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

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July 1, 2021

Abstract

Does job loss cause less economic damage if your parents are higher-income, and what are the implications for intergenerational mobility? In this paper we show that following a layoff, adult children born to parents in the bottom 20% of the income distribution have almost double the unemployment compared with those born to parents in the top 20%, with 64% higher present discounted value losses in earnings. Next, we show that these disparate impacts of job loss have important implications for inequality and intergenerational mobility. They increase the 80:20 income inequality ratio for those impacted by 6.4% and increase the rank-rank coefficient by 30%, implying large reductions in intergenerational mobility. In a simulation based on our main results, we show that 2.9% of the total rank-rank correlation when the child is 40 can be explained by 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 much of these differences in the impacts of job loss between children of low- and high-income parents can be explained by "baked in" advantages.

[*]We thank seminar participants at USC Marshall, University of Helsinki, and VATT as well as Kenneth Ahern, Clare Balboni, Natalie Bau, Lori Beaman, Pascaline Dupas, Flavio Hafner, Kristiina Huttunen, Ilyana Kuziemko, Oyebola Okunogbe, Mikko Silliman, Carolyn Sloane, Roope Uusitalo, and Laurel Wheeler for helpful comments.

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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 (Chetty *et al.*, 2014b; Helsø, 2021; Modalsli, 2017; Solon, 1992; Björklund and Jäntti, 1997; Corak, 2020). 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 (Jacobson *et al.*, 1993; Couch and Placzek, 2010). However, this literature has not focused on how the response to labor market shocks might 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 future 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.[1] 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 human capital) 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

[1]There is a long tradition of using this approach to identify the impacts of job loss. See the summary at the end of this section for examples.

would miss the full effects and be incorrect, we will explore possible underlying mechanisms at the end of the paper.

We use our rich data to present three new findings. The first key finding of this paper shows 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 2 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 64% higher for adult children in the bottom 20% relative to the losses experienced by those with parents in the top 20%.[2][3]

Second, motivated by the cyclical impacts of job loss that have been shown in many papers (Aaronson *et al.*, 2004; Farber, 2017; Davis and Von Wachter, 2011; Schmieder *et al.*, 2018), 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.

Third, 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 the 80:20 ratio. Using our estimates of the PDV of job loss for the two groups we find that the disparate impact of job loss increases earnings inequality by 6.4% for those affected. Next, we estimate the impact our main results have for intergenerational mobility.

[2] When we consider the PDV of earnings losses as a fraction of pre-layoff earnings, the gap is even larger with 84% higher losses for those in the bottom 20% versus the top 20%.

[3] 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%.

We estimate a simple extension to the calculation of the rank-rank coefficient from Chetty *et al.* (2014a).[4] To capture how job loss impacts intergenerational mobility, we allow the rank-rank regression coefficient to vary with job loss.[5] Using this approach we find that the rank-rank coefficient in the 6 years following the layoff is 30% 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 put these results in context, we run a back of the envelope simulation where we take all individuals aged 30 and simulate 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 the 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 8.54% of the total growth in the rank-rank correlation from age 30 to age 40 can be explained by the disparate impacts and incidence of job loss. Put another way, our results imply that 2.9% of the rank-rank correlation at age 40 can be explained by 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 response to these gaps. First, high-income parents could invest more in childhood (or provide

[4] 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.

[5] 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.

genetic advantages), leading to "baked-in" 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.[6]

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 36% (51%) of the difference between the two groups in employment (earnings) job loss scars is explained by pre-existing observable differences in education between the two groups.

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 and/or job opportunities. While we do not observe 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, or in the same industry as their father. 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) and Jäntti and Jenkins (2015).[7] 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. Aaronson and Mazumder (2008) show that in the United States intergenerational mobility has declined significantly since

[6]There is broad evidence that higher-income parents invest more in their children. For example, see Jackson *et al.* (2014) and Miller (2018) for examples of differences in school spending by parental income and also Becker *et al.* (2018), Carneiro *et al.* (2021) and Attanasio *et al.* (2020) 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.

[7]See also Mogstad and Torsvik (2021) for a more recent review.

1980.Jäntti and Jenkins (2015) shows that there is greater intergenerational mobility in the Nordic countries compared with the United States (in this paper's Section 2 we document that the majority of Finnish children born into the bottom 20% do not remain there), but less mobility when compared with other Nordic countries.[8]

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 could still be 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. For example, our results suggest that measuring intergenerational mobility correlations when children are in their late twenties or early thirties might misrepresent "true" overall mobility. If parental income differences cause children to react differently to labor market shocks, then intergenerational mobility will depend on the full career trajectory, and will not be set early on.

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 Jacobson *et al.* (1993), Couch and Placzek (2010), and Lachowska *et al.* (2020).[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 (Lindo, 2011; Willage and Willén, 2020; Rege *et al.*, 2011; Oreopoulos *et al.*, 2008; Huttunen and Riukula, 2019), 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

[8]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 (Katz *et al.*, 2001; Ludwig *et al.*, 2013; Chetty *et al.*, 2014a, 2016; Chyn, 2018). 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.

[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; Gathmann *et al.*, 2021).

[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

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 remainder of the paper is organized as follows: Section 2 describes the institutional background and data. Section 3 presents our empirical specification. Section 4 presents the main results. Section 5 discusses impacts on income inequality and intergenerational mobility. Section 5 examines mechanisms. Section 7 concludes.

2 Institutional Context and Data

We study the relationship between parental income and impacts of job loss in Finland, for those who experience job loss during the period 1991 to 2010. 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.[11] Notably, almost none of the children born into the bottom 20% remain in the bottom 20% as adults. Over 80% of these children have moved out of the bottom two quintiles by their mid-thirties.[12] This is a striking result because it suggests that conditional on entering the labor force, this group is doing relatively well and is potentially positively selected. 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 sample. We see that when we compare our estimation sample, those who have jobs, to the full sample, intergenerational mobility is much higher for our estimation sample. This fact is important for our study as it suggests that our results do not simply capture the

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 Figure 1 we only look at adult children from our estimation sample as described in Section 3 who were between 32 and 36 years of age and had job tenure of at least 1 year before the layoff, as we are studying the impact of job loss. The figure would look slightly 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%.

[12]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.

effect of the adult children born into poverty themselves being the poorest (or richest) in society, as most have managed a level of success that exceeds that of their parents. By virtue of having a full time job people will have left the bottom 20%, since the majority of the bottom 20% of the income distribution consists of people with extremely low labor market earnings. Our study asks how precarious this success is: can these children, 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 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 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.[13] GDP dropped by 5.9% in 1991 and by 0.7% further in 1993.[14] 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

[13]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`.

[14]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`.

vary 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.

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 1988–2015. 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 to examine whether their plant closed down during our study period. We focus on individuals who were working in private sector plants 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 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 earlier studies, we define displaced workers as individuals who involuntarily separate from their jobs due to exogenous shocks.[15] The data cover all (Finnish) private sector plants from 1988 to 2016, and we must first define plant closures and downsizing plants. 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 an exiting plant 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 exiting plants 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.[16] Then we merge the plant exit data with the individual-level data.

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

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

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

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). 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. The comparison group consists of all workers who were not displaced between years t and $t+1$. Importantly, we allow workers in the control group to separate for reasons other than displacement, including voluntary job changes and sickness. 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 in a robustness check. Our approach closely follows the approach taken in Huttunen *et al.* (2018) and Huttunen and Riukula (2019).

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. 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 take the average of this total labor market earnings figure from 1988 until the year of the displacement of the adult child.[17] We rank the resulting average earnings and select adult children of parents in specified earnings groups (for most of the paper, in the bottom and top 20%). We focus on workers aged 25–35 as the earnings data is only available from 1988 onward and we want to include parental earnings before the retirement age. In robustness exercises described in Subsection 4.1, we show that our results are not sensitive to a variety of alternative approaches to identifying children of poorer versus richer parents, such as including taxable benefits in addition to labor market earnings when defining parental income groups.

