instead of the intergenerational income elasticity measure that is based on log earnings correlations as it overcomes issues with zero earnings, which are particularly relevant when considering impacts of job loss on mobility.

[4]This is similar to the approach in Pekkarinen *et al.* (2009), except they estimate the impact of an education reform on the intergenerational income correlation. In our case we estimate the impact of job loss on intergenerational mobility and use the rank-rank specification.

response to these gaps. First, high-income parents could invest more in childhood (or provide genetic advantages), leading to advantages such as higher human capital. To better understand this possibility, we examine the extent to which differences in education between the two groups might explain the differences in outcomes we have documented.[5]

We develop a methodological extension to the traditional Blinder-Oaxaca decomposition to our setting where the object of interest, the job loss scar, is estimated, and explain the assumptions required for such an exercise to hold. Using this approach, we find that approximately 28% (46%) of the difference between the two groups in employment (earnings) job loss scars is explained by observable differences in education between the two groups. These results suggest an important equalizing role of investments by parents in education early in childhood that extends well into adulthood.

The second period in which parents might provide transfers to their children to mitigate the impacts of job loss is at the time of job loss. Parents might step in to smooth housing consumption through cohabitation, or smooth liquidity shocks by providing monetary transfers or job opportunities. While we are limited in our ability to address the former two in our data, we directly observe and can test the latter. We examine the possibility that children of high-income parents might bounce back faster because they are hired by their father's firm. We find this is not the case. Instead, following a layoff, children of high-income parents are less likely to work at the same firm as their father than before it (children of low-income parents are unaffected).

This paper is the first to bring together two important bodies of literature: that analyzing intergenerational mobility and that analyzing the impacts of job loss. The literature on intergenerational mobility is large, and a good overview can be found in Black and Devereux (2010), Jäntti and Jenkins (2015), and Corak (2013). The following examples highlight the extent of this issue: Chetty *et al.* (2014a) show that in the United States a 10 percentile increase in the parents' income rank is correlated with a 3.4 percentile increase in the adult child's income rank. Aaron-

[5]There is broad evidence that higher-income parents invest more in their children. For example, see Miller (2018) and Jackson *et al.* (2014) for examples of differences in school spending by parental income and also Carneiro *et al.* (2021), Attanasio *et al.* (2020), and Becker *et al.* (2018), for theory and evidence of impacts of differential investments by parental income in childhood. Given this evidence, we view education as a possible mechanism and not something to be "controlled for" in the main results. Controlling for education in this context would be akin to controlling for occupation in a gender wage gap regression - it would control for one of the outcomes of having high-income parents.

son and Mazumder (2008) show that in the United States intergenerational mobility has declined significantly since 1980. Jäntti and Jenkins (2015) shows that there is greater intergenerational mobility in the Nordic countries compared with the United States. We find that the overall intergenerational mobility correlation in Finland is two-thirds the size of the same figure for the United States[6], suggesting that even in Nordic countries where mobility is higher this is still an important phenomenon.[7]

Our paper contributes to this literature by focusing on how parental income inequality might partially determine labor market interactions in adulthood. Our paper shows that the impact of labor market shocks during adulthood is determined in part by the inequality experienced in childhood, leading to lower mobility and a vicious cycle. These results have important implications for the intergenerational mobility literature and contribute to a rich debate on when in the adult child's life these correlations should be calculated and what you might capture at different ages. Our results suggest that measuring intergenerational mobility correlations when children are in their twenties or early thirties might misrepresent "true" overall mobility. If parental income differences cause children to react differently to labor market shocks, then overall intergenerational mobility will depend on the full career trajectory, and will not be set early on.[8]

This paper also contributes to a large literature studying the impacts and incidence of job loss. Many papers have documented that layoffs lead to long-term losses in both employment and earnings. Prominent examples in this literature include Lachowska *et al.* (2020), Couch and

[6]We find the rank-rank correlation is 0.19 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).

[7]Other papers have tried to understand what causes the strong correlation between parents' income and child's income. Black *et al.* (2019) find that environmental factors explain much more of intergenerational wealth transmission compared with inherent talent. A large literature suggests that geographic location during childhood plays an important role in determining intergenerational mobility (Chyn, 2018; Chetty *et al.*, 2016, 2014a; Ludwig *et al.*, 2013; Katz *et al.*, 2001). In addition, there are a number of papers that link parental income to educational advantages, such as Chetty *et al.* (2020), who show that there is enormous parental income segregation across universities, and discuss how changing the sorting across universities could dramatically increase intergenerational mobility.

[8]Our results are consistent with the idea that current income may not accurately capture long-run income. For example, Haider and Solon (2006) state that "the association between parentsâ and childrenâs long-run income is susceptible to dramatic underestimation when current income variables are used as proxies for long-run income." The evidence in our paper shows a substantive reason why this may be the case beyond just measurement error, namely that labor market shocks can differentially impact the permanent incomes of adult children from high' versus low-income parents. Related to the results in this paper, Bütikofer *et al.* (2018) find that a large positive economic shock (the Norwegian oil boom) in adulthood has positive impacts on mobility.

Placzek (2010), and Jacobson *et al.* (1993).[9] Our work extends this important literature in three ways. First, we show that the impacts of job loss vary substantially according to parent's income. While a number of papers explore 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), this is the first paper to ask whether parental income changes the impact of job loss experienced by their children.[10] Second, we provide innovative evidence on the mechanisms behind these results. In particular, our straightforward extension of the Blinder-Oaxaca decomposition to analyze the underlying drivers can easily be applied in other applications. Third, we show that these differences in the impact of job loss have important implications for inequality and intergenerational mobility.

The paper is organized as follows. The next section describes the data and institutional background. Section 3 presents our empirical specification. Section 4 presents the main results. Section 5 discusses impacts on income inequality and intergenerational mobility. Section 6 examines mechanisms. Section 7 concludes.

2 Data and Institutional Context

2.1 Data

Our primary data set is the Finnish linked employer-employee data set (known as FLEED), which covers all Finnish residents between the ages of 16 and 70 years in the period 1988–2016.[11] The unique person identification codes allow us to follow individuals over time. Likewise, unique firm and plant codes allow us to identify each worker's employer and observe job separations. We focus on individuals who were working in Finland in 1991–2010. We label these years "base years," b. We construct separate samples for each base year b by including observations for each

[9] In addition to impacts on future employment and earnings, research also shows impacts of job loss on health (Black *et al.*, 2015; Ahammer and Packham, 2020; Sullivan and Von Wachter, 2009).

[10] By showing disparate impacts by parental income band, we also contribute to a broader literature examining 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. In a recent paper, East and Simon (2020) show that low-income workers are also less protected against the earnings costs of job loss.

[11] In a few cases, for example in Figure 1 Panel B and in the simulation, we pull the earnings data from the folk modules. Folk modules have the same data as in the FLEED but in a different format.

worker 3 years prior to the base year b and 6 years after. In the analyses we pool these 18 base-year samples into a panel spanning the years from 1988 to 2016.

In line with most of the literature studying the impact of job loss, we focus on displaced workers (the adult children of interest in this paper) defined as individuals who involuntarily separate from their jobs due to exogenous shocks, specifically a plant closure.[12] A plant closure can be thought of as an exogenous shock to a worker's career since it results in separation of all the plant's workers and is not related to the worker's own job performance. Our data consist of all (Finnish) private sector plants from 1988 to 2016. Here a plant is a production unit (for goods or services) that is owned by one firm (or enterprise), is located on one site, and operates within one industry. 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 $t+1$. We also confirm that these are real plant closures. Those plant closures for which 70% or more of the workforce is working in a single new plant in the following year are not considered as real closures.[13] Then we merge the plant closure data with the individual-level data.

We label workers "displaced" if their plant closed down during t and $t+1$, or if they separated 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"), following Huttunen and Kellokumpu (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 more than three years of tenure in base year b, although we relax this assumption to only 1 year in a robustness check and results are identical. Our approach closely follows the approach taken in Huttunen *et al.* (2018) and Huttunen and Riukula (2019).

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. In

[12]This excludes workers who experience endogenous separations such as being fired for cause, where we would expect to see larger effects on earnings and employment.

[13]This is to rule out cases where the same firm may simply have been reclassified.

robustness checks we also use the more recent matching procedure from Schmieder *et al.* (2018) to construct the control group, and find that the results are identical to our main results.

We focus on adult children aged 25–35 at the time of displacement since the earnings data is only available from 1988 onward and we must be able to calculate their parents' earnings before their parents reach the retirement age. 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.[14] Parental earnings, like child earnings, come from FLEED, administrative data covering all Finnish residents. We are able to match biological parents to children using unique identifiers established at birth.

We measure parental earnings by taking the average of total labor market earnings of both parents from 1988 until the year of the displacement of their adult child.[15] We rank the resulting average earnings and select adult children of parents in specified earnings groups (for much of the paper, in the bottom and top 20%). Table A.1 provides summary statistics for our estimation samples of adult children.[16] However, it is important to note that the rankings of the adult children into parental income groups are very robust to alternative ways to measure the parents' incomes. In robustness exercises we show that our results are not sensitive to a variety of alternative approaches to identifying children of low- versus high-income parents, such as including taxable benefits in addition to labor market earnings when defining parental income groups, and only using earnings of parents from 1988-1990.[17]

Our main analysis considers three outcomes for the adult children. First, we look at an individual's employment status as measured at the end of the calendar year. Second, we study an individual's relative earnings, which we construct by comparing that individual's labor and en-

[14]We restrict to heterosexual parents as it is more straightforward to build earnings panels for these parents. This excludes a very small number of same-sex parent households.

[15]We do not alter parental earnings calculations in response to family breakup, and use biological parents throughout.

[16]Descriptive statistics for growth years appear in Appendix Table A.2 and recession years in Appendix Table A.3.

[17]We have also replicated the results using only the earnings of the father at age 55. Note that while measurement in this literature is taken very seriously, for example see Jácome *et al.* (2021), Ward (2021), and Deutscher and Mazumder (2021) for discussions of these issues, we find that our results are robust to all alternative measurement approaches we are able to implement, both in terms of when the income of the parents is measured as well as what we include in parental income.

trepreneurial earnings each year with his average annual labor and entrepreneur earnings in the 3 years before the layoff. Before we build the relative earnings, all earnings are deflated to 2013 euros using the consumer price index. We include 0s in our earnings variable, when this occurs for a given worker. This earnings measure gives a relative interpretation of magnitudes but does not suffer from the problems that arise from zero earnings. 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.

When we turn to mechanisms we will also look at whether adult children join any of their father's current or previous firms. For this outcome, for each period t, we construct a set of employers the father has had between the years 1988 and t. Then we define an indicator variable that takes the value of 1 if an individual's employer at the time t is among the set of father's employers, and 0 otherwise.

2.2 Institutional Context and Descriptive Results

Before turning to our empirical strategy and results, it is useful to characterize the relationship between parent and child income in Finland for the full population and also for our estimation sample prior to the job loss shock. In Figure 1 Panel A we show the percentage of working adult children (our estimation sample) in each earnings quintile in early adulthood, separately for those born to parents in different earnings quintiles as specified on the x-axis.[18] Notably, almost none of the children born into the bottom 20% who have jobs (preceding job loss) remain in the bottom 20% as adults. Over 80% of these children have moved out of the bottom two quintiles by their mid-thirties.[19] This is a striking result because it suggests that conditional on entering the labor

[18] In Figure 1 we only look at adult children from our estimation sample as described in Section 3. Notably we restrict to those with job tenure of at least 3 years before the layoff, as we are studying the impact of job loss, although our main results are robust to only requiring 1 year of job tenure. The figure would look different if we were to include the full population. In particular, restricting to those who are employed (a necessary precursor to job loss) is a major reason why so few adult children are in the bottom 20%.

[19] A similar figure from the United States can be found in Chetty *et al.* (2014a), which shows less mobility. The results are consistent with other papers, such as Suoniemi (2017) and Jäntti *et al.* (2006), that show that Finland (and other Nordic countries) experiences more intergenerational mobility than the United States.

force, this group is doing relatively well. However, while obtaining a job seems to move adult children out of the bottom of the income distribution, this figure still suggests a strong correlation between parental income and the adult child's income for our estimation sample. Almost half of those born into the top 20% are in the top 20% themselves (compared with other adult children in their birth cohort) while only just over 20% of those who were born into the bottom 20% find themselves in the top 20% prior to job loss.

Next, consider Figure 1 Panel B, which graphs the rank-rank correlation as in Chetty *et al.* (2014a) for our estimation sample and the full population. The correlation between the rank of the parents and the rank of the child for the estimation sample of 0.122 is far from 0, suggesting that parental income plays an important role in determining the child's future income, as has been shown in this literature. The overall rank-rank correlation we estimate of 0.190 for the full population in Finland, albeit about two-thirds the size of the equivalent correlation in the United States,[20] also indicates an important role for parental incomes in determining the child's income.

The results in these graphs are consistent with the fact that by virtue of having a full-time job most people will have left the bottom 20%, since the bottom 20% of the income distribution consists of people with extremely low labor market earnings. Thus, obtaining a job serves an important equalizing role. Our study asks how precarious this success is: can children who were born poor, conditional on entering the labor market and thus leaving the bottom 20%, withstand a labor market shock in the same way as adult children of richer parents? If not, what are the implications for intergenerational mobility?

Since we focus on the effects of job loss as our labor market shock in this paper, it is also important to understand the economic conditions during the years we study and how the Finnish system deals with job loss. Finland went through three economic periods during the years 1990–2015, our period of study, which we will leverage in our analysis. The first one was referred to in Finland as the Great Depression of the 1990s, which was due to the deregulation of the financial markets in the 1980s. This led to an unexpected bubble in the stock and real estate

[20]Chetty *et al.* (2014a) find that in the United States the rank-rank correlation between individual rank and family income rank is 0.287 (see Table 1 row 7 of Chetty *et al.* (2014a)). Our equivalent rank-rank correlation of 0.190 is thus 66% of the United States rank-rank correlation.

markets, and coupled with the decline of the Soviet Union, a large recession occurred in Finland. The unemployment rate of 15- to 64-year-olds rose from 3.2% in 1990 to 6.7% in 1991, and to a staggering 16.5% in 1993.[21] GDP dropped by 5.9% in 1991 and by 0.7% further in 1993.[22] Starting in 1994, Finland went through a recovery phase that lasted until the first years of the 2000s. During the recovery period, 1994–2007, the Finnish growth rate averaged 4%, higher than the European Union average. The unemployment rate stayed at a higher rate than before the depression and reached its lowest point (6.4%) in 2008, after which it started growing again. In that year, Finland was hit by the global crisis, and in 2009 GDP dropped by 8.1%, the largest annual drop since 1918 and the Finnish Civil War. The unemployment rate rose to 8.5% in 2010. In our analysis we will look at all years for our main results, but will also estimate the effects separately for growth and recession years.

In Finland, all workers who lose their jobs 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. For example, 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. Most workers in Finland contribute to insurance payments either through membership in labor unions or through unemployment insurance institutions.

3 Empirical Strategy

Figure 2 presents descriptive results on the impact of job loss due to plant closures for adult children born to parents in the top 20% of the income distribution versus adult children born to parents in the bottom 20% of the income distribution. The figure also shows the evolution of labor

[21]Official Statistics of Finland (OSF): Labour force survey [e-publication]. ISSN=1798-7857. Helsinki: Statistics Finland [referred: 3.12.2020]. Access method: `http://www.stat.fi/til/tyti/tau_en.html`.

[22]Official Statistics of Finland (OSF): Annual national accounts [e-publication]. ISSN=1798-0623. Helsinki: Statistics Finland [referred: 3.12.2020]. Access method: `http://www.stat.fi/til/vtp/tau_en.html`.

market outcomes for the control group of adult children who are not displaced by layoffs. The figure shows clearly different patterns, with adult children whose parents are in the bottom 20% of the income distribution experiencing much larger and longer-term decreases in employment and earnings following the displacement. However, these results, while evocative, are merely descriptive.

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:

$$Y_{ibt} = \alpha_{ib} + \beta' \mathbf{X}_{ibt} + \sum_{j=-3}^{6} \delta_j D_{b,t-j} + \pi_b + \gamma_t + \epsilon_{ibt}, \tag{1}$$

where Y_{ibt} is the outcome variable for worker i in base-year sample b at time t. The variables $D_{b,t-j}$ indicate whether an individual was displaced in year $t-j$, t being the observation year. The parameters of interest are the δ_js that measure, for example, the earnings differentials of displaced workers relative to non-displaced workers in pre- and post-displacement years $j \in [-3, ..., 6]$. 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 (-3 to 6 years).[23] Finally, individual fixed effects, α_{ib}, are included to control for permanent differences in earnings between displaced and non-displaced workers (in a given base-year b). The worker–base-year fixed effects should also account for a large part of the unobservable characteristics. When including worker–base-year fixed effects, time-invariant base-year controls cannot be included, but X_{ibt} includes 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.

[23]Both year effects and baseline year dummies are required due to tenure restrictions, see Schmieder *et al.* (2018) for additional discussion.

Our key identifying assumption is that displaced and non-displaced individuals' outcomes would have similar trends in the absence of plant closure. We provide 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. We also show that estimates are identical when we use alternative control groups in the robustness checks, such as using matching as in Schmieder *et al.* (2018).

The event study estimates based on equation 1 are the main estimates of interest, but difference-in-difference (DiD) estimates are also reported for each specification in the graphs (detailed estimates reported in Appendix Tables A.4-A.8). The DiD estimates are based on differences between displaced and non-displaced workers after versus before the layoff. These estimates are reported throughout the paper as an alternative measure of the disparate impacts. 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.

In robustness checks, base-year characteristics are added to X_{ibt} such as gender, tenure, education level, and industry, and individual fixed effects are removed.[24] A second robustness check uses a matching exercise that is similar to Schmieder *et al.* (2018) (see Section 6 for more details).[25] The results are unchanged with these robustness exercises.

4 Main Results

The first set of main results, in Figure 3, shows the impact of a layoff on earnings and employment in the subsequent 6 years for individuals with low- versus high-income parents. It is useful to note the complete absence of pre-trends, an important affirmation that the no-anticipation assumption necessary for the event study to identify the effects holds in this setting. While the absence of pre-trends is mechanical for employment, that is not the case for earnings. Moreover, when we relax

[24]These estimates are reported in Columns 3 and 4 of Appendix Tables A.4-A.8.

[25]Results for this exercise are shown in Figure B.9

the assumption of 3 years of employment prior to the layoff in Appendix Figure B.5, which does not force pre-trends for employment to be parallel, we still see a complete absence of pre-trends.

As prior studies have found, those who are laid off experience a severe negative short-term effect on employment and earnings, as well as long-run negative impacts, with lower employment and lower earnings for years post layoff. However, the impact is much more pronounced for individuals with parents in the bottom 20% of the income distribution compared with those with parents in the top 20%. Specifically, individuals with low-income parents have almost double the non-employment compared with individuals with high-income parents. Note that this result is not necessarily obvious a priori. A standard job search model where the 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% stay unemployed for longer, in order to wait for a better job to arrive. Individuals born to low-income parents also experience much larger earnings losses in the years post layoff. Overall, the differences are significant at the 95% level in the first three years post layoff for earnings and for every year post layoff for employment.

The impact is large in absolute terms as well. For example, in the first year post layoff, relative to the control group, 20.7% of adult children of low-income parents are still not employed. The comparable number for adult children of high-income parents is 11.4% of those of high-income parents. In the second year post layoff, those with low-income parents have an 18.4% drop in earnings relative to their average earnings in the 3 years preceding the layoff (relative to the control group), compared with an 8.9% drop in earnings for those with high-income parents.[26] These results are important as they indicate another way in which intergenerational mobility might be reduced. If adult children whose parents are in the bottom 20% of the income distribution have a looser grip on the job ladder leading to greater scarring in terms of employment and earnings, then we would expect this to exacerbate intergenerational inequality. This hypothesis will be tested in Section 5.

The 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, over the 6 years post

[26]See Appendix Table A.10 for these numbers.

layoff, these estimates show that those with parents in the bottom 20% experience a 10 percentage point average drop in employment (relative to the control group) versus a 4.9 percentage point average drop for those with parents in the top 20%. This represents a 104%[27] larger increase in non employment for those with parents in the bottom versus the top group, and the difference is statistically significant. The reduction in earnings in the six years post layoff is 112%[28] higher for those whose parents are in the bottom versus the top income group, and again, this difference is statistically significant.[29]

Results are even more pronounced with narrower parental income bands. Figure 4 shows even larger differences post layoff between adult children whose parents are in the bottom 10% versus top 10%. We also present results where we restrict parental earnings groups to the bottom 30% and top 30%. The overall takeaway is consistent: adult children of lower income parents experience larger impacts of layoffs in terms of both employment and earnings, with results getting stronger the lower/higher the parental income cut-offs become. While much of this paper focuses on the bottom and top 20%, it is important to show that the patterns we observe are not due to arbitrarily chosen cut-offs in the parental income quintiles, but that they show consistent patterns across all cut-offs. We will extend the analysis to the full population when we estimate impacts on intergenerational mobility in Section 5.

Motivated by the finding in the job loss literature that the impact of job loss varies with the economic conditions (Aaronson *et al.*, 2004; Farber, 2017; Davis and Von Wachter, 2011; Schmieder *et al.*, 2018), we next investigate the cyclicality of the disparate impact of job loss by parental income group. To do this, we divide the sample into layoffs that occurred during periods where GDP was growing and periods when GDP was shrinking and the economy was in recession. As Figure 5 illustrates, Finland experienced two recession periods during our time period, a deep recession from 1991 to 1993 and a milder recession from 2008 to 2010.[30]

[27] $10/4.9 = 2.04$

[28] $0.106/0.050 = 2.12$

[29] Detailed DiD estimates appear in Appendix Tables A.4–A.6 and detailed yearly event study estimates appear in Appendix Tables A.9–A.11.

[30] During the global Great Recession, Finland experienced a "double dip" recession with an immediate drop in GDP in 2008–2009, a period with some GDP recover, and then another drop in GDP from 2012 to 2014. While our data covers the years up until 2016, since we follow workers 6 years after the layoff we cannot include the 2012–2014 recession years.

Figure 6 documents an interesting pattern between the state of the economy when the displacement occurred and the disparate impact of job loss.[31] Unsurprisingly, the overall impact of a layoff is larger in recession years. When the entire economy is shrinking and jobs are hard to find, a layoff leads to persistently larger drops in employments and earnings. However, the differences between adult children of low- versus high-income parents are much more pronounced in growth years compared with recession years, as demonstrated by both the event study graphs and the DiD estimates. The DiD estimates show that the employment drop is 3[32] times larger for low-income children compared with high-income children in growth years. In contrast, in recession years the employment drop is 1.5[33] times higher for low income children compared with high income children. When it comes to earnings, the earnings drop is 3.4[34] times larger for low-income children in growth years, and 1.64[35] times larger for low-income children in recession years. These heterogeneous results are consistent with the possibility that during recession years, it is simply much more difficult to find a new job, much less a well-paying new job, compared with growth years. Thus, it may be that in recession years there is only so much that family connections and other advantages can do for children of high-income parents. In periods of growth there are more jobs and better-paying jobs available to those who are laid off, allowing for more leveraging of advantage.[36]

4.1 Robustness

We perform several robustness checks of our results, which can be found in the Online Appendix. Figure B.3 shows that the results are robust to alternative measures of earnings for the adult child such as real earnings as opposed to relative earnings. Figure B.4 shows that our results hold if instead of using both parents' incomes to determine their income quintile, we use labor market earnings plus benefits for the years 1988-1990. Figure B.5 shows that our results hold if we only

[31] Appendix Figures B.1-B.2 show the event studies separately by year, which are consistent with the main results presented here but are interesting in terms of fully disaggregating the results at the yearly level.

[32] 0.075/0.025=3

[33] 0.137/0.090=1.52

[34] 0.064/0.019=3.37

[35] 0.169/0.103=1.64

[36] It could also be the case that those who are laid off are different in recession versus growth years.

require 1 year of tenure before the layoff as opposed to the restriction of 3 years required in the main results.[37] Together, these robustness checks suggest that no matter how we approach the data, we always find gaps in the impacts of job loss on employment and earnings between adult children of low- versus high-income parents, as in our main results.[38]

We also graph the overall job loss scar in Figure B.6 without separating into low- versus high-income parents. We present these results both for our age group of 25–35 but also for the full age distribution. We find significant scarring and much more persistent earnings losses when we expand to all ages (we restrict to younger ages, 25–35, in order to be able to match to parents and observe parental earnings in our main results). Note that this result is consistent with earlier work showing that older workers suffer more following a displacement (see, e.g., Chan and Huff Stevens 2001).

5 Implications of the Disparate Impacts of Job Loss for Intragenerational and Intergenerational Mobility

In the preceding section we showed that job loss is experienced very differently by adult children of low- versus high-income parents. In this section we ask to what degree the disparate impacts of job loss contribute to overall earnings inequality and intergenerational mobility.

5.1 Impacts on Intragenerational Mobility

To capture the total impact on earnings, we first calculate the PDV of job loss as in Von Wachter and Davis (2011). We then use these estimates to quantify the overall impact on earnings inequality. The PDV is calculated using the following equation:

$$PDV_{Loss} = \sum_{s=1}^{6} \bar{\delta}_s \frac{1}{(1+r)^{s-1}}, \tag{2}$$

[37]The latter restriction is standard in the literature which is why we use it in our main estimates. However this restricts to individuals with strong attachment to the labor force, and as we showed in Table A.1 as a result we have a slightly smaller number of observations of children in the bottom 20%, so it is useful to show that our results are robust to this restriction.

[38]Results on growth and recession years are similarly robust to these alternative data choices.

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. Note that for these results, we use the matching estimates described in more detail in Section 6, but these give almost identical results compared to our main estimates (see Appendix Figure B.9).

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 €17,667 compared with a PDV of €8,096 for children with parents in the top 20%. In other words, the bottom 20% experiences 118%[39] 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 using average earnings for the two groups in the 3 years before the layoff, in order to show the PDV of earnings losses in terms of total years of earnings lost. Column 2 shows that while those with parents in the top 20% lose just under a fourth of a year's pre-layoff earnings, those with parents in the bottom 20% lose almost two thirds a year's pre-layoff earnings. These numbers correspond to PDV earnings losses that are 159% [40] higher for adult children in the bottom 20% in terms of pre-layoff earnings.

These estimates are interesting, but except for showing that the earnings losses for the bottom 20% are larger, they do not reveal the full impact of job loss on earnings inequality. To understand the overall impact on earnings inequality, we estimate equation 3 for those who lose their jobs. Additionally, we use the matching procedure described in more detail in Section 6 to construct counterfactual earnings and estimate equation 3 had individuals not lost their jobs. Thus, we have

$$PDV_{Earnings} = \sum_{s=1}^{6} \bar{Y}_s \frac{1}{(1+r)^{s-1}}, \tag{3}$$

where $\bar{Y}_s$ is the average earnings either for those who lost their jobs or for the counterfactual group of the (observed) job loss group in year s after the displacement. With these estimates, reported in columns 3 and 4 of Table 1, we can characterize the percentage change in our version

[39] $17667/8096 = 2.18$

[40] $.603/.232 = 2.59$

of the S80:S20 ratio, a common approach to measuring inequality, using the following equation:

$$\Delta inequality = \frac{PDV^{Top\,20}_{Earnings}/PDV^{Bottom\,20}_{Earnings}}{PDV^{Top\,20}_{Earnings,counterfactual}/PDV^{Bottom\,20}_{Earnings,counterfactual}}. \tag{4}$$

Note that normally the S80:S20 is the income held by the wealthiest 20% relative to the income held by the poorest 20%. In our version we change this to be the earnings held by the children born to the wealthiest 20% of parents relative to the earnings held by the children born to the poorest 20% of parents. We find that inequality, defined by equation 4 as the percentage increase in the earnings ratio between the top 20% and bottom 20%, increases by 8% following a job loss for those affected (see Table 1 column 5).

5.2 Impacts on Intergenerational Mobility

Next, we turn to implications of the disparate impacts of job loss on intergenerational mobility. We measure intergenerational mobility using associations between percentile ranks as opposed to correlation of log earnings between parents and children because rank measures of mobility better deal with the presence of zero earnings compared with log earnings, which is particularly relevant in the context of job loss (see Chetty *et al.* (2014a) for a more detailed discussion).[41] Figure 7 plots the results of event studies showing how the percentile rank changes as the result of a layoff for adult children of parents in the bottom versus top 20%. The figure shows that there are persistent differences. While both groups experience a drop in percentile rank following a layoff, the effects are larger for the adult children of parents in the bottom 20%, and the difference is statistically significant in all 6 years following the layoff.

An interesting question is whether conditional on the adult child's rank before job loss, we still see disparate impacts on the rank post job loss. If there were no differences conditional on pre-displacement rank, then the overall impact on the rank we show in Figure 7 could primarily be a "composition" effect. Namely, the impacts we observe are driven by the differences in rank pre-displacement (as seen in Figure 1), but if we compare adult children of low- versus high-

[41]The main results all hold if we use log earnings-log earnings specifications instead. Those results are available upon request.

income parents with similar ranks before displacement we do not find differential impacts on post-displacement ranks. To address this question, we again estimate the impact of job loss on rank, but this time condition on the rank of the child before job loss. We show these results in Figure 8. We find that in every case there is a gap in the job scar conditional on pre-displacement rank, and this is especially stark (and significant) at the top two thirds of the pre-displacement income rank distribution. Thus, these results suggest that there is an important "level" effect in the sense that even among those in the same pre-displacement rank there is still a difference in the impact of job loss.