Before turning to descriptive statistics and results, it is useful to formally define our outcome variables. Our main analysis considers two outcomes. 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 entrepreneurial earnings

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

each year with his average yearly 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. Our main earnings measure lets us have a relative interpretation of magnitudes but does not suffer from the problems that arise from zero earnings.

To study the impact of the layoff on an individual's yearly earnings rank, we construct the individual's yearly earnings rank by comparing an individual's labor earnings relative to all individuals in the same birth cohort.

To study whether individuals work for any of the father's current or previous employers, 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.

Table 1 provides summary statistics for adult children of parents in the bottom 20% and those of parents in the top 20%.[18] Notice that there are fewer observations in the bottom 20%. The reduced number of observations is in part because the requirement that individuals be employed (and thus can be laid off) removes a slightly larger number of those in the bottom 20% compared with the top 20%, since the bottom 20% have a lower employment rate.[19][20]

Figure 2 presents descriptive results on the impact of job loss for these two groups. 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. In the next section we describe our empirical strategy to pinpoint the impacts of layoffs, and how these might differ between children of low- and high-income parents.

[18] Descriptive statistics for growth years appear in Appendix Table A.1 and recession years in Appendix Table A.2.

[19] The selection into employment is beyond the scope of this paper, but if anything this would seem to suggest that the bottom 20% who are employed and studied here are positively selected from that group.

[20] In a robustness check, we only require tenure of 1 year before the layoff (see Appendix Figure B.5) and find that the results are almost identical.

3 Empirical Strategy

The labor market effects of job loss are identified using 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).[21] 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.

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

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

closure not taken place.

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.3-A.7). 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 region, occupation, education, industry, and field of study, and individual fixed effects are removed.[22] A second robustness check uses a matching exercise that is similar to Schmieder *et al.* (2018) (see Section 6 for more details).[23] 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.

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

[22]These estimates are reported in Columns 3 and 4 of Appendix Tables A.3-A.7.
[23]Results for this exercise are shown in Figure B.11

the non-employment compared with individuals with high-income parents. This is potentially a surprising outcome as 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% are able and do 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 second year 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, 20.6% of adult children of low-income parents are still not employed compared with 13.1% of those of high-income parents. In the second year post layoff, those with low-income parents have an 18.5% drop in earnings relative to their average earnings in the 3 years preceding the layoff, compared with an 11% drop in earnings for those with high-income parents.[24] 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 layoff, these estimates show that those with parents in the bottom 20% experience a 10.2 percentage point average drop in employment versus a 5.7 percentage point average drop for those with parents in the top 20%. This represents a 79%[25] 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 71%[26] higher for those whose parents are in the bottom versus the top income group, and again, this difference is statistically significant.[27]

[24] See Appendix Table A.9 for these numbers.

[25] $10.2/5.7 = 1.7894$

[26] $0.108/0.063 = 1.7142$

[27] Detailed DiD estimates appear in Appendix Tables A.3–A.5 and detailed yearly event study estimates appear in Appendix Tables A.8–A.10.

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 most of this paper still 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, becoming even stronger if we move to narrower cut-offs.

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.[28]

Figure 6 documents an interesting pattern between the state of the economy when the displacement occurred and the disparate impact of job loss. 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 gap in employment between children of low- versus high-income parents is 44% larger in growth years versus recession years (0.052 vs 0.036), consistent with the overall patterns in the event study graphs. When it comes to earnings, there are much smaller differences in earnings losses in recession years compared to growth

[28]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.

years (0.047 vs 0.048). 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.[29][30]

4.1 Robustness

We perform several robustness checks of our results, which are detailed in Appendix B. Figure B.3 shows that the results are robust to alternative measures of earnings 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 require 1 year of tenure before the layoff as opposed to the restriction of 3 years required in the main results.[31] 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.[32]

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

[29] 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.

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

[31] 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 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.

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

2001).

5 Implications of the Disparate Impacts of Job Loss for Earnings Inequality 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. 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:

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

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

Table 2, column 1, presents estimates of the PDV for children of parents in the bottom versus the top 20%. In the 6 years post layoff, the estimates show that adult children with parents in the bottom 20% experience a PDV of job loss of €18,177 compared with a PDV of €11,577 for children with parents in the top 20%. In other words, the bottom 20% experiences 64%[33] 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 over a third 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 84% [34] higher for adult children in the bottom 20% in terms of pre-layoff earnings.

[33] $11577/18177 = 0.636$

[34] $0.335 \times 1.844 = 0.618$

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 2, we can characterize the percentage change in the 80:20 ratio, a common approach to measuring inequality, using the following equation:

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

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 6.4% following a job loss for those affected (see Table 2 column 5).

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).[35] 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

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

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.

This figure is 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. 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 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.[36] 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.13, 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 0.028 and is statistically significant. The fact that it is positive means that layoffs are experienced differently by adult children of low- and high-income parents, and as a result there is an increase in the correlation between the percentile income rank of the parents and the percentile rank of the 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 30%[37] as a result of job loss.

The results from Table 3 show the overall impact of job loss on intergenerational mobility. We

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

[37] As in Pekkarinen *et al.* (2009), this is calculated as $0.30 = 0.028/0.094$

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 8. 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 0.05 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" correlations, 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 8, 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 capital earnings and 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.

5.1 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 the disparate impacts and incidence of job loss explain overall rank-rank correlations.

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.15) 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 rate for that decile, 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.[38] 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:

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

Where y_t refers to earnings in period t and y_{t+1} refer to earnings the following year. "$losses_{decile}$" 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. "$growth_{age,decile}$" 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.[39]

We graph the rank-rank correlation for each age as the shocks accumulate in Figure 9.[40] We find that the rank-rank correlation is increasing as the child ages, but that the increase is larger

[38] 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.

[39] 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.

[40] The estimates are also reported in Appendix Table A.14

when there is job loss included. Based on our estimates, absent job loss the rank-rank correlation would grow from 0.1234 at age 30 to 0.1823 at age 40. With job loss, the rank-rank correlation grows from 0.1251 at age 30 to 0.1895 at age 40. The simulation results imply that 8.54%[41] of the increase in the intergenerational rank-rank correlation from age 30 to age 40 can be explained by the disparate impacts of job loss. An alternative way to frame these results is in terms of the rank-rank correlation at age 40. According to our estimates, 2.9%[42] of the total rank-rank correlation at age 40 can be explained by the disparate impact and incidence of job loss in the preceding decade.

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.14 which shows, for example, that the probability of unemployment is 69.8% 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 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

What explains 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[43]) which results in "baked-in" advantages

[41]This is equal to the growth in the rank-rank correlation with job loss minus the growth in the rank-rank correlation without job loss relative to the growth in the rank-rank correlation with job loss. In numbers, this is equal to $\frac{(0.1895-0.1251)-(0.1823-0.1234)}{0.1895-0.1251}$, using the estimates for the rank-rank correlations at each age reported in Appendix Table A.14.

[42]This is equal to the growth in the rank-rank correlation with job loss minus the growth in the rank-rank correlation without job loss relative to rank-rank correlation at age 40. In numbers, this is equal to $\frac{(0.1895-0.1251)-(0.1823-0.1234)}{0.1895}$.

[43]For evidence on the role of nature versus nurture in educational attainment, see, for example, Black *et al.* (2005). However, 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,

such as higher human capital when entering the labor market. This in turn could be associated with better responses to labor market shocks in adulthood.[44] Alternatively, parents might intervene directly at the time of job loss. We view both "baked-in" advantages and direct intervention by parents at the time of job loss as potential benefits from having high-income parents, but the policy implications of which of the two is most relevant are very different.

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 10 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, using the matching procedure described in more detail below. The figure indicates that whether one has parents in the top 20% or bottom 20%, the higher one's education level, the smaller the job loss scar in both employment and earnings. In fact, at the highest level of education, a post-graduate degree, the scar is not statistically significantly different from zero for both employment and earnings. In contrast, those with only a basic education experience large employment and earnings job scars.

However, there are important differences in the job scar by education group across adult children of low- and high-income parents. 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 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

whether earlier advantage is genetic or investment based is not important, although the policy implications might be very different.