These figures are revealing, but another way to capture the impact of job loss on intergenerational mobility is to estimate the impact directly within a rank-rank regression framework, where we will additionally expand the analysis to consider all parental income ranks and not just the bottom and top 20%. Specifically, consider the following rank-rank regression:

$$R_C = a + \beta R_P + \epsilon_i, \tag{5}$$

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

$$\beta = \beta_1 + \beta_2 D_C Post + \beta_3 D_c + \beta_4 Post, \tag{6}$$

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 5 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:

$$R_C = \alpha + \beta_1 R_P + \beta_2 R_P D_C Post + \beta_3 R_P D_C + \beta_4 R_P Post + \beta_5 D_C + \beta_6 Post + \beta_7 D_C Post + \varepsilon_i. \tag{7}$$

This exercise is similar in spirit to what is done in Pekkarinen *et al.* (2009), when they estimate the impact of an education reform on the intergenerational income correlation. Our main differences compared with their specification is that we estimate the impact of job loss on intergenerational mobility and use the rank-rank specification.

Table 3 reports results from this exercise. Note the higher number of observations compared with Table A.1 is because each displaced and non-displaced individual appears each year as a separate observation and additionally in this table we include children in all income quintiles.[42] The regression coefficient of interest is β_2, which measures the effect of job loss on intergenerational mobility, above and beyond the direct impact of the layoff on the child's rank (captured by β_7). We first note that as in previous work, there is a positive correlation between the income rank of parents and that of their child, with the estimate of β_1 equal to 0.094 when nothing else is included, meaning that the child's rank is correlated with the parents' rank. Note that this is lower than the full population, as we showed in Figure 1. In that figure we showed that the rank-rank correlation for the full population using all taxable income is 0.190. This value is similar to estimates of rank-rank correlations in other Nordic countries, but lower than the same figure in the United States. However, our estimation sample restricts to those who work (a necessary precondition to experience job loss) and we focus on labor market earnings. These restrictions lead to the rank-rank correlations reported in the first row of Table 3. As we showed in Figure 1, the restriction to working younger adults (our estimation sample) lowers the rank-rank correlation, suggesting that entering the labor force likely serves as an equalizer. We also replicate the results from Table 3 using total income instead of labor market earnings in Appendix Table A.14, which increases the raw rank-rank correlation. We discuss this in more detail at the end of this section.

Second, we find that a layoff leads to very large and negative impacts on the adult child's rank, captured by β_7. This result is not surprising given the amount of earnings losses and employment losses caused by a layoff, which one could guess would lead to a fall in rank in the overall income distribution. The coefficient of interest, β_2, is 0.032 and is statistically significant. The fact that it is positive means that layoffs are experienced differently by adult children of low- and high-income

[42] Results are similar if we only look at the bottom and top 20%.

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 child. Conceptually, this effect is equivalent to job loss causing the slope of the line representing the relationship between parents and child rank to grow steeper. Compared to the overall rank-rank correlation of 0.094, our results suggest that intergenerational mobility decreases by 34%[43] as a result of job loss.

The results from Table 3 show the overall impact of job loss on intergenerational mobility. We might also be interested in the yearly effects, in part because based on the main results it appears that the gaps in the impacts of job loss are largest in the first few years after it and then fade out somewhat. A natural question based on these results is whether we have identified a transitory impact on intergenerational mobility or a permanent impact on intergenerational mobility. To capture annual impacts on the rank-rank coefficient, we estimate the following regression for the full income distribution (not just the bottom and top 20%):

$$\begin{aligned} R_{C,t} = \alpha + \beta_1 R_P + \sum_{j=-3}^{6} \beta_{2,t} D_{b,t-j} R_P + \sum_{j=-3}^{6} \beta_{3,t} D_{b,t-j} \\ + \beta_4 R_P D_C + \beta_5 R_P Year + \beta_6 Year + \beta_7 Displaced_C + \varepsilon_{i,t}, \end{aligned} \tag{8}$$

where Year stands for year fixed effects.

We present the estimates of the main coefficients of interest, $\beta_{2,t}$, in Figure 9. We find that there are no pre-trends, which is expected if the job loss is quasi-random. We show that immediately following the layoff there is large jump in the Displacement x Rank x Time coefficient β_2. The results show that the rank-rank correlation goes up to approximately 0.06 by the second year after the layoff. The coefficient then decreases over time and is around 0.02 six years after the layoff but still statistically significant. In sum, across multiple specifications and approaches to capture the impact on intergenerational mobility, results consistently show that the disparate impacts of job loss documented in this paper also lead to significant decreases in intergenerational mobility, that appear to persist well beyond the initial shock of the job loss.

Given the intergenerational mobility literature is largely interested in "permanent" correla-

[43] As in Pekkarinen *et al.* (2009), this is calculated as $0.032/0.094 = 0.34$

tions, it is arguably more interesting that we find that the disparate responses to job loss lead to long-term changes in the rank-rank correlation. We also note that our finding that disparate impacts of a negative labor market shock affect rank-rank correlations long term suggests that perhaps it is not quite right to think of a permanent and fixed rank-rank correlation for a given parent-child distribution. Our results suggest that as adult children of low-income parents respond differently to labor market shocks, this can lead the rank-rank correlation to increase as the children age for substantive reasons. This insight is a key takeaway from our paper.

It is interesting to consider the extent to which including benefits might mitigate the effects documented in Figure 9, given the generous social welfare system that exists in Finland. Of course, labor supply decisions may also be endogenous to the existing welfare system, which is beyond the scope of this paper to examine. However, in Appendix Figure B.7 we re-estimate equation 8, but instead of using labor market earnings as the measure of income used to calculate ranks, we use total taxable income (which also includes taxable benefits) to calculate the income rank for both parents and children. First, we find that the raw rank-rank correlation is even larger when we use all taxable income, with β_1 equal to 0.119 when no other variables are included in the regression.

Given greater benefits generosity at the bottom of the earnings distribution, we expected this approach to reduce the estimated effects of job loss on intergenerational mobility. Instead, the impact of job loss on the rank-rank coefficient is almost identical. This is especially visible in Appendix Figure B.7. In fact, the point estimate of the impact on the rank-rank coefficient is marginally larger 6 years post layoff and still statistically significant. Together, these results suggests that labor market shocks in adulthood, and in particular job loss, play an important role in determining intergenerational mobility and perpetuating inequality.

5.3 Simulation Estimates of the Contribution to Overall Intergenerational Mobility

We have shown that the disparate impacts of job loss have large impacts on intergenerational mobility for those impacted. In this subsection we present a simulation to provide suggestive evidence on the extent to which this phenomenon explains overall rank-rank correlations in the full population. For the purpose of this exercise, we include not only the disparate impacts of job loss, but also the disparate incidence of job loss which we can identify from the data.

We start with the earnings of all individuals aged 30 in 2000-2019. We divide individuals into deciles according to their parents' earnings at age 30, where parental earnings are calculated as described in Section 2. For each decile we calculate the probability of transitioning from employment to unemployment (see Appendix Table A.16) and the average growth in wages that would occur for a working individual at each age and within each decile who does not become unemployed (see Appendix Figure B.8). For this exercise we include all unemployment when calculating the unemployment transition probabilities by decile. Thus we include fires and quits, in addition to layoffs.

To run the simulation, we assign the starting earnings at age 30 to be equal to the person's actual earnings in the data. For each person we then draw from a uniform distribution. If the resulting number is less than the unemployment transition probability for that decile (see Appendix Table A.16), we assign the person to be unemployed and apply the earnings losses calculated as described in Section 3 for six years following the simulation layoff. After the six years are complete, we assume the person becomes employed.[44] If the person does not become unemployed, we apply the age-decile-specific wage growth absent job loss. 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, in order to estimate the rank-rank correlation. We call this the "Job Loss Simulation". In addition, we run an alternative simulation where we do not allow for unemployment. 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} refer to earnings the following year. "$losses_{decile,t}$"

[44]Note that for ease of computation, once the six years are up we assign people the earnings they would have received absent the job loss. This is conservative, and will cause us to understate the true contribution of job loss to rank-rank correlations.

refers to the estimated earnings losses experienced by an individual each year in the six years following a job loss. These earnings losses are estimated as described in the previous sections, but in this case estimating separately by decile. The time subscript refers to the fact that the estimated cost of job loss changes in each year following the job loss. "$growth_{age,decile}$" refers to the age and decile specific earnings growth accumulated between year t and $t+1$ in the absence of job loss. We calculate the resulting rank-rank correlations for each age within birth cohorts.[45]

We graph the rank-rank correlation for each age as the shocks accumulate in Figure 10.[46] We find that the rank-rank correlation is increasing 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 0.1232 at age 30 to 0.1928 at age 40. With job loss, the rank-rank correlation grows from 0.1250 at age 30 to 0.2003 at age 40. The simulation results imply that the increase in the intergenerational rank-rank correlation from age 30 to age 40 is 8.19%[47] 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 3.9%[48] higher at age 40 when we take into account the disparate incidence and impact of job loss.

Note that our simulation takes into account not only the disparate impacts of job loss, but also the disparate incidence of job loss. We find that those in the bottom deciles are more likely to transition into unemployment compared with individuals in the top deciles (see Appendix Table A.15 which shows, for example, that the probability of unemployment is 68.6%[49] higher for the bottom decile compared to the top decile). This disparate incidence enters into the simulation directly, as it affects whether an individual falls into unemployment in each year in the simulation. Thus the simulation captures the fact that the adult children of low-income parents experience a twofold blow when it comes to job loss relative to their peers with high-income parents. First

[45]To capture the uncertainty in the job loss simulation we repeat the exercise 1000 times and take the mean rank-rank correlation for each age.

[46]The estimates are also reported in Appendix Table A.15

[47] $\frac{(0.2003-0.1250)}{(0.1928-0.1232)} = 1.0819$, using the estimates for the rank-rank correlations at each age reported in Appendix Table A.15.

[48]0.2003/0.1928=1.0389. Note that .0057 ((0.2003-0.1250)-(0.1928-0.1232)), or 2.8%, of the overall .2003 rank-rank correlation at age 40 is explained by the disparate incidence and impact of job loss.

[49]5.97/3.54=1.686

they are more likely to be displaced. Second, once displaced they experience greater earnings losses compared with adult children of high-income parents.

6 Testing Mechanisms: Early Versus Later Life Transfers

We have shown that job loss leads to large differences in later earnings and employment depending on if you were born rich or poor, with important implications for intergenerational mobility. What mechanisms might explain these starkly different impacts? We consider two possible periods in which high-income parents might provide advantages for their children. First, high-income parents might invest more in childhood (or provide genetic advantages[50]) which results in higher human capital when entering the labor market. This in turn could be associated with better responses to labor market shocks in adulthood.[51] Alternatively, parents might intervene directly at the time of job loss. We view both of these possible investments by parents as potential benefits from having high-income parents, but the policy implications of which of the two is most relevant are very different.

6.1 Early Life Transfers: Education

To test whether human capital differences between children of low- and high-income parents might explain the disparate effects of job loss we have documented, we estimate the role education plays in the gaps. Figure 11 shows that there is a strong gradient between level of education and the job loss scar. Panel A (B) shows how the individual-level job loss scars in employment (earnings) vary with education level. Earnings and employment job scars are one half to one third as large for those with a tertiary degree compared with those who only have basic education.

However, there are important differences in the job scar by education group across adult

[50]For evidence on the role of nature versus nurture in educational attainment, see, for example, Black *et al.* (2005). While genetics appears to play a role, most studies do not find that differences in human capital are fully explained by genetics. Moreover, in terms of our question, namely to what extent human capital differences measured by education explain our results, whether earlier advantage is genetic or investment based is not important, although the policy implications might be very different.

[51]This is the classic channel modeled in Becker and Tomes (1986) and Becker and Tomes (1979), although that model does not explicitly take into account later life dynamics based on earlier life advantages, such as at the time of job loss.

children of low- and high-income parents. For employment, the two groups always experience significantly different job scars. In particular, those with only a secondary education have much larger employment and earnings job loss scars if they are also in the bottom 20% relative to those in the top 20%, and these differences are significant. This is particularly noteworthy given that in Table A.1 we showed 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.

These figures are suggestive, but to formalize the relative importance of education in explaining the overall disparate impacts of job loss that we have documented, 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 decompose the job scar gaps using a Blinder-Oaxaca decomposition with a methodological extension we introduce to complete this exercise in our setting.

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 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 matching 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 as defined in Section 3, 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.

With counterfactual earnings in hand, drawn from this matching procedure, we can then estimate the following regression to decompose the overall job loss scar into the explained and unexplained portions:

$$\hat{\Delta}_t = \underbrace{\Sigma_k \left(\hat{\beta}_k^H - \hat{\beta}_k^*\right) E\left[X_{kit}^H\right] + \Sigma_k \left(\hat{\beta}_k^* - \hat{\beta}_k^L\right) E\left[X_{kit}^L\right]}_{\text{Unexplained}} + \underbrace{\Sigma_k \hat{\beta}_k^* \left(E\left[X_{kit}^H\right] - E\left[X_{kit}^L\right]\right)}_{\text{Explained by difference in pre-determined endowments}}, \tag{9}$$

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 9 is the "unexplained" part, while the second term is the "explained" part (Fortin *et al.*, 2011).[52]

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

$$\begin{aligned} &E\left[\hat{\beta}_k^H, \hat{\beta}_k^L, \hat{\beta}_k^* | \hat{Y}_{it}^{No\,Layoff,H} - Y_{it}^{Layoff,H}, \hat{Y}_{it}^{No\,Layoff,L} - Y_{it}^{Layoff,L}\right] \\ -&E\left[\hat{\beta}_k^H, \hat{\beta}_k^L, \hat{\beta}_k^* | Y_{it}^{No\,Layoff,H} - Y_{it}^{Layoff,H}, Y_{it}^{No\,Layoff,L} - Y_{it}^{Layoff,L}\right] = 0, \end{aligned} \tag{10}$$

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

[52] 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.

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

$$E\left[\hat{\beta}_k^H | \left(\left(\hat{Y}_{it}^{No\,Layoff,H} - Y_{it}^{Layoff,H}\right) |X_{kit}\right)\right] - E\left[\hat{\beta}_k^H | Y_{it}^{No\,Layoff,H} - Y_{it}^{Layoff,H}\right] = 0. \quad (11)$$

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. Appendix Figure B.9 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. The approach we outline here could easily be used in other settings where researchers wish to estimate a decomposition of an estimated object, not only job loss scars but also objects in other contexts, such as child penalties.

Table 2 reports estimates from equation 9 with education as the pre-determined endowment in X_{kit}. Note again that observable differences in education across the two groups could be due to income differences among parents, which is why we do not control for them in the main results and instead view them as a potential mechanism behind the main effects we find. In the language of Fortin *et al.* (2011), the differences in endowments may be a direct consequence of the treatment, namely being children of the bottom 20% or top 20%, and so should not be controlled for when one is interested in the impact of job loss by parental income (for more details, see page 36 of Fortin *et al.* 2011).

Table 2 shows that using this approach, estimates suggest that observable differences in the education of adult children of low- versus high-income parents accounts for 28% of the difference in the impact of job loss on employment and 46% of the difference in the impact of job loss on earnings across all years. When we estimate the decomposition separately for growth and recession years, we find very different patterns. In growth years, only 23% of employment gaps and 46% of earnings gaps are explained by observed differences in education. In recession years, 43% of employment gaps and 55% of earnings gaps are explained by education. Overall, these results suggest that while having or lacking a baked-in advantage in terms of education plays a substantial role in determining the differential impacts of job loss, there is still quite a bit that is unexplained, particularly in growth years, when as shown in previous sections the gaps in job loss scars by parental income are the largest.

6.2 Later Life Transfers: Hiring in the Same Firm

A second possible explanation for our main results is that parents intervene directly at the time of the job loss. This could happen in a number of ways. Parents might provide cash transfers to their children to help them smooth the income drop from job loss and give their children time to find better jobs. Parents could provide in-kind transfers, for example they could allow their children to temporarily move in while the child searches for a new job. Such actions could allow children of higher income parents, who may be better positioned to provide such transfers, to find a job more quickly or hold out for a better paying job. Third, when individuals with high-income parents are laid off, their parents could use their connections to employ them in their own firms (the current firm or a previous firm in which the parent has worked) or use broader connections to obtain jobs in the same narrow industry. While we are limited in our ability to analyze the first two possible investments in our data, we observe the third and test it directly.

Figure 12 explores this possible explanation with respect to fathers' current and past employers and shows that the opposite is true.[53] As Panel A shows, while children of parents in the top 20% are more likely to work in the same firm as their father before a layoff, after a layoff there is a drop in the percent of children in the top 20% working in the same firm as their fathers. Causal estimates shown in Panel B show a statistically significant negative effect post layoff for children of parents in the top 20% and no significant effect of the layoff on working in the same firm as one's father for children in the bottom 20% of the income distribution. Moreover, our results show that this negative effect for children of high-income parents is statistically significantly different from the null effect for children of low-income parents. Thus, if anything, this mechanism appears to

[53]Regression results are reported in Appendix Table A.12 for Panel B and Appendix Table A.13 for Panel D.

go in the opposite direction than the original hypothesis suggested.[54]

This evidence suggests that high-income fathers are not helping their children recover more quickly by directly employing them in the same firm or using connections to get employment in the same industry to a greater degree than low-income fathers. They are perhaps using such advantages before the layoff occurs, given the differences by parental income in the likelihood to work in the same firm or industry observed before the layoff, consistent with results from Corak and Piraino (2011) in Canada and Staiger (2020) i n the United States.[55] We might worry, then, that these results are mechanical, given the fact that a much higher fraction of individuals with parents in the top 20% work at the same firm or industry as their father before the displacement. To address this concern, Appendix Figure B.12 repeats the Figure 12 exercise but conditions on individuals not working for any of their father's previous employers prior to the layoff. Under this condition, the figure shows that those whose parents are in the top 20% are now slightly more likely to work for one of the father's employers post layoff, but the effect size is small and statistically insignificant between them and those with parents in the bottom 20% in every year but the first year post layoff. Thus we can rule out this mechanism as driving our main results. However, it may still be possible that broader network based effects occur that cause disparities in the impacts of job loss, consistent with the models in Calvo-Armengol and Jackson (2004) and Jackson (2021).

7 Conclusion

This paper documented two important new findings. First, while getting a job can be a great source of mobility, those who were born into lower income families seem to have a more precarious perch on the job ladder, and when they fall off they struggle more to recover. There are large, significant, and sustained gaps in the employment (and to a lesser extent, earnings) job loss scars experienced by adult children of low- versus high-income parents, with adult children of

[54] Appendix Figure B.10 shows the equivalent results for father's industry.

[55] In our main results we include all firms where the father has worked in his lifetime prior to the layoff. However, in Appendix Figure B.11, we instead look only at the firm where the father works in the year before the layoff and the results are similar.

low-income parents experiencing greater losses following a layoff.

Second, these disparate impacts of job loss translate to significant effects on earnings inequality and intergenerational mobility. Specifically, job loss causes an 8% increase in earnings inequality for those affected after 6 years, and a 34% increase in the rank-rank correlation for those affected, which implies substantial decreases in intergenerational inequality. We also find that the impact on intergenerational mobility is still significant even 6 years after the job loss. In a simulation, we show that the overall rank-rank correlation at age 40 is 3.9% higher due to disparate impacts and incidence of job loss in the preceding decade. These estimates show that the disparate impacts of labor market shocks in adulthood stemming from inequality in childhood have long-term impacts on future earnings inequality and reduce intergenerational mobility.

In addition, we presented suggestive evidence on mechanisms. We ruled out one obvious way parents might provide transfers to mitigate the impacts of job loss at the time of job loss, namely by getting their children hired into the same firm or a prior firm. Following a layoff, adult children of high-income parents are less likely to work in the same firm as their parents. However, there are other ways parents might make transfers to their children at the time of job loss that are productive avenues for future research. For one example, parents could provide cash transfers which we are unable to observe in our data. In contrast, we did find evidence of parents making transfers to children earlier in life that mitigate the impact of job loss. We introduced a straightforward methodological extension to the Blinder-Oaxaca decomposition to our setting and show that differences in educational attainment play an important role in explaining the disparate impacts of job loss in adulthood.

These results deepen our understanding of the many ways in which parental poverty leads to intergenerational impacts. While much of the previous literature on intergenerational mobility has focused on quantifying overall intergenerational mobility, and early life causes, this paper shows that the impact of labor market shocks on adult children may vary substantially by parental income, and this in turn can reduce mobility, leading to a vicious cycle. As such, this paper fills a key gap in the literature and increases our understanding of how inequality transmits across generations.

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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	8.096	0.232	209.107	201.011	1.080
Bottom 20	17.667	0.603	160.368	142.702	

Notes: Column 1 shows estimates of the PDV of job loss in the 6 years following the layoff derived by Equation (2). Column 3 shows estimates of the PDV of earnings over 6 years for those not laid off (per the matching exercise described in Section 6), derived by Equation (3); and column 4 for those laid off, also derived by Equation (3). The column 3 and 4 estimates are used to calculate the change in inequality using Equation (4), shown in column 5. Denomination is in €1000s accounting for inflation in columns 1, 3, and 4.

Table 2: Decomposition of Differences in Employment and Earnings Job Loss Scars

	Differences in Job Loss Scar	Percentage Explained by Education
Panel A: Employment		
All years	0.076	27.74%
Growth years	0.077	23.20%
Recession years	0.065	43.39%
Panel B: Earnings		
All years	0.071	45.66%
Growth years	0.072	45.61%
Recession years	0.057	54.88%

Notes: Table shows the decomposition of the differences in employment (Panel A) and earnings (Panel B) 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 (9) for all years, then restricting to only growth years and recession years. For growth and recession years, see Figure 5.

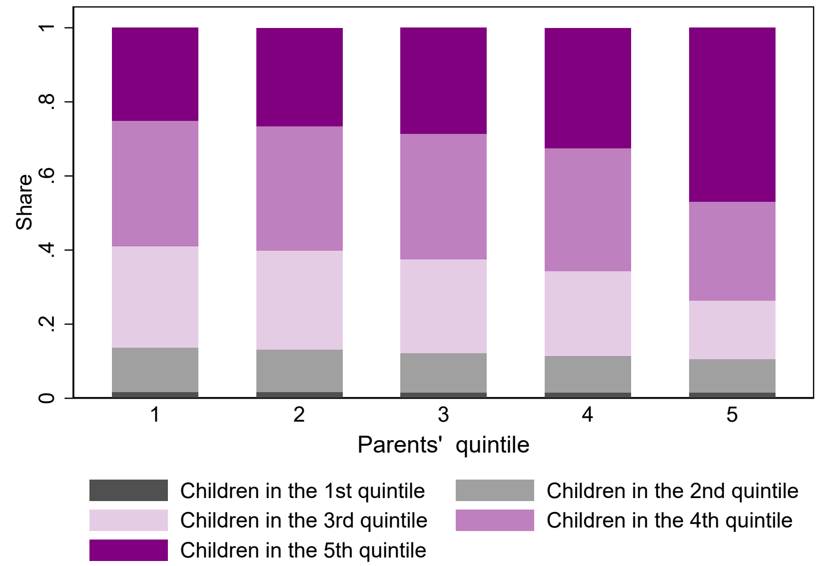
Table 3: Impacts of Job Loss on Intergenerational Mobility

Independent Variable	(1)	(2)	(3)	(4)
Family rank (β_1)	0.094	0.094	0.094	0.073
	(0.001)	(0.001)	(0.001)	(0.001)
Displaced (β_5)		-2.226	0.771	0.446
		(0.132)	(0.120)	(0.255)
Post (β_6)			-7.331	-9.102
			(0.021)	(0.044)
Displaced $\times$ Post (β_7)			-5.006	-6.761
			(0.138)	(0.293)
Family rank $\times$ Displaced $\times$ Post (β_2)				0.032
				(0.005)
Family rank $\times$ Displaced (β_3)				0.007
				(0.004)
Family rank $\times$ Post (β_4)				0.035
				(0.001)
Observations	15,058,265	15,058,265	15,058,265	15,058,265

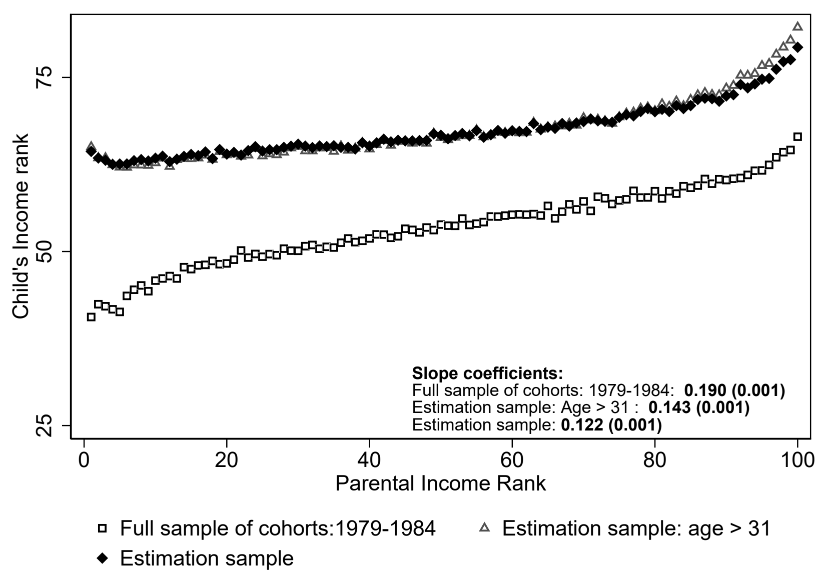
Notes: The table shows the impact of displacement on the rank-rank regression coefficient. The dependent variable is the child's yearly earnings percentile rank in the earnings distribution of children in the same birth cohort. Each of the columns show a different regression specification. Column 1 regresses 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. 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' earnings rank together and separately with displacement and a post-period indicator. 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.

Figure 1: Intergenerational Mobility in Finland

(a) Movement Across Quintiles in Estimation Sample



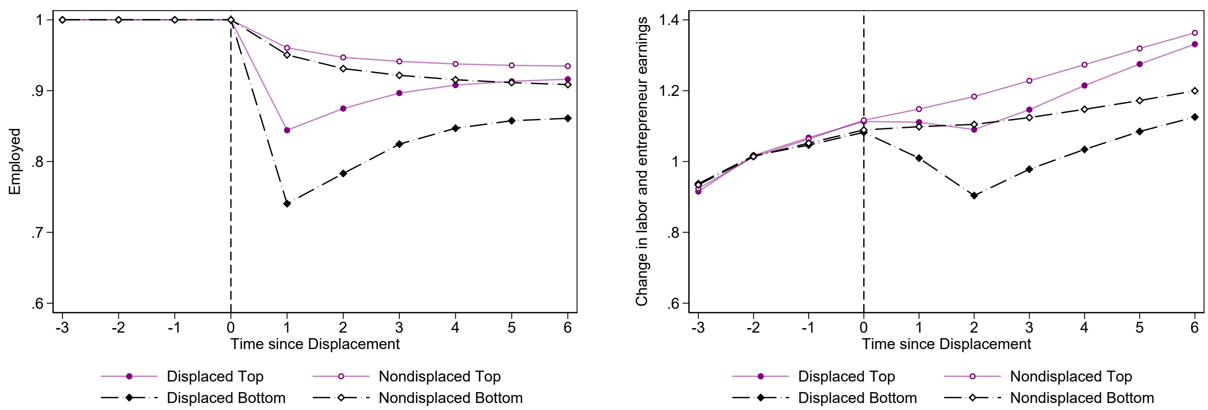
(b) Rank-Rank Correlation Using Full Population vs. Our Sample



Note: Figure Panel A shows the percentage of children born into each income quintile who are in a different income quintile in their mid-thirties. We construct the figure using the working individuals in our main sample who were between the ages of 32 and 36 one year before being laid off. Section 2.1 explains how the parental income groups are defined. Panel B plots the percentile income (based on all taxable income) rank of the child (y-axis) versus the percentile rank of the parents (x-axis) for three groups. First, we plot this relationship for the entire population shown in grey squares. Next we plot this relationship for the sample analyzed in this paper as described in Sections 2.1 and 3, depicted in black diamonds. Last we plot the relationship for our sample but restricting to those over age 31, depicted in grey triangles. Estimates from the OLS regression given by Equation (4) 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, which is why the estimated rank-rank coefficient for our sample is not identical to the result in Table 3, which only uses labor market earnings to be consistent with the rest of the paper. The control group may contain the same individual multiple times. To construct both figures, we take the observation at which the individual is oldest at the time 0.

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

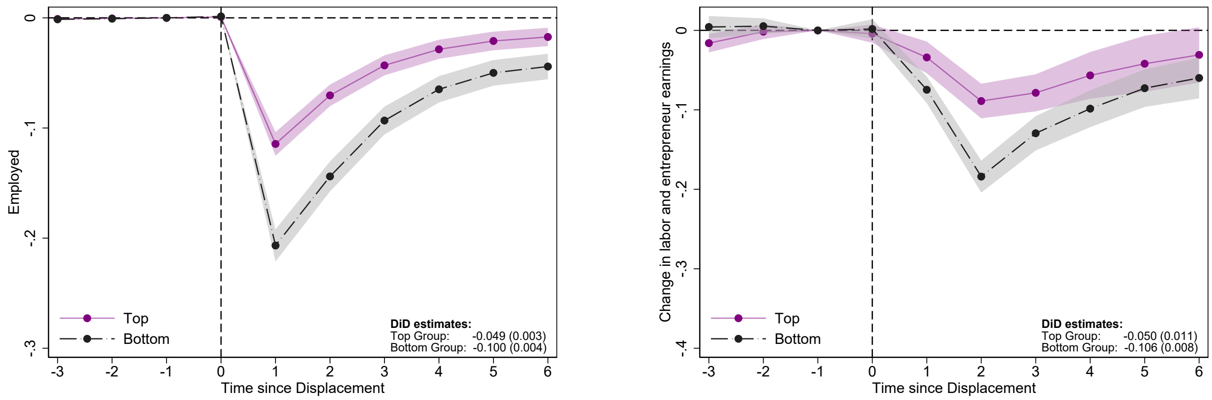
(a) Employment (b) Relative Earnings



Note: Panel A (B) shows employment (relative earnings) of displaced and non-displaced individuals 3 years before and 6 years after the job loss by parental income group. Employment is measured at the end of the year. Relative earnings compare yearly earnings to the mean of yearly earnings 1 to 3 years before displacement. Sample construction and data as defined in Section 2.1.