[44]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.

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). 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).[45]

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.

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

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

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.11 shows that the estimated job loss scars when estimating counterfactual earnings in this way are almost identical to the main results, which

[45] The trade-off is that it can inadvertently put a bit too much weight on the explained portion.

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 4 reports results 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 4 shows that using this approach, estimates suggest that observable differences in the education of adult children of low- versus high-income parents accounts for 36% of the difference in the impact of job loss on employment and 51% 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 only 41% of earnings gaps are explained by observed differences in education. In recession years, 65% of employment gaps and 74% 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.

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 do not observe the first two possible investments in our data, we observe the third and can test it directly.

Figure 11 explores this possible explanation[46] with respect to fathers' employers and industry and shows that the opposite is true. As Panel A (C) shows, while children of parents in the top 20% are more likely to work in the same firm (industry) 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 (industry) as their fathers. Causal estimates shown in Panel B (D) 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 either the same firm or industry 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 go in the opposite direction than the original hypothesis suggested.

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.[47] However, we might worry 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. Appendix Figure B.10 repeats the Figure 11 exercise but conditions on individuals not working for any of their father's previous employers (industries)

[46]Regression results are reported in Appendix Table A.11 for Panel B and Appendix Table A.12 for Panel D.

[47]In our main results we include all firms (industries) where the father has worked in his lifetime prior to the layoff. However, in Appendix Figure B.9, we instead look only at the firm or industry where the father works in the year before the layoff and the results are similar.

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.

7 Conclusion

This paper used administrative data from Finland to document three important new findings. First, 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 low-income parents experiencing greater losses following a layoff. Second, we showed that while the overall job loss scars for both groups are larger in periods of recession, the disparities in the size of the job loss scars are larger in periods when the economy is growing.

Third, these disparate impacts of job loss translate to significant effects on earnings inequality and intergenerational mobility. Specifically, job loss causes a 6.4% increase in earnings inequality for those affected after 6 years, and a 30% increase in the rank-rank correlation, 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 2.9% of the overall rank-rank correlation at age 40 can be explained by 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 industry. Following a layoff, adult children of high-income parents are less likely to work in the same firm and industry 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, in particular parents could provide cash transfers which we are unable to observe in our data. We also present evidence in terms 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 a relatively large portion of the disparate impacts of job loss by parental income can be explained by "baked in" advantages, specifically differences in educational attainment across children whose parents are in the bottom 20% of the income distribution versus those whose parents are in the top 20%.

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 the extent of the issue, and early life causes, this is the first paper to show 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.

References

Aaronson, D., Christopher, S. *et al.* (2004). Employment growth in higher-paying sectors. *Chicago Fed Letter*, **206**.

— and Mazumder, B. (2008). Intergenerational economic mobility in the United States, 1940 to 2000. *Journal of Human Resources*, **43** (1), 139–172.

Ahammer, A. and Packham, A. (2020). *Dying to Work: Effects of Unemployment Insurance on Health*. Tech. rep., National Bureau of Economic Research.

Attanasio, O., Meghir, C. and Nix, E. (2020). Human capital development and parental investment in India. *Review of Economic Studies*, **87** (6), 2511–2541.

Becker, G. S., Kominers, S. D., Murphy, K. M. and Spenkuch, J. L. (2018). A theory of intergenerational mobility. *Journal of Political Economy*, **126** (S1), S7–S25.

— and Tomes, N. (1979). An equilibrium theory of the distribution of income and intergenerational mobility. *Journal of political Economy*, **87** (6), 1153–1189.

— and — (1986). Human capital and the rise and fall of families. *Journal of Labor Economics*, **4** (3, Part 2), S1–S39.

Björklund, A. and Jäntti, M. (1997). Intergenerational income mobility in Sweden compared to the United States. *The American Economic Review*, **87** (5), 1009–1018.

Black, S., Devereux, P., , Lundborg, P. and Majlesi, K. (2019). Poor little rich kids? The role of nature versus nurture in wealth and other economic outcomes and behaviors. *Review of Economic Studies*.

— and Devereux, P. J. (2010). *Recent developments in intergenerational mobility*. Tech. rep., National Bureau of Economic Research.

—, — and Salvanes, K. G. (2015). Losing heart? The effect of job displacement on health. *ILR Review*, **68** (4), 833–861.

Black, S. E., Devereux, P. J. and Salvanes, K. G. (2005). Why the apple doesn't fall far: Understanding intergenerational transmission of human capital. *American Economic Review*, **95** (1), 437–449.

Carneiro, P., Garcia, I. L., Salvanes, K. G. and Tominey, E. (2021). Intergenerational mobility and the timing of parental income. *Journal of Political Economy*, **129** (3), 757–788.

Chan, S. and Huff Stevens, A. (2001). Job loss and employment patterns of older workers. *Journal of Labor Economics*, **19** (2), 484–521.

Chetty, R., Friedman, J. N., Saez, E., Turner, N. and Yagan, D. (2020). Income segregation and intergenerational mobility across colleges in the United States. *Quarterly Journal of Economics*, **135** (3), 1567–1633.

—, Hendren, N. and Katz, L. F. (2016). The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment. *American Economic Review*, **106** (4), 855–902.

—, —, Kline, P. and Saez, E. (2014a). Where is the land of opportunity? The geography of intergenerational mobility in the United States. *Quarterly Journal of Economics*, **129** (4), 1553–1623.

—, —, —, — and Turner, N. (2014b). Is the United States still a land of opportunity? Recent trends in intergenerational mobility. *American Economic Review*, **104** (5), 141–47.

Chyn, E. (2018). Moved to opportunity: The long-run effects of public housing demolition on children. *American Economic Review*, **108** (10), 3028–56.

Corak, M. (2020). The Canadian geography of intergenerational income mobility. *The Economic Journal*, **130** (631), 2134–2174.

— and Piraino, P. (2011). The intergenerational transmission of employers. *Journal of Labor Economics*, **29** (1), 37–68.

Couch, K. A. and Placzek, D. W. (2010). Earnings losses of displaced workers revisited. *American Economic Review*, **100** (1), 572–89.

Davis, S. J. and Von Wachter, T. M. (2011). *Recessions and the cost of job loss.* Tech. rep., National Bureau of Economic Research.

East, C. N. and Simon, D. (2020). *How Well Insured are Job Losers? Efficacy of the Public Safety Net.* Tech. rep., National Bureau of Economic Research.

Farber, H. S. (2017). Employment, hours, and earnings consequences of job loss: US evidence from the displaced workers survey. *Journal of Labor Economics*, **35** (S1), S235–S272.

Fortin, N., Lemieux, T. and Firpo, S. (2011). Decomposition methods in economics. In *Handbook of labor economics*, vol. 4, Elsevier, pp. 1–102.

Gathmann, C., Huttunen, K., Jernström, L., Sääksvuori, L. and Stitzing, R. (2021). *In Sickness and in Health: Job Displacement and Health Spillovers in Couples.* Tech. rep., CEPR Discussion Paper No. DP15856.

Goodman-Bacon, A. (2018). *Difference-in-Differences with Variation in Treatment Timing*. Working Paper 25018, National Bureau of Economic Research.

Helsø, A.-L. (2021). Intergenerational income mobility in Denmark and the United States. *The Scandinavian Journal of Economics*, **123** (2), 508–531.

Hoynes, H., Miller, D. L. and Schaller, J. (2012). Who suffers during recessions? *Journal of Economic Perspectives*, **26** (3), 27–48.

Huttunen, K. and Kellokumpu, J. (2016). The effect of job displacement on couples fertility decisions. *Journal of Labor Economics*, **34** (2), 403–442.

—, Møen, J. and Salvanes, K. G. (2018). Job loss and regional mobility. *Journal of Labor Economics*, **36** (2), 479–509.

— and Riukula, K. (2019). *Parental Job Loss and Children's Careers*. Tech. rep., IZA Discussion Papers.