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

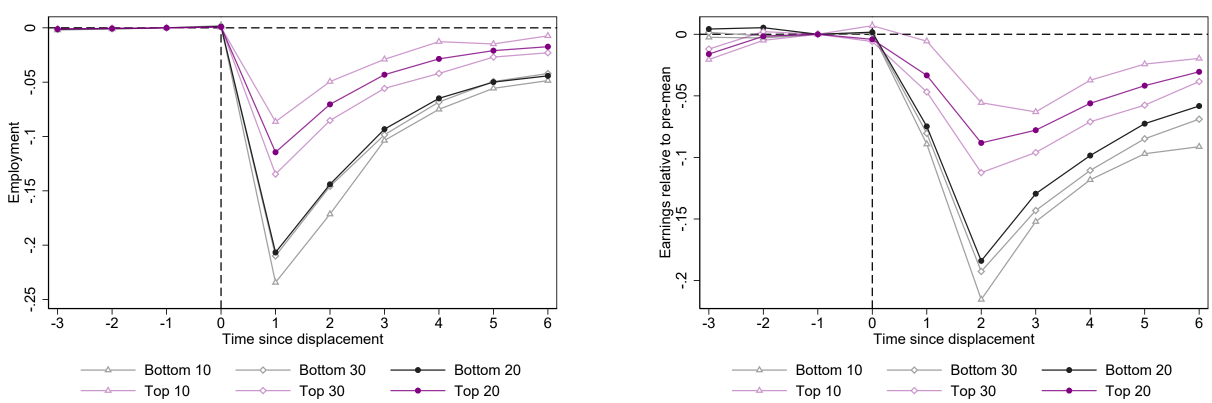
(a) Employment (b) Earnings Relative to Pre-mean



Note: Figures plot the estimates of δ_t obtained using Equation (1) separately for top and bottom parental income groups. 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.

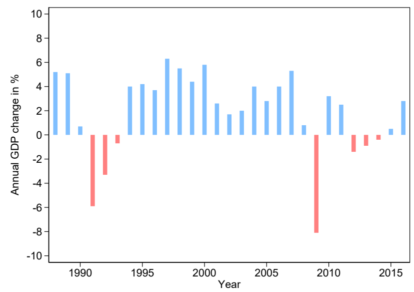
Figure 4: Impacts of Job Loss on Employment and Earnings by Parental Income Group, Bottom vs. Top 10%, 20%, and 30%

(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. Sample construction and data as defined in Section 2.1.

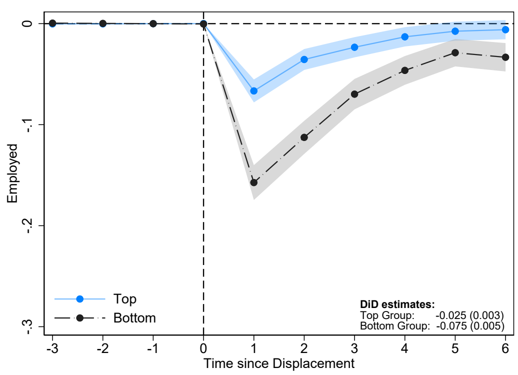
Figure 5: GDP Growth in Finland, 1988–2017



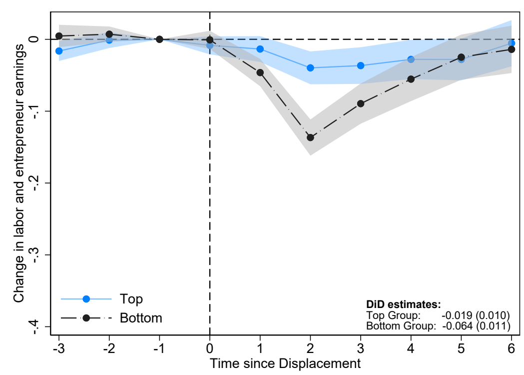
Note: The figure depicts years of growth (in blue) and recession (in red) in Finland used for the analysis.

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

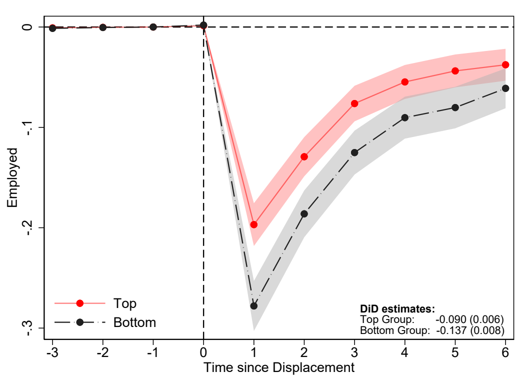
(a) Economy Growing: Employment



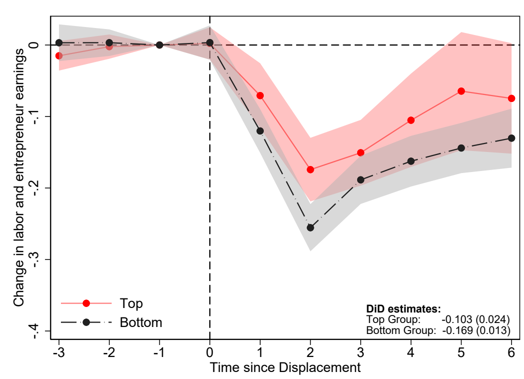
(b) Economy Growing: Relative Earnings



(c) Economy Shrinking: Employment

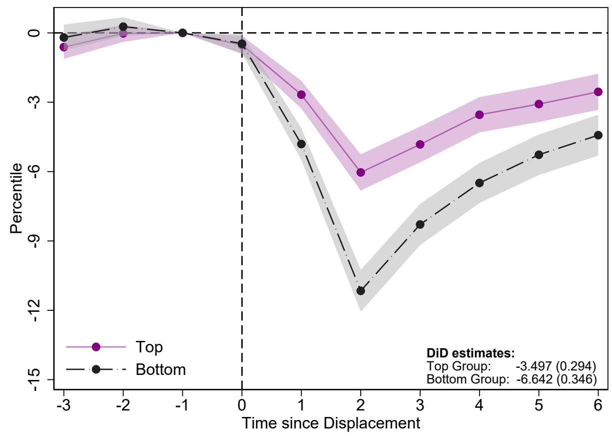


(d) Economy Shrinking: Relative Earnings



Note: Figures plot the estimates of δ_t obtained using Equation (1) separately for top and bottom 20% parental income groups. Panel A (C) shows the impact of job loss on employment when the economy is growing (shrinking). Panel B (D) shows the impact of job loss on relative earnings when the economy is growing (shrinking). 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 7: Impacts of Job Loss on Percentile Rank by Parental Earnings Group, Bottom vs. Top 20%

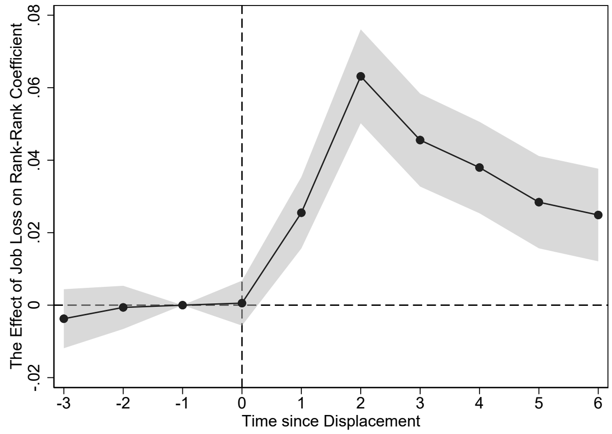


Note: Figure plots the estimates of δ_t obtained using Equation (1) separately for top and bottom parental income groups. The outcome is an individual's earnings rank within the birth cohort. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered 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. Sample construction and data as defined in Section 2.1.

Figure 8: Impacts of Job Loss on Percentile Earnings Rank for Adult Children Born into the Bottom (Purple) vs. Top (Black) 20% Conditional on the Adult Child's Pre-Displacement Income Rank (X-Axis)

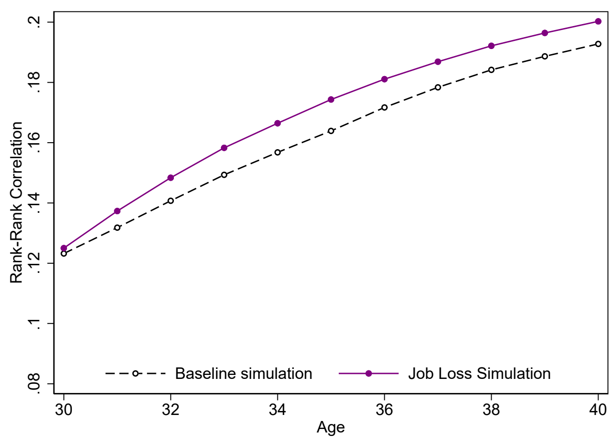
Note: Figure plots the DiD estimates obtained using an alternative version of Equation (1) in which event study dummies are collapsed into a single displacement indicator separately for top and bottom parental income groups, and for those in the bottom third, middle third, and top third of the pre-displacement income rank. 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. In other words, the figure shows that when we compare adult children who were born to parents in the top 20% (purple) versus the bottom 20% (black), even when the adult children are themselves in the same earnings tercile before their job loss, we still see striking differences in the impact of job loss. This suggests that our results are not driven entirely be a "composition" effect. See pages 19-20 for more detailed discussion. Sample construction and data as defined in Section 2.1.

Figure 9: Estimated Impacts of Job Loss on Intergenerational Mobility



Note: Figure plots the estimates of β_{2t} obtained using equation (8) using all income groups. The outcome is a child'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. Sample construction and data as defined in Section 2.1.

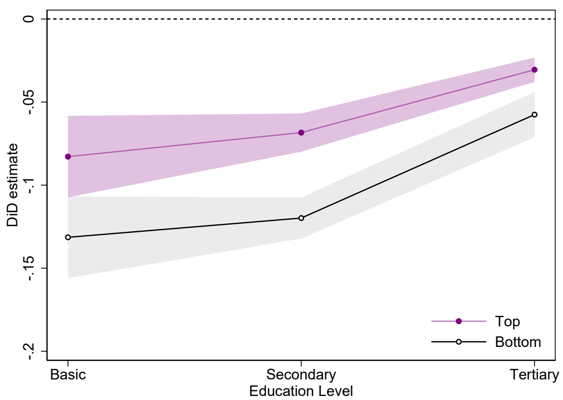
Figure 10: Simulation: Contribution of Disparate Impacts of Job Loss to Overall Intergenerational Mobility



Note: Figure plots the estimates from the simulation described in Section 5.3. 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 Appendix Figure B.8. 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 Simulation". For this simulation we additionally allow individuals to fall into unemployment, using the decile-specific unemployment rates calculated from the data and reported in Appendix Table A.16. See Section 5.3 for more details. For point estimates, see Appendix Table A.15.

Figure 11: Education Gradient in Employment and Earnings Job Loss Scars by Parental Income Group, Bottom vs. Top 20%

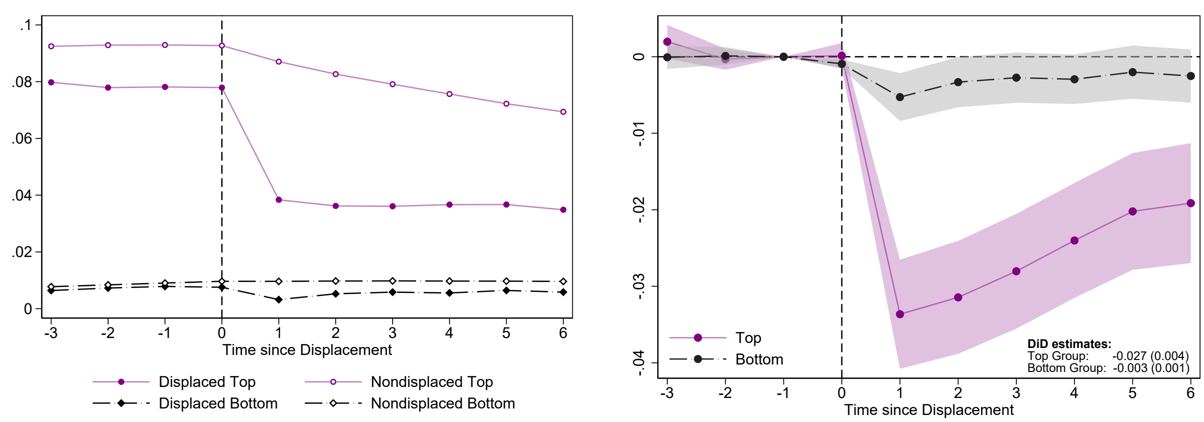
(a) Employment (b) Relative Earnings



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.

Figure 12: 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 3 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. Sample construction and data as defined in Section 2.1.