Jackson, C. K., Johnson, R. and Persico, C. (2014). *The effect of school finance reforms on the distribution of spending, academic achievement, and adult outcomes*. Tech. rep., National Bureau of Economic Research.

Jacobson, L. S., LaLonde, R. J. and Sullivan, D. G. (1993). Earnings losses of displaced workers. *American Economic Review*, pp. 685–709.

Jäntti, M., Bratsberg, B., Roed, K., Raaum, O., Naylor, R., Osterbacka, E., Bjorklund, A. and Eriksson, T. (2006). American exceptionalism in a new light: A comparison of intergenerational earnings mobility in the Nordic countries, the United Kingdom and the United States.

Jäntti, M. and Jenkins, S. P. (2015). Income mobility. In *Handbook of income distribution*, vol. 2, Elsevier, pp. 807–935.

Katz, L. F., Kling, J. R. and Liebman, J. B. (2001). Moving to opportunity in Boston: Early results of a randomized mobility experiment. *Quarterly Journal of Economics*, **116** (2), 607–654.

Lachowska, M., Mas, A. and Woodbury, S. A. (2020). Sources of displaced workers' long-term earnings losses. *American Economic Review*, **110** (10), 3231–66.

Lindo, J. M. (2011). Parental job loss and infant health. *Journal of Health Economics*, **30** (5), 869–879.

Ludwig, J., Duncan, G. J., Gennetian, L. A., Katz, L. F., Kessler, R. C., Kling, J. R. and Sanbonmatsu, L. (2013). Long-term neighborhood effects on low-income families: Evidence from moving to opportunity. *American Economic Review*, **103** (3), 226–31.

Miller, C. L. (2018). The effect of education spending on student achievement. In *Proceedings. Annual Conference on Taxation and Minutes of the Annual Meeting of the National Tax Association*, JSTOR, vol. 111, pp. 1–121.

Modalsli, J. (2017). Intergenerational mobility in Norway, 1865–2011. *The Scandinavian Journal of Economics*, **119** (1), 34–71.

Mogstad, M. and Torsvik, G. (2021). *Family Background, Neighborhoods and Intergenerational Mobility*. Tech. rep., National Bureau of Economic Research.

Neumark, D. (1988). Employers' discriminatory behavior and the estimation of wage discrimination. *Journal of Human Resources*, pp. 279–295.

Oaxaca, R. L. and Ransom, M. R. (1994). On discrimination and the decomposition of wage differentials. *Journal of Econometrics*, **61** (1), 5–21.

Oreopoulos, P., Page, M. and Stevens, A. H. (2008). The intergenerational effects of worker displacement. *Journal of Labor Economics*, **26** (3), 455–483.

Pekkarinen, T., Uusitalo, R. and Kerr, S. (2009). School tracking and intergenerational income mobility: Evidence from the Finnish comprehensive school reform. *Journal of Public Economics*, **93** (7-8), 965–973.

Rege, M., Telle, K. and Votruba, M. (2011). Parental job loss and children's school performance. *Review of Economic Studies*, **78** (4), 1462–1489.

Schmieder, J., von Wachter, T. and Heining, J. (2018). *The costs of job displacement over the business cycle and its sources: Evidence from Germany*. Tech. rep., UCLA, Mimeo.

Solon, G. (1992). Intergenerational income mobility in the United States. *The American Economic Review*, pp. 393–408.

Sullivan, D. and Von Wachter, T. (2009). Job displacement and mortality: An analysis using administrative data. *Quarterly Journal of Economics*, **124** (3), 1265–1306.

Sun, L. and Abraham, S. (2020). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*.

Suoniemi, I. (2017). *Intergenerational mobility and equal opportunity, evidence from Finland*. Tech. rep.

Von Wachter, T. and Davis, S. J. (2011). Recessions and the costs of job loss. *Brookings Papers on Economic Activity*, **42** (2), 1–72.

Willage, B. and Willén, A. (2020). Postpartum job loss: Transitory effect on mothers, long-run damage to children.

Table 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	30.741	30.712	0.565
Female	0.350	0.361	0.196
Number of children	0.889	0.915	0.186
Tenure, years	4.780	5.277	0.000
Plant size	90.081	103.145	0.000
Primary education only	0.160	0.150	0.086
Secondary education only	0.554	0.567	0.114
Tertiary education	0.284	0.280	0.585
Experience, years	10.379	10.435	0.568
Married	0.397	0.412	0.073
Real labor earnings in 1000s (€)	31.172	30.221	0.000
Real income in 1000s (€)	32.757	31.505	0.000
Observations	3497	267989	
Panel B: Adult Children Whose Parents Are in the Top 20%			
Age	30.711	30.763	0.226
Female	0.357	0.376	0.009
Number of children	0.771	0.832	0.000
Tenure, years	4.523	4.953	0.000
Plant size	95.642	115.767	0.000
Primary education only	0.111	0.094	0.000
Secondary education only	0.396	0.415	0.010
Tertiary education	0.492	0.488	0.575
Experience, years	9.152	9.081	0.465
Married	0.442	0.456	0.072
Real earnings in 1000s (€)	37.895	36.509	0.000
Real income in 1000s (€)	39.753	38.115	0.000
Observations	4547	290762	

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

Table 2: 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	11.577	0.335	207.516	195.939	1.064
Bottom 20	18.177	0.618	161.278	143.101	

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 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)		-2.243	0.759	0.519
		(0.133)	(0.119)	(0.252)
Post (β_6)			-5.142	-6.904
			(0.032)	(0.049)
Displaced $\times$ Post (β_7)			-5.013	-6.561
			(0.136)	(0.289)
Family rank $\times$ Displaced $\times$ Post (β_2)				0.028
				(0.005)
Family Rank $\times$ Displaced (β_3)				0.005
				(0.004)
Family Rank $\times$ Post (β_4)				0.034
				(0.001)
Observations	14,053,640	14,053,640	14,053,640	14,053,640

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.

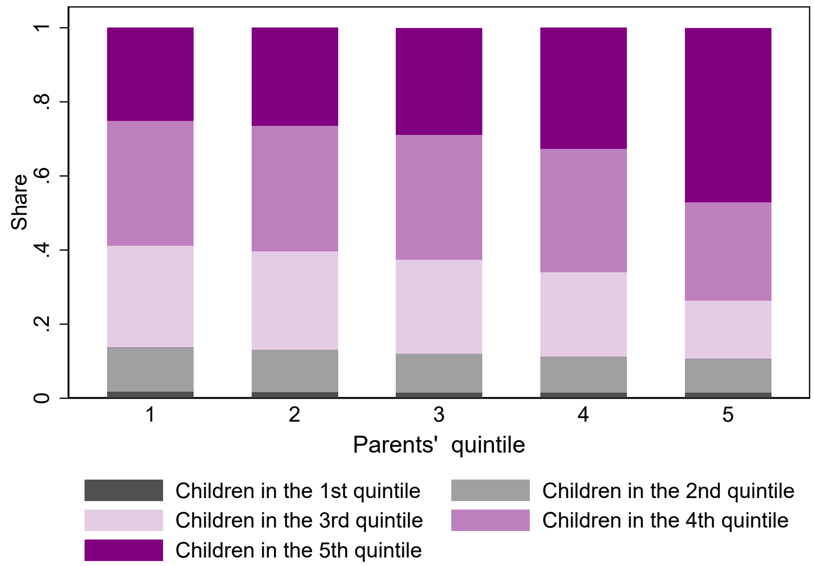
Table 4: Decomposition of Differences in Employment and Earnings Job Loss Scars

	Difference in job loss scar	Percentage explained by education
Panel A: Employment		
All years	0.065	35.551%
Growth years	0.076	22.941%
Recession years	0.051	65.221%
Panel B: Earnings		
All years	0.066	51.331%
Growth years	0.077	41.478%
Recession years	0.050	74.061%