Online Appendix

A Additional Tables

Table A.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	30.698	30.665	0.521
Female	0.350	0.362	0.170
Number of children	0.892	0.911	0.325
Tenure, years	4.761	5.259	0.000
Plant size	89.795	103.133	0.000
Primary education only	0.160	0.149	0.081
Secondary education only	0.554	0.568	0.096
Tertiary education	0.284	0.279	0.545
Experience, years	10.335	10.406	0.474
Married	0.397	0.412	0.092
Real earnings in 1000s (€)	31.067	30.145	0.000
Real income in 1000s (€)	32.658	31.433	0.000
Observations	3,442	264,292	
Panel B: Adult Children Whose Parents Are in the Top 20%			
Age	30.843	30.909	0.139
Female	0.358	0.374	0.033
Number of children	0.783	0.845	0.000
Tenure, years	4.587	5.021	0.000
Plant size	97.494	116.080	0.000
Primary education only	0.105	0.092	0.006
Secondary education only	0.388	0.408	0.008
Tertiary education	0.506	0.496	0.206
Experience, years	9.176	9.135	0.672
Married	0.446	0.460	0.064
Real earnings in 1000s (€)	38.519	36.851	0.000
Real income in 1000s (€)	40.346	38.455	0.000
Observations	4,300	278,815	

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

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

	Displaced	Not displaced	P-value
Panel A: Bottom 20%			
Age	30.789	30.736	0.421
Female	0.356	0.350	0.537
Number of children	0.867	0.909	0.098
Tenure, years	5.139	5.520	0.000
Plant size	103.551	104.492	0.706
Primary education only	0.159	0.149	0.207
Secondary education only	0.551	0.569	0.096
Tertiary education	0.287	0.279	0.415
Experience, years	10.428	10.441	0.889
Married	0.369	0.407	0.001
Real earnings in 1000s (€)	31.629	30.204	0.000
Real income in 1000s (€)	33.032	31.356	0.000
Observations	2065	183194	
Panel B: Adult Children Whose Parents Are in the Top 20%			
Age	30.989	31.025	0.518
Female	0.358	0.363	0.577
Number of children	0.783	0.855	0.000
Tenure, years	4.825	5.284	0.000
Plant size	103.533	117.059	0.000
Primary education only	0.100	0.092	0.190
Secondary education only	0.390	0.416	0.005
Tertiary education	0.509	0.489	0.034
Experience, years	9.074	9.161	0.291
Married	0.444	0.459	0.116
Real earnings in 1000s (€)	39.808	37.085	0.000
Real income in 1000s (€)	41.243	38.553	0.000
Observations	2740	190536	

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

	Displaced	Not displaced	P-value
Panel A: Bottom 20%			
Age	30.562	30.505	0.492
Female	0.341	0.388	0.000
Number of children	0.929	0.916	0.676
Tenure, years	4.193	4.670	0.000
Plant size	69.166	100.063	0.000
Primary education only	0.161	0.150	0.229
Secondary education only	0.558	0.566	0.595
Tertiary education	0.279	0.279	0.962
Experience, years	10.196	10.328	0.557
Married	0.440	0.423	0.203
Real earnings in 1000s (€)	30.225	30.012	0.548
Real income in 1000s (€)	32.097	31.607	0.143
Observations	1377	81098	
Panel B: Adult Children Whose Parents Are in the Top 20%			
Age	30.587	30.659	0.333
Female	0.359	0.398	0.002
Number of children	0.782	0.822	0.132
Tenure, years	4.169	4.453	0.000
Plant size	86.888	113.969	0.000
Primary education only	0.113	0.093	0.005
Secondary education only	0.386	0.391	0.669
Tertiary education	0.500	0.512	0.346
Experience, years	9.354	9.078	0.249
Married	0.451	0.464	0.294
Real earnings in 1000s (€)	36.254	36.345	0.857
Real income in 1000s (€)	38.769	38.244	0.322
Observations	1560	88279	

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 A.4: The Effect of Job Loss on Employment

	(1)	(2)	(3)	(4)
Top 20				
DiD Estimate	-0.049	-0.050	-0.050	-0.049
	(0.003)	(0.003)	(0.003)	(0.003)
Bottom 20				
DiD Estimate	-0.100	-0.102	-0.102	-0.099
	(0.004)	(0.005)	(0.005)	(0.004)
Individual fixed effects	✓			
Base year fixed effects	✓	✓		
Year fixed effects	✓	✓	✓	
Displaced fixed effects		✓	✓	✓
Controls			✓	✓
Base year $\times$ time fixed effects				✓
N Top 20	2,819,839	2,819,839	2,819,839	2,819,839
N Bottom 20	2,671,751	2,671,751	2,671,751	2,671,751
Non-displaced mean Top 20	0.966	0.966	0.966	0.966
Non-displaced mean Bottom 20	0.954	0.954	0.954	0.954

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 $\times$ time fixed effects. Standard errors clustered at the individual level appear in parentheses.

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

	(1)	(2)	(3)	(4)
Top 20				
DiD Estimate	-0.050	-0.053	-0.054	-0.049
	(0.011)	(0.011)	(0.011)	(0.011)
Bottom 20				
DiD Estimate	-0.106	-0.110	-0.111	-0.106
	(0.008)	(0.008)	(0.008)	(0.008)
Individual fixed effects	✓			
Base year fixed effects	✓	✓		
Year fixed effects	✓	✓	✓	
Displaced fixed effects		✓	✓	✓
Controls			✓	✓
Base year × time fixed effects				✓
N Top 20	2,819,839	2,819,839	2,819,839	2,819,839
N Bottom 20	2,671,751	2,671,751	2,671,751	2,671,751
Non-displaced mean Top 20	1.163	1.163	1.163	1.163
Non-displaced mean Bottom 20	1.093	1.093	1.093	1.093

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 × time fixed effects. Standard errors clustered at the individual level appear in parentheses.

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

	(1)	(2)	(3)	(4)
Top 20				
DiD Estimate	-1.894	-1.927	-1.911	-1.890
	(0.264)	(0.264)	(0.264)	(0.264)
Bottom 20				
DiD Estimate	-3.392	-3.476	-3.460	-3.432
	(0.213)	(0.216)	(0.215)	(0.215)
Individual fixed effects	✓			
Base year fixed effects	✓	✓		
Year fixed effects	✓	✓	✓	
Displaced fixed effects		✓	✓	✓
Controls			✓	✓
Base year $\times$ time fixed effects				✓
N Top 20	2,819,839	2,819,839	2,819,839	2,819,839
N Bottom 20	2,671,751	2,671,751	2,671,751	2,671,751
Non-displaced mean Top 20	37.923	37.923	37.923	37.923
Non-displaced mean Bottom 20	29.989	29.989	29.989	29.989

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 A.7: The Effect of Job Loss on Working for Any of Father's Prior Firms

	(1)	(2)	(3)	(4)
Top 20				
DiD Estimate	-0.027	-0.027	-0.027	-0.027
	(0.004)	(0.004)	(0.004)	(0.004)
Bottom 20				
DiD Estimate	-0.003	-0.003	-0.003	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)
Individual fixed effects	✓			
Base year fixed effects	✓	✓		
Year fixed effects	✓	✓	✓	
Displaced fixed effects		✓	✓	✓
Controls			✓	✓
Base year $\times$ time fixed effects				✓
N Top 20	2,819,839	2,819,839	2,819,839	2,819,839
N Bottom 20	2,671,751	2,671,751	2,671,751	2,671,751
Non-displaced mean Top 20	0.084	0.084	0.084	0.084
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 A.8: The Effect of Job Loss on Working for Any of Father's Prior Industries

	(1)	(2)	(3)	(4)
Top 20				
DiD Estimate	-0.009	-0.009	-0.009	-0.009
	(0.004)	(0.004)	(0.004)	(0.004)
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	2,819,839	2,819,839	2,819,839	2,819,839
N Bottom 20	2,671,751	2,671,751	2,671,751	2,671,751
Non-displaced mean Top 20	0.085	0.085	0.085	0.085
Non-displaced mean Bottom 20	0.014	0.014	0.014	0.014

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 A.9: 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)
-3	-0.001	-0.001	-0.001	-0.001	0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
-2	-0.001	-0.000	-0.000	-0.000	0.000	-0.000
	(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	0.002	0.001	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1	-0.207	-0.114	-0.278	-0.197	-0.157	-0.067
	(0.007)	(0.006)	(0.013)	(0.011)	(0.009)	(0.006)
2	-0.144	-0.070	-0.186	-0.129	-0.113	-0.035
	(0.007)	(0.005)	(0.012)	(0.010)	(0.008)	(0.005)
3	-0.093	-0.043	-0.125	-0.076	-0.070	-0.023
	(0.006)	(0.005)	(0.011)	(0.009)	(0.008)	(0.005)
4	-0.065	-0.029	-0.090	-0.055	-0.046	-0.013
	(0.006)	(0.004)	(0.011)	(0.009)	(0.007)	(0.005)
5	-0.050	-0.021	-0.080	-0.044	-0.029	-0.007
	(0.006)	(0.004)	(0.011)	(0.008)	(0.007)	(0.005)
6	-0.044	-0.017	-0.061	-0.038	-0.033	-0.006
	(0.006)	(0.004)	(0.010)	(0.008)	(0.007)	(0.005)
N	2,671,751	2,819,839	823,051	894,679	1,848,700	1,925,160

Notes: The table shows event time coefficients underlying Figure 3 A, 6 A, and 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 A.10: 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)
-3	0.004	-0.016	0.003	-0.015	0.005	-0.016
	(0.007)	(0.006)	(0.013)	(0.011)	(0.008)	(0.007)
-2	0.005	-0.002	0.003	-0.002	0.007	-0.001
	(0.005)	(0.005)	(0.009)	(0.009)	(0.005)	(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	0.002	-0.004	0.003	0.002	-0.001	-0.008
	(0.006)	(0.006)	(0.012)	(0.011)	(0.006)	(0.006)
1	-0.075	-0.034	-0.120	-0.071	-0.046	-0.013
	(0.009)	(0.010)	(0.016)	(0.023)	(0.010)	(0.009)
2	-0.184	-0.089	-0.256	-0.174	-0.137	-0.040
	(0.010)	(0.011)	(0.017)	(0.023)	(0.013)	(0.012)
3	-0.129	-0.079	-0.189	-0.151	-0.089	-0.037
	(0.011)	(0.012)	(0.017)	(0.023)	(0.014)	(0.013)
4	-0.098	-0.057	-0.162	-0.105	-0.055	-0.028
	(0.012)	(0.015)	(0.018)	(0.033)	(0.016)	(0.014)
5	-0.073	-0.042	-0.144	-0.065	-0.025	-0.028
	(0.012)	(0.018)	(0.018)	(0.042)	(0.016)	(0.015)
6	-0.060	-0.031	-0.130	-0.075	-0.014	-0.005
	(0.013)	(0.018)	(0.021)	(0.039)	(0.017)	(0.016)
N	2,671,751	2,819,839	823,051	894,679	1,848,700	1,925,160

Notes: The table shows event time coefficients underlying Figure 3 B, 6 B, and 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 A.11: 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)
-3	-0.289	-1.077	-0.360	-0.535	-0.208	-1.372
	(0.153)	(0.287)	(0.257)	(0.329)	(0.189)	(0.409)
-2	0.049	-0.291	0.046	-0.242	0.073	-0.320
	(0.111)	(0.322)	(0.198)	(0.268)	(0.129)	(0.481)
-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	-0.166	0.037	-0.352	-0.304	-0.054	0.224
	(0.128)	(0.398)	(0.211)	(0.281)	(0.160)	(0.604)
1	-2.300	-1.306	-3.747	-2.794	-1.350	-0.465
	(0.206)	(0.309)	(0.338)	(0.400)	(0.256)	(0.427)
2	-5.585	-2.938	-7.720	-5.958	-4.148	-1.212
	(0.266)	(0.311)	(0.418)	(0.487)	(0.340)	(0.399)
3	-4.188	-2.897	-5.964	-5.382	-2.975	-1.471
	(0.270)	(0.386)	(0.417)	(0.476)	(0.351)	(0.540)
4	-3.476	-2.442	-5.232	-4.668	-2.285	-1.171
	(0.274)	(0.389)	(0.440)	(0.502)	(0.348)	(0.538)
5	-2.889	-2.103	-4.790	-4.185	-1.612	-0.922
	(0.283)	(0.446)	(0.446)	(0.552)	(0.363)	(0.624)
6	-2.521	-1.680	-4.585	-4.232	-1.182	-0.265
	(0.301)	(0.482)	(0.504)	(0.626)	(0.375)	(0.665)
N	2,671,751	2,819,839	823,051	894,679	1,848,700	1,925,160

Notes: The table shows event time coefficients underlying Figure B.3. 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 A.12: 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 (1)	Bottom (2)	Top (3)	Bottom (4)	Top (5)	Bottom (6)	Top (7)
-3	-0.000	0.002	0.000	0.002	-0.000	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
-2	0.000	-0.000	-0.001	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	0.000	-0.000	0.001	-0.001	-0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
1	-0.005	-0.034	-0.005	-0.046	-0.005	-0.027
	(0.002)	(0.004)	(0.002)	(0.007)	(0.002)	(0.004)
2	-0.003	-0.031	-0.004	-0.039	-0.003	-0.027
	(0.002)	(0.004)	(0.002)	(0.007)	(0.002)	(0.005)
3	-0.003	-0.028	-0.003	-0.034	-0.002	-0.025
	(0.002)	(0.004)	(0.002)	(0.007)	(0.002)	(0.005)
4	-0.003	-0.024	-0.003	-0.030	-0.003	-0.020
	(0.002)	(0.004)	(0.002)	(0.007)	(0.002)	(0.005)
5	-0.002	-0.020	0.000	-0.025	-0.004	-0.017
	(0.002)	(0.004)	(0.003)	(0.007)	(0.002)	(0.005)
6	-0.003	-0.019	-0.000	-0.024	-0.004	-0.016
	(0.002)	(0.004)	(0.003)	(0.007)	(0.002)	(0.005)
N	2,671,751	2,819,839	823,051	894,679	1,848,700	1,925,160

Notes: The table shows event time coefficients underlying Figure 12 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 A.13: The Effect of Job Loss 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)
-3	-0.000	0.004	0.002	-0.000	-0.002	0.007
	(0.002)	(0.003)	(0.002)	(0.005)	(0.002)	(0.003)
-2	-0.001	0.003	-0.001	0.002	-0.001	0.004
	(0.001)	(0.002)	(0.001)	(0.004)	(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	-0.003	-0.001	-0.002
	(0.001)	(0.002)	(0.001)	(0.004)	(0.002)	(0.003)
1	-0.004	-0.022	-0.004	-0.042	-0.003	-0.010
	(0.002)	(0.004)	(0.003)	(0.007)	(0.002)	(0.005)
2	-0.001	-0.016	-0.002	-0.033	-0.001	-0.006
	(0.002)	(0.004)	(0.003)	(0.008)	(0.003)	(0.005)
3	0.001	-0.010	0.003	-0.027	-0.001	-0.000
	(0.002)	(0.004)	(0.003)	(0.008)	(0.003)	(0.005)
4	0.001	-0.003	0.002	-0.023	0.001	0.009
	(0.002)	(0.004)	(0.003)	(0.008)	(0.003)	(0.005)
5	0.002	0.002	0.007	-0.018	-0.001	0.014
	(0.002)	(0.004)	(0.003)	(0.008)	(0.003)	(0.005)
6	0.004	0.005	0.008	-0.018	0.002	0.018
	(0.002)	(0.004)	(0.003)	(0.008)	(0.003)	(0.005)
N	2,671,751	2,819,839	823,051	894,679	1,848,700	1,925,160

Notes: The table shows event time coefficients underlying Figure 12 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 A.14: Impacts of Job Loss on Intergenerational Mobility When Ranks Are Defined Using Income

Independent Variable	(1)	(2)	(3)	(4)
Family rank (β_1)	0.119	0.119	0.119	0.097
	(0.001)	(0.001)	(0.001)	(0.001)
Displaced (β_5)		-1.115	1.041	0.729
		(0.131)	(0.127)	(0.271)
Post (β_6)			-6.388	-8.246
			(0.019)	(0.039)
Displaced $\times$ Post (β_7)			-3.601	-5.130
			(0.119)	(0.248)
Family rank $\times$ Displaced $\times$ Post (β_2)				0.029
				(0.004)
Family rank $\times$ Displaced (β_3)				0.007
				(0.005)
Family rank $\times$ Post (β_4)				0.037
				(0.001)
Observations	15,058,265	15,058,265	15,058,265	15,058,265

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 A.15: Simulation Results

	Baseline Simulation	Job Loss Simulation
Age	Rank-Rank Correlation	Rank-Rank Correlation
(1)	(2)	(3)
30	0.1232	0.1250
		(0.0001)
31	0.1318	0.1373
		(0.0001)
32	0.1407	0.1484
		(0.0001)
33	0.1493	0.1583
		(0.0001)
34	0.1568	0.1665
		(0.0001)
35	0.1639	0.1743
		(0.0001)
36	0.1717	0.1811
		(0.0001)
37	0.1784	0.1869
		(0.0001)
38	0.1842	0.1921
		(0.0001)
39	0.1887	0.1964
		(0.0001)
40	0.1928	0.2003
		(0.0001)

Notes: This table displays the estimates from the simulation exercise described in Section 5.3 and shown in Figure 10. 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 B.8. 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 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 A.16. Column 2 results are without any uncertainty so we simply report the estimates. To capture the uncertainty of job loss in Column 3, 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.

Table A.16: Unemployment Transition Probabilities

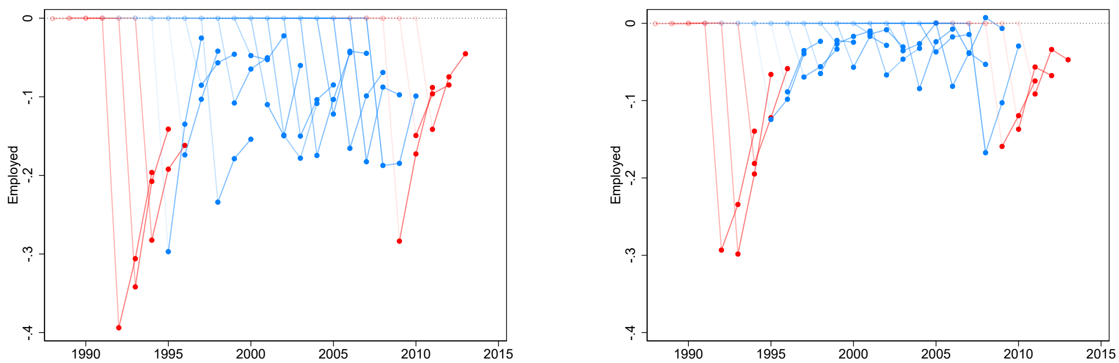
Parental Income Decile (1)	**P(Unemployed$_{t+1}$| Employed$_t$)** (2)
1 (Bottom Decile)	5.97%
2	5.68%
3	5.49%
4	5.26%
5	5.00%
6	4.77%
7	4.56%
8	4.30%
9	3.99%
10 (Top Decile)	3.54%

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 5.3 and shown in Figure 10 and Appendix Table A.15.

B Additional Figures

Figure B.1: Impact of Job Loss on Employment for Adult Children with Parents in the Bottom 20% vs. Top 20%, by Year of Job Loss

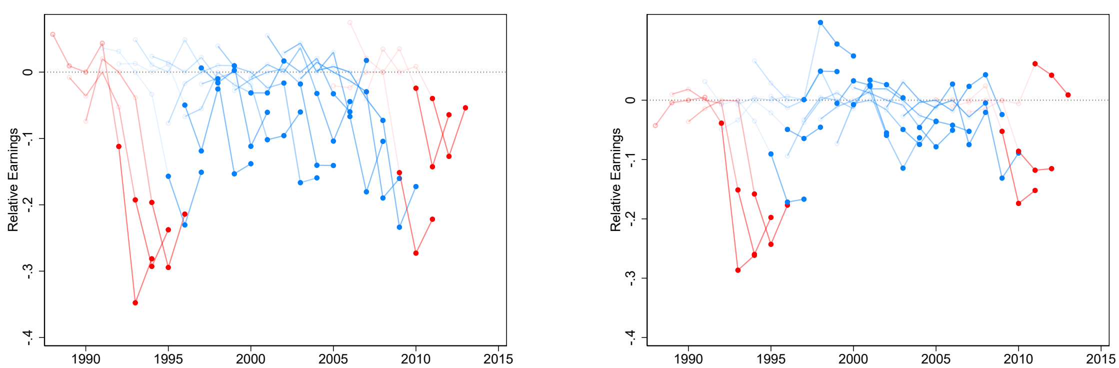
(a) Bottom 20% (b) Top 20%



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. Sample construction and data as defined in Section 2.1.

Figure B.2: Impact of Job Loss on Relative Earnings for Adult Children with Parents in the Bottom 20% vs. Top 20%, by Year of Job Loss

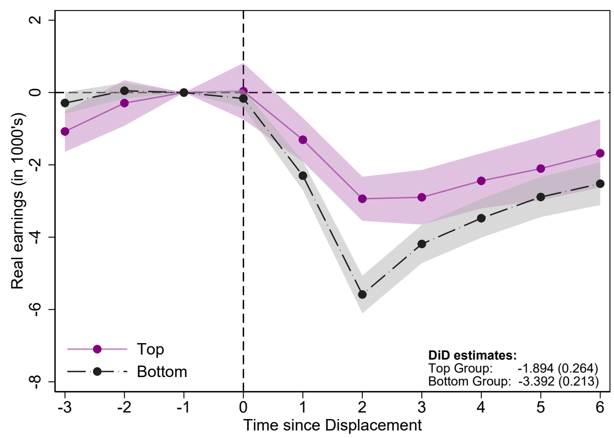
(a) Bottom 20% (b) Top 20%



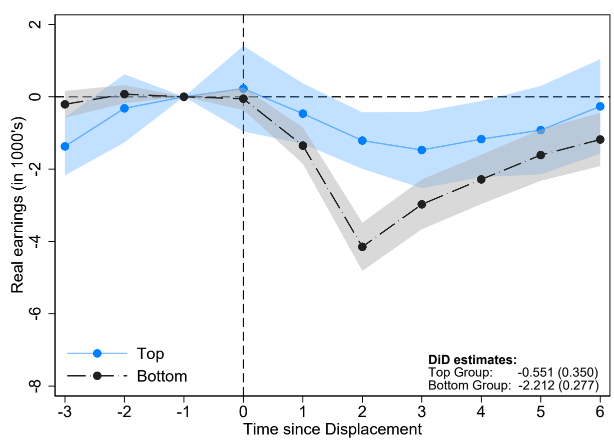
Note: Figures plot the estimates of δ_t obtained using equation 1 separately for different treatment waves. For presentation purposes, we only show the first three years after layoff. Panel A (B) shows the impact for individuals whose parents belong to the bottom (top) 20% of the income distribution. The dependent variable is labor and entrepreneurial earnings relative to the mean of yearly earnings 1–3 years before displacement. Sample construction and data as defined in Section 2.1.

Figure B.3: Impacts of Job Loss on Real Earnings by Parental Earnings Groups, Bottom vs. Top 20%

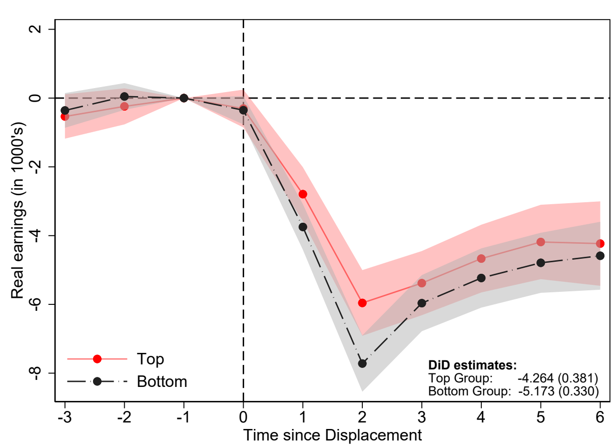
(a) All Years



(b) Growth Years



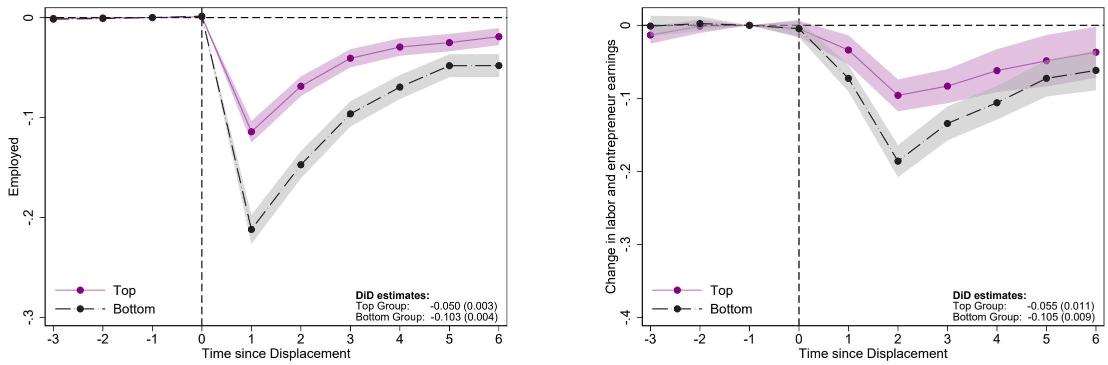
(c) Recession Years



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. Sample construction and data as defined in Section 2.1.

Figure B.4: 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

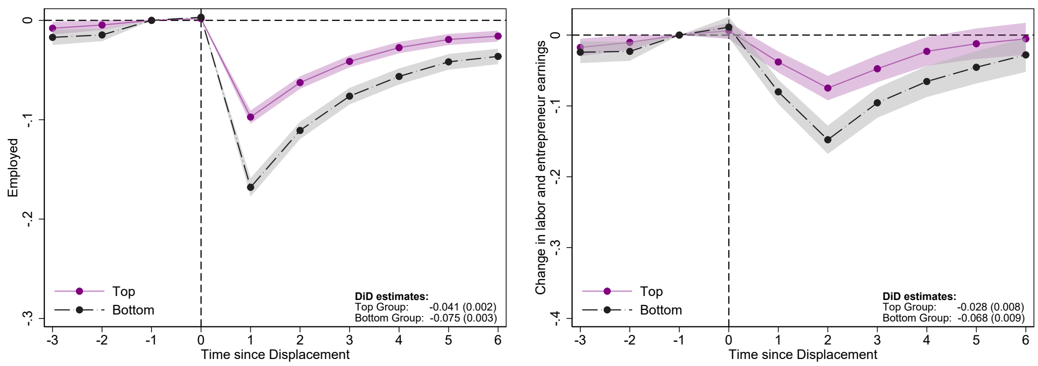
(a) Employment (b) Earnings Relative to Pre-mean



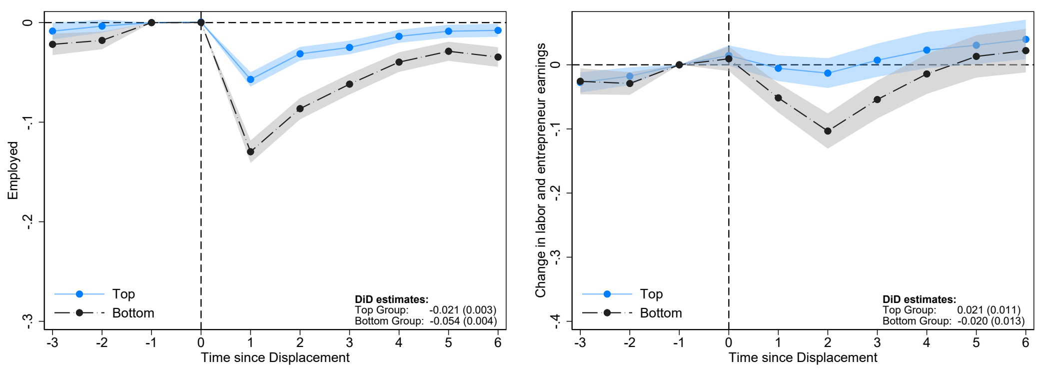
Note: Figures plot the estimated impacts of job loss on future employment and earnings and show that these results are robust to alternative approaches to defining parental income. Figures plot the estimates of δ_t obtained using Equation (1) separately for bottom and top parental income quintiles. In 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. Sample construction and data as defined in Section 2.1.

Figure B.5: Impacts of Job Loss by Parental Earnings Groups With Only 1 Year Tenure Required Instead of 3

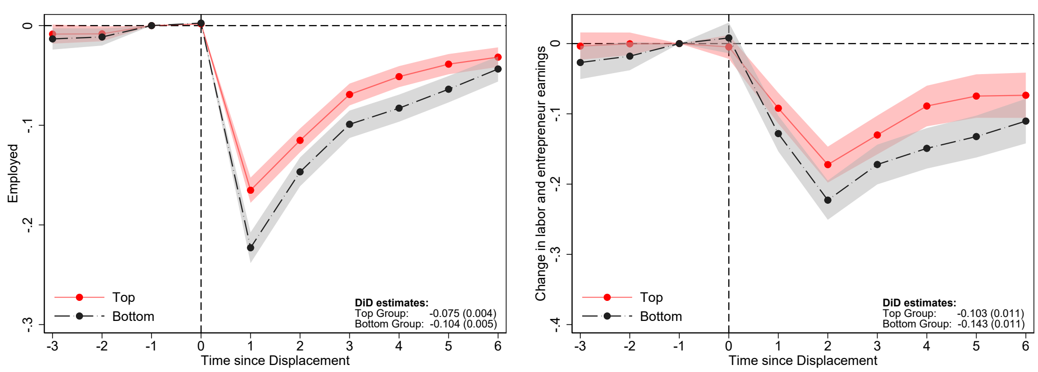
(a) Effects on Employment (Left) and Earnings (Right) for All Years