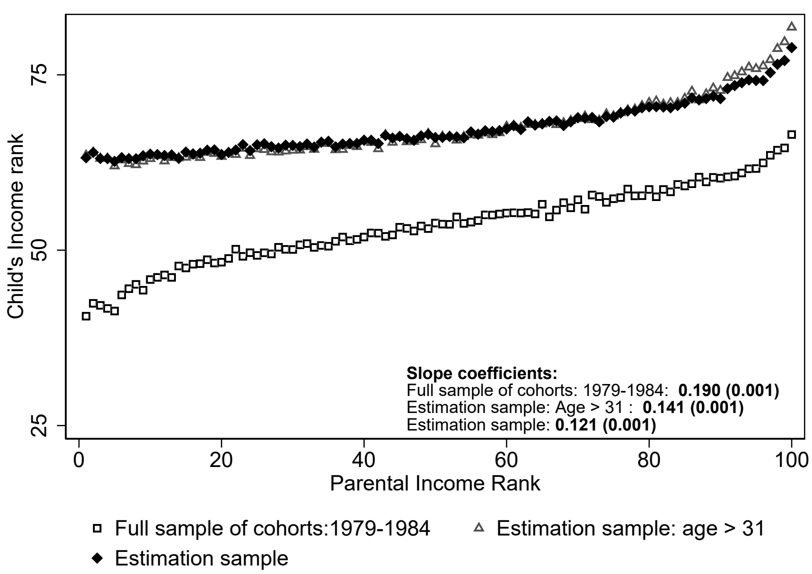
Notes: Table shows the decomposition of the differences in employment (Panel A) and earnings (Panel B) job loss scars between children of parents in the bottom 20% of the income distribution versus the top 20% into the explained and unexplained parts. Estimates are based on Equation (9) for all years, then restricting to only growth years and recession years. For growth and recession years, see Figure 5.

Figure 1: Intergenerational Mobility in Finland

(a) Movement Across Quintiles in Estimation Sample

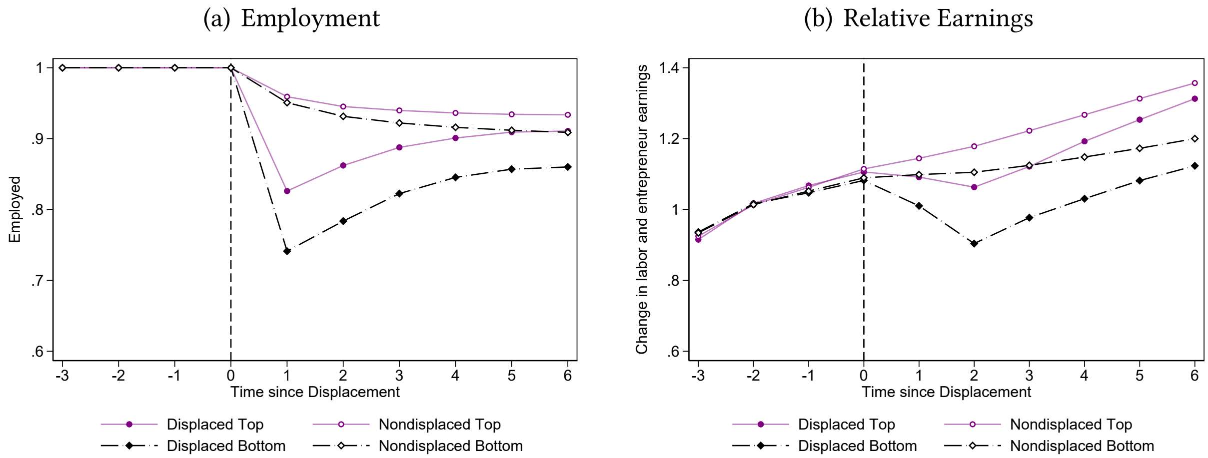


(b) Rank-Rank Correlation Using Full Population vs. Our Sample



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.

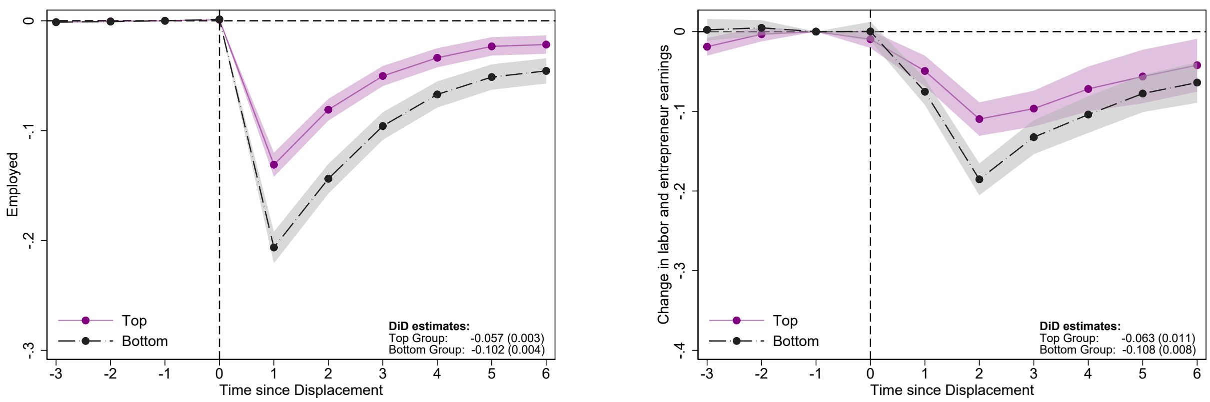
Figure 2: Raw Patterns of Employment and Relative Earnings Before and After Job Loss by Parental Income Group, Bottom vs. Top 20%



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%

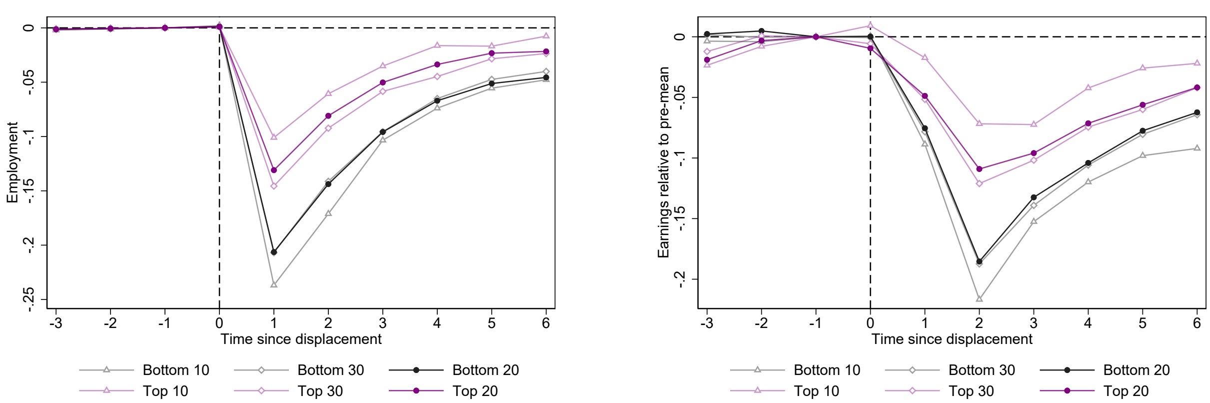
(a) Employment (b) Earnings Relative to Pre-mean



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.

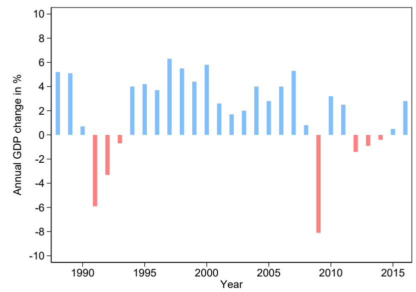
Figure 4: Impacts of Job Loss on Employment and Earnings by Parental Income Group, Bottom vs. Top 10%, 20%, and 30%

(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.

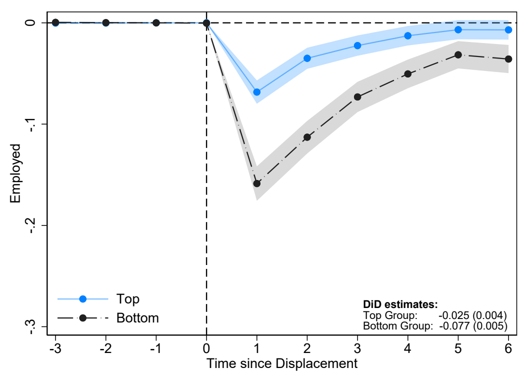
Figure 5: GDP Growth in Finland, 1988–2017



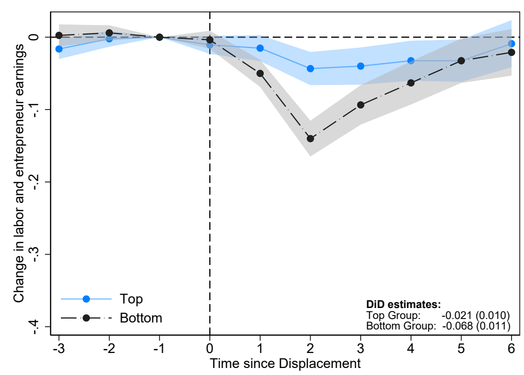
Note: The figure depicts years of growth (in blue) and recession (in red) in Finland used for the analysis.

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

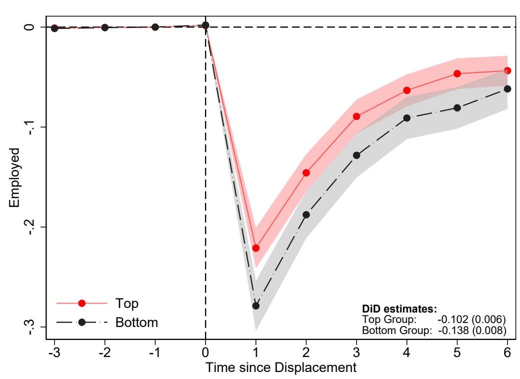
(a) Economy Growing: Employment



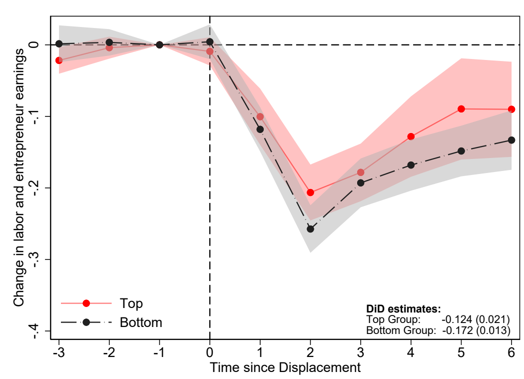
(b) Economy Growing: Relative Earnings



(c) Economy Shrinking: Employment

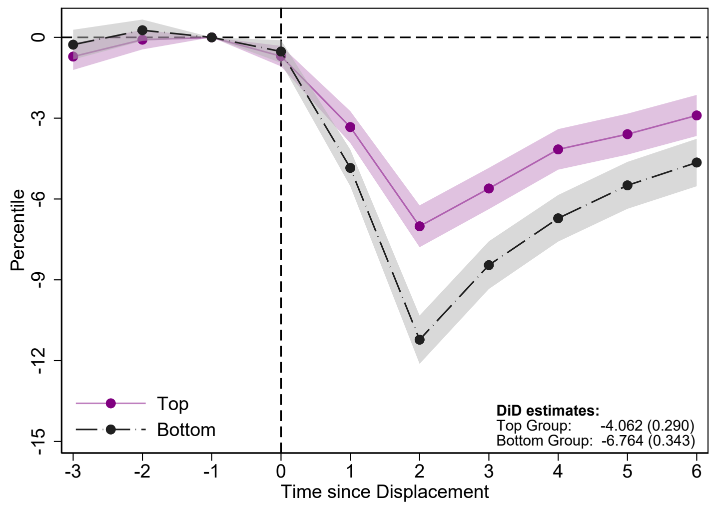


(d) Economy Shrinking: Relative Earnings



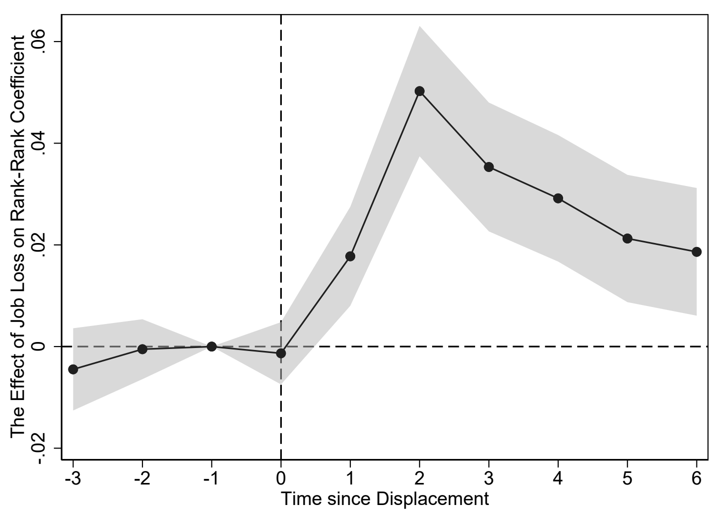
Note: Figures plot the estimates of δ_t obtained using Equation (1) separately for top and bottom 20% parental income groups. Panel A (C) shows the impact of job loss on employment when the economy is growing (shrinking). Panel B (D) shows the impact of job loss on relative earnings when the economy 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%



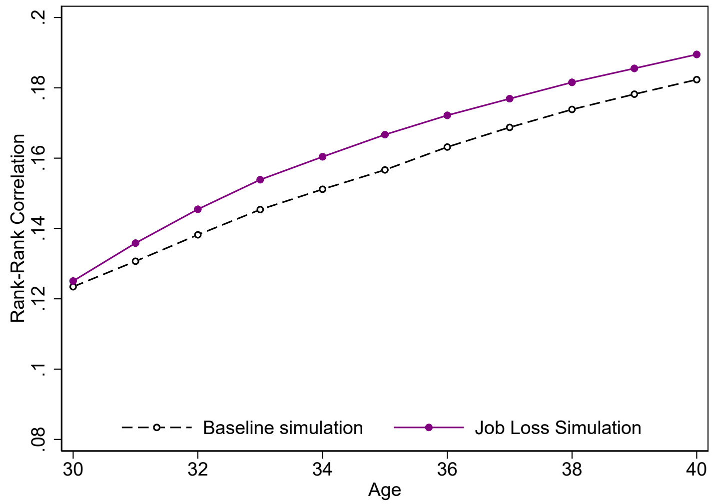
Note: Figure plots the estimates of δ_t obtained using Equation (1) separately for top and bottom parental income groups. The outcome is an individual's earnings rank within the birth cohort. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered 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: Estimated Impacts of Job Loss on Intergenerational Mobility



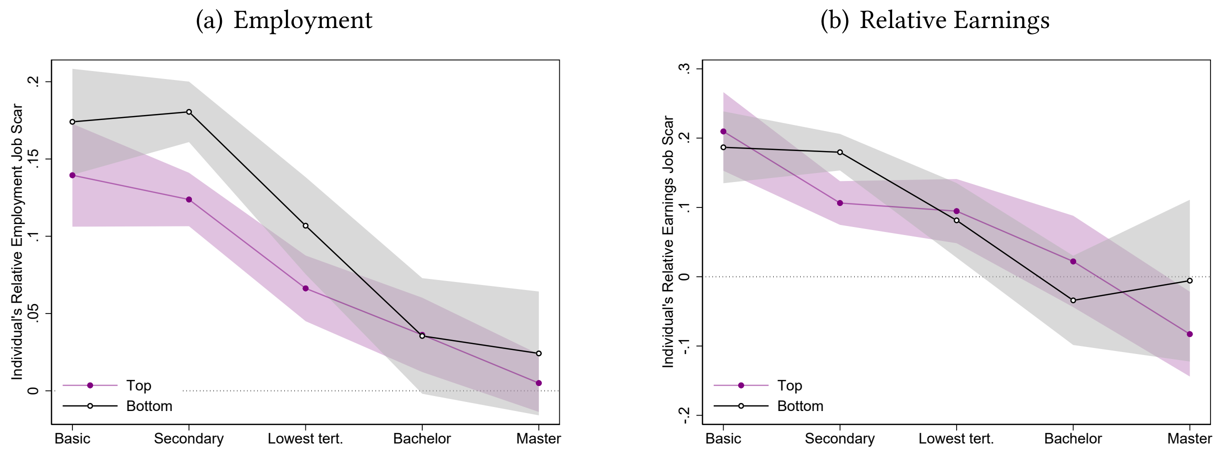
Note: Figure plots the estimates of β_{2t} obtained using equation (8) using all income groups. The outcome is a child's earnings rank within the birth cohort. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level.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