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

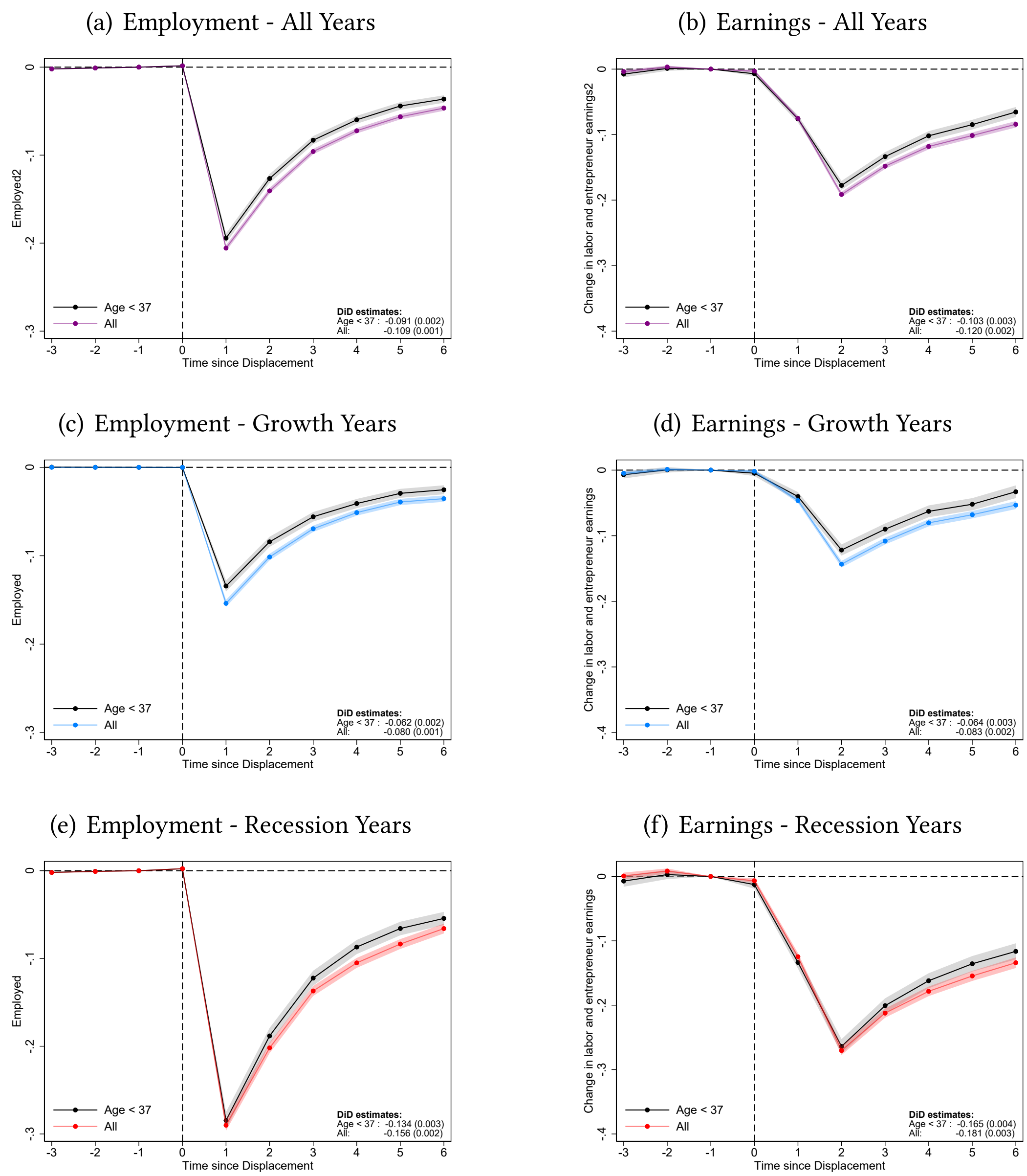


(c) Effects on Employment (Left) and Earnings (Right) for Recession Years



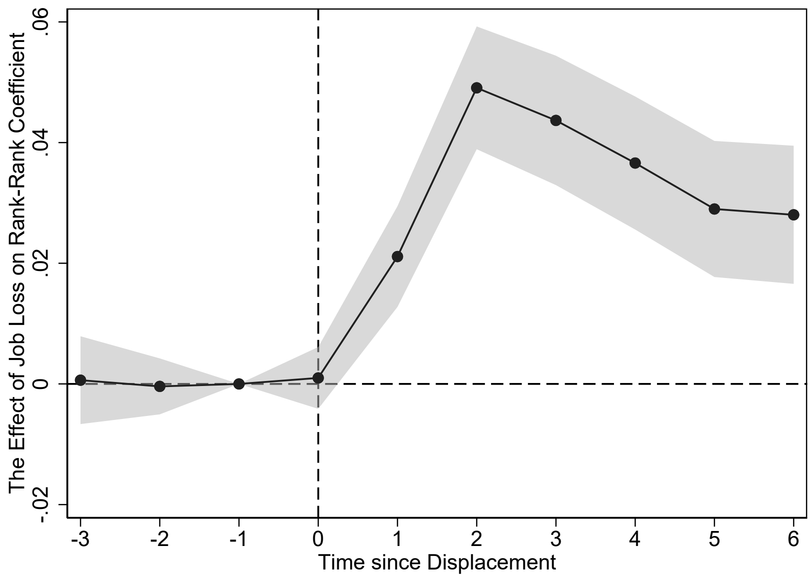
Note: Figures plot the estimated impacts of job loss on employment and earnings, and show that that these results are robust to only including 1 year of tenure before layoff as opposed to the 3 years in the main analysis. Figures plot the estimates of δ_t obtained using Equation (1) separately for bottom 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. Sample construction and data as defined in Section 2.1.

Figure B.6: Impacts of Job Loss on Employment (Left) and Earnings (Right) for the Full Population Aged 25–55 vs Those Aged 25–36



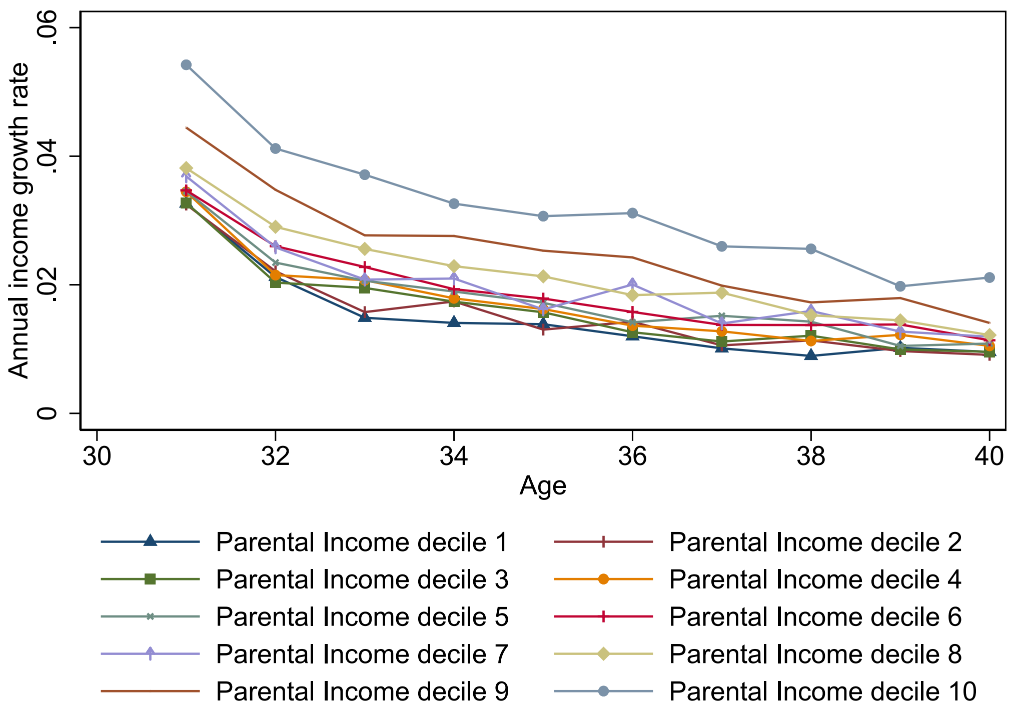
Note: Figure shows estimated impacts of job loss on future employment and earnings for the full population with all income groups for those aged 25–36 vs those aged 25–55. Panels A and B show results for layoffs in all years, Panels C and D for layoffs that occurs in growth years, and Panels E and F 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. Sample construction and data as defined in Section 2.1.

Figure B.7: Estimated Impacts of Job Loss on Intergenerational Mobility Using Earnings Plus Taxable Benefits to Define Income Ranks



Note: Figures plot the estimates of β_{2t} obtained using equation 8 using all income groups. The outcome is a child's income rank (which includes earnings plus taxable benefits) within the birth cohort. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level. Sample construction and data as defined in Section 2.1.

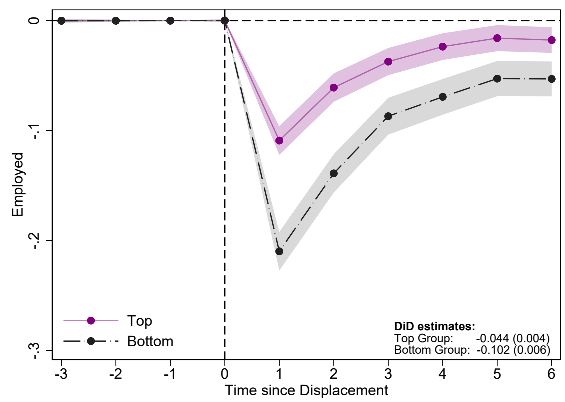
Figure B.8: Income Growth Rates by Parental Income Groups



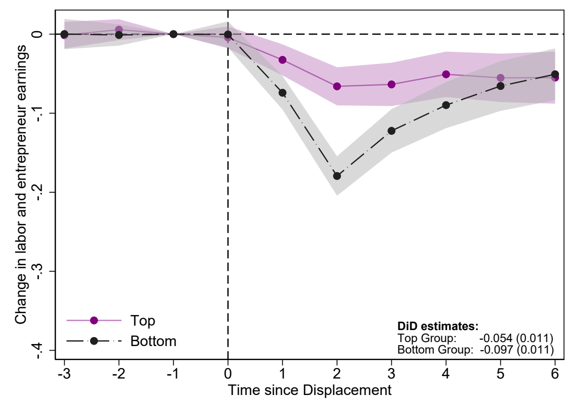
Note: This figure displays the age-decile-specific earnings growth rates. Earnings growth within each age and within each decile is calculated using the entire population. These estimated growth rates are used to produce the "Baseline Simulation" and "Job Loss Simulation" estimates as described in Section 5.3, with results reported in Figure 10 and Appendix Table A.15.

Figure B.9: Impacts of Job Loss on Employment and Earnings Using the Matching Approach by Parental Earnings Groups, Bottom vs. Top 20%

(a) Employment



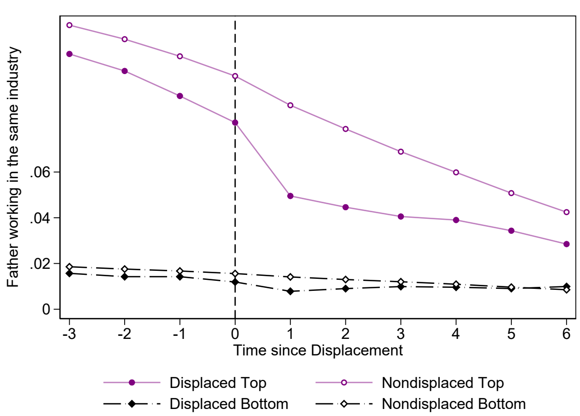
(b) Earnings Relative to Pre-Mean



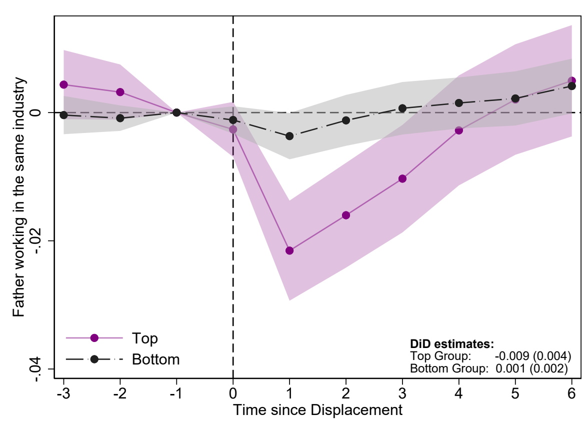
Note: Figures show the estimated impacts of job loss on future employment and earnings for the matched sample using the two-step matching estimator described in Section 6. In Panel A (B), the outcome is employment (relative earnings). Employment is measured at the end of the year. Relative earnings compare yearly labor and entrepreneurial earnings to the mean of yearly earnings 1–3 years before layoff. 95 percent confidence intervals appear as shaded bands around point estimates. DiD estimates are obtained by collapsing event study dummies 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 B.10: 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



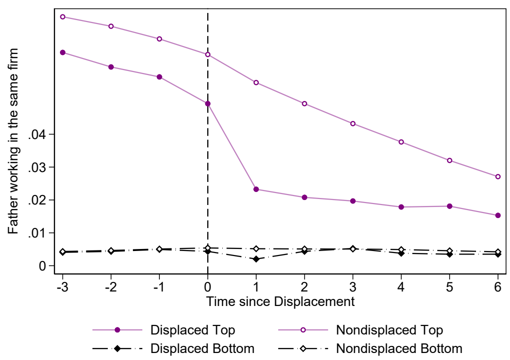
(b) Working in the same Industry as Father



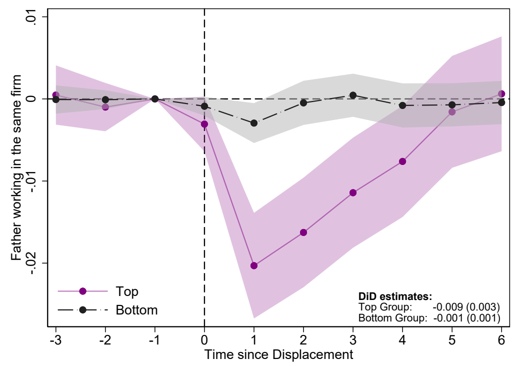
Note: Panel A shows the yearly probability of working for any of the father's industries for displaced and non-displaced individuals 3 years before and 6 years after the layoff by parental income group. The set of father's industries at year t contains all industries the father has had between years 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. Sample construction and data as defined in Section 2.1.

Figure B.11: 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



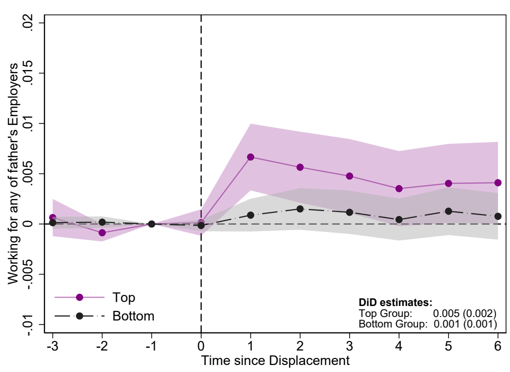
(b) Working in the Same Firm as Father



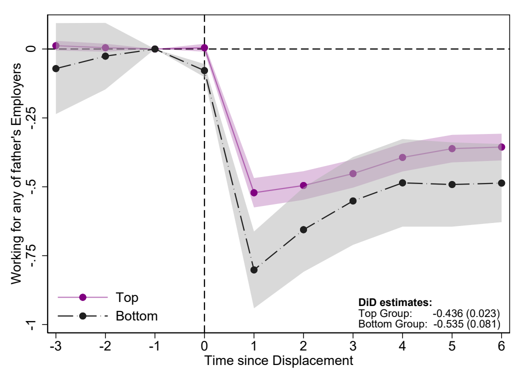
Note: Panel A shows the yearly probability of working in the same firm as the father. Panel B shows the estimates of δ_t obtained using Equation (1) separately for the top and bottom parental income groups. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard 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. Sample construction and data as defined in Section 2.1.

Figure B.12: Impacts of Job Loss on Working in the Same Firm as One's Father by Parental Earnings Group, Conditioned on Whether a Child and 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. The set of the father's employers at year t contains all employers the father has had between years 1988 and t. Estimates of δ_t obtained using Equation (1) separately for the top and bottom 20% parental income groups. Panel A restricts analysis to individuals not working in the same firm as the father at time 0. Panel B restricts analysis to those sharing the same employer with the father at time 0. 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.