Figure 9: Results from simulations



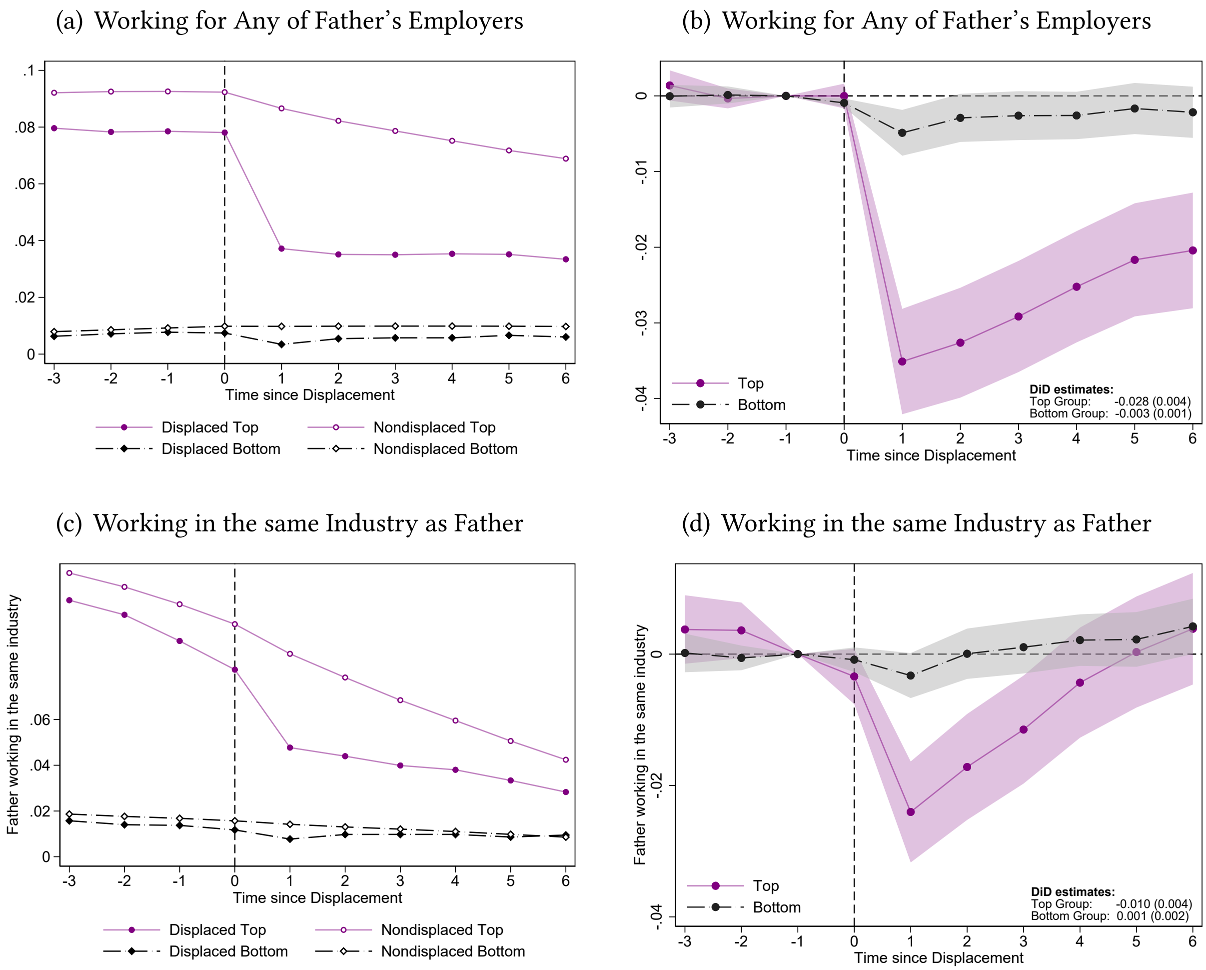
Note: Figure plots the estimates from the simulation described in Section 5.1. The black dashed line represents the trajectory of the rank-rank correlation calculated separately for each age where the earnings at age 30 are equal to the earnings in the data, and the earnings from age 31 to age 40 are 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.15. See Section 5.1 for more details. For point estimates, see Appendix Table A.14.

Figure 10: Education Gradient in Employment and Earnings Job Loss Scars by Parental Income Group, Bottom vs. Top 20%



Note: Figures show the education–job loss scar gradient in employment and earnings by parental earnings group. The individual-level job loss scar is constructed by comparing outcomes of the displaced individual and a matched individual who is not displaced using the two-step matching procedure described in Section 6. The plotted β_j estimates are obtained from a regression $s_i = \alpha + \sum_{j=1}^{4} D_{ij}\beta_j + e_i$ where s_i is the individual level job loss scar and D_{ij}s are education-level dummies. Basic education is the omitted category. Lowest tertiary is a degree that is not considered a full bachelor degree, for example in the past nursing degrees would be in this category (not received in the universities, but a post secondary degree). This category has since been abolished and nurses (for example) get a bachelors degree. We obtain the standard errors by bootstrapping 500 times.

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



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 C shows the yearly probability of working in the same industry as the father does. Panels B and D show 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 for Growth Years

	Displaced	Not displaced	P-value
	Panel A: Bottom 20%		
Age	30.797	30.752	0.480
Female	0.355	0.349	0.552
Number of children	0.861	0.909	0.054
Tenure, years	5.141	5.525	0.000
Plant size	103.417	104.453	0.673
Primary education only	0.159	0.150	0.253
Secondary education only	0.551	0.569	0.101
Tertiary education	0.288	0.279	0.367
Experience, years	10.437	10.453	0.863
Married	0.369	0.405	0.001
Real earnings in 1000s (€)	31.678	30.267	0.000
Real income in 1000s (€)	33.079	31.419	0.000
Observations	2141	188078	
	Panel B: Top 20%		
Age	30.891	30.934	0.441
Female	0.358	0.364	0.466
Number of children	0.771	0.845	0.000
Tenure, years	4.809	5.255	0.000
Plant size	103.560	116.875	0.000
Primary education only	0.101	0.092	0.092
Secondary education only	0.391	0.417	0.007
Tertiary education	0.506	0.489	0.073
Experience, years	9.019	9.073	0.511
Married	0.443	0.457	0.141
Real earnings in 1000s (€)	39.697	37.043	0.000
Real income in 1000s (€)	41.150	38.521	0.000
Observations	2707	187455	

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

	Displaced	Not displaced	P-value
Panel A: Bottom 20%			
Age	30.653	30.620	0.683
Female	0.342	0.388	0.001
Number of children	0.933	0.928	0.885
Tenure, years	4.211	4.692	0.000
Plant size	69.027	100.066	0.000
Primary education only	0.162	0.149	0.182
Secondary education only	0.558	0.563	0.709
Tertiary education	0.279	0.283	0.745
Experience, years	10.288	10.391	0.642
Married	0.442	0.427	0.282
Real earnings in 1000s (€)	30.374	30.112	0.467
Real income in 1000s (€)	32.249	31.707	0.110
Observations	1356	79911	
Panel B: Top 20%			
Age	30.445	30.453	0.902
Female	0.355	0.396	0.000
Number of children	0.772	0.809	0.122
Tenure, years	4.103	4.403	0.000
Plant size	83.992	113.756	0.000
Primary education only	0.125	0.099	0.000
Secondary education only	0.402	0.410	0.477
Tertiary education	0.472	0.487	0.204
Experience, years	9.349	9.096	0.251
Married	0.442	0.454	0.312
Real earnings in 1000s (€)	35.244	35.542	0.510
Real income in 1000s (€)	37.698	37.380	0.498
Observations	1840	103307	

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.3: The Effect of Job Loss on Employment

	(1)	(2)	(3)	(4)
Top 20				
DiD Estimate	-0.057	-0.058	-0.057	-0.056
	0.003	0.003	0.005	0.003
Bottom 20				
DiD Estimate	-0.102	-0.103	-0.103	-0.101
	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 in 1000s Top 20	2,941.413	2,941.413	2,938.229	2,938.229
N in 1000s Bottom 20	2,709.160	2,709.160	2,706.705	2,706.705
Non-displaced mean Top 20	0.965	0.965	0.965	0.965
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: region, occupation, education, industry, and field of study. 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.4: The Effect of Job Loss on Relative Earnings

	(1)	(2)	(3)	(4)
Top 20				
DiD Estimate	-0.063	-0.068	-0.067	-0.062
	0.011	0.011	0.008	0.011
Bottom 20				
DiD Estimate	-0.108	-0.112	-0.112	-0.108
	0.008	0.008	0.008	0.008
Individual fixed effects	✓			
Base year fixed effects	✓	✓		
Year fixed effects	✓	✓	✓	
Displaced fixed effects		✓	✓	✓
Controls			✓	✓
Base year $\times$ time fixed effects				✓
N in 1000s Top 20	2,941.403	2,941.403	2,938.219	2,938.219
N in 1000s Bottom 20	2,709.160	2,709.160	2,706.705	2,706.705
Non-displaced mean Top 20	1.159	1.159	1.159	1.159
Non-displaced mean Bottom 20	1.094	1.094	1.094	1.094

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: region, occupation, education, industry, and field of study. 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 Real Earnings in Thousands

	(1)	(2)	(3)	(4)
Top 20				
DiD Estimate	-2.224	-2.287	-2.251	-2.205
	0.253	0.255	0.215	0.254
Bottom 20				
DiD Estimate	-3.467	-3.551	-3.548	-3.498
	0.212	0.215	0.215	0.214
Individual fixed effects	✓			
Base year fixed effects	✓	✓		
Year fixed effects	✓	✓	✓	
Displaced fixed effects		✓	✓	✓
Controls			✓	✓
Base year $\times$ time fixed effects				✓
N in 1000s Top 20	2,941.413	2,941.413	2,938.229	2,938.229
N in 1000s Bottom 20	2,709.160	2,709.160	2,706.705	2,706.705
Non-displaced mean Top 20	37.531	37.531	37.531	37.531
Non-displaced mean Bottom 20	30.066	30.066	30.066	30.066

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: region, occupation, education, industry, and field of study. 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.6: The Effect of Job Loss on Working for Any of Father's Prior Firms

	(1)	(2)	(3)	(4)
Top 20				
DiD Estimate	-0.028	-0.029	-0.028	-0.028
	0.004	0.004	0.001	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 in 1000s Top 20	2,941.413	2,941.413	2,938.229	2,938.229
N in 1000s Bottom 20	2,709.160	2,709.160	2,706.705	2,706.705
Non-displaced mean Top 20	0.083	0.083	0.083	0.083
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: region, occupation, education, industry, and field of study. 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 Industries

	(1)	(2)	(3)	(4)
Top 20				
DiD Estimate	-0.010	-0.011	-0.011	-0.010
	0.004	0.004	0.002	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 in 1000s Top 20	2,941.413	2,941.413	2,938.229	2,938.229
N in 1000s Bottom 20	2,709.160	2,709.160	2,706.705	2,706.705
Non-displaced mean Top 20	0.084	0.084	0.084	0.084
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: region, occupation, education, industry, and field of study. 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 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	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
-2	-0.001	-0.001	-0.001	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
-1	0.000	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	-0.206	-0.131	-0.279	-0.221	-0.159	-0.068
	(0.007)	(0.006)	(0.013)	(0.010)	(0.009)	(0.006)
2	-0.144	-0.081	-0.188	-0.146	-0.113	-0.035
	(0.007)	(0.005)	(0.012)	(0.009)	(0.008)	(0.005)
3	-0.096	-0.050	-0.128	-0.089	-0.073	-0.022
	(0.006)	(0.005)	(0.011)	(0.009)	(0.008)	(0.005)
4	-0.067	-0.034	-0.091	-0.063	-0.050	-0.013
	(0.006)	(0.004)	(0.011)	(0.008)	(0.007)	(0.005)
5	-0.051	-0.023	-0.081	-0.047	-0.032	-0.007
	(0.006)	(0.004)	(0.011)	(0.008)	(0.007)	(0.005)
6	-0.046	-0.022	-0.062	-0.044	-0.036	-0.007
	(0.006)	(0.004)	(0.010)	(0.008)	(0.007)	(0.005)
N	2,709,160	2,941,413	811,012	1,047,279	1,898,148	1,894,134

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.9: 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	0.002	-0.019	0.001	-0.022	0.002	-0.016
	(0.007)	(0.006)	(0.013)	(0.009)	(0.008)	(0.007)
-2	0.005	-0.003	0.003	-0.004	0.006	-0.002
	(0.005)	(0.005)	(0.009)	(0.008)	(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	0.000	-0.010	0.004	-0.009	-0.004	-0.011
	(0.006)	(0.006)	(0.012)	(0.010)	(0.006)	(0.006)
1	-0.075	-0.049	-0.118	-0.100	-0.050	-0.015
	(0.008)	(0.010)	(0.016)	(0.020)	(0.010)	(0.009)
2	-0.185	-0.110	-0.257	-0.206	-0.140	-0.043
	(0.010)	(0.011)	(0.017)	(0.020)	(0.013)	(0.012)
3	-0.132	-0.097	-0.193	-0.178	-0.094	-0.040
	(0.011)	(0.011)	(0.017)	(0.021)	(0.014)	(0.013)
4	-0.104	-0.072	-0.168	-0.128	-0.063	-0.033
	(0.012)	(0.014)	(0.018)	(0.029)	(0.015)	(0.014)
5	-0.078	-0.056	-0.148	-0.090	-0.033	-0.033
	(0.012)	(0.017)	(0.018)	(0.036)	(0.016)	(0.015)
6	-0.064	-0.042	-0.133	-0.090	-0.021	-0.009
	(0.013)	(0.017)	(0.021)	(0.034)	(0.016)	(0.017)
N	2,709,160	2,941,403	811,012	1,047,269	1,898,148	1,894,134

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.10: The Effect of Job Loss on Real Earnings

Dependent variable: Real earnings in thousands

	All		Recession		Growth	
Time	Bottom	Top	Bottom	Top	Bottom	Top
(1)	(2)	(3)	(4)	(5)	(6)	(7)
-3	-0.348	-1.073	-0.405	-0.646	-0.282	-1.354
	(0.152)	(0.273)	(0.258)	(0.292)	(0.187)	(0.413)
-2	0.022	-0.271	0.037	-0.201	0.033	-0.321
	(0.109)	(0.305)	(0.198)	(0.236)	(0.126)	(0.486)
-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	-0.216	-0.060	-0.344	-0.451	-0.146	0.197
	(0.128)	(0.377)	(0.213)	(0.247)	(0.160)	(0.611)
1	-2.340	-1.635	-3.730	-3.408	-1.474	-0.438
	(0.206)	(0.296)	(0.343)	(0.361)	(0.256)	(0.431)
2	-5.645	-3.392	-7.815	-6.625	-4.257	-1.188
	(0.265)	(0.299)	(0.423)	(0.436)	(0.337)	(0.401)
3	-4.291	-3.301	-6.124	-5.958	-3.103	-1.486
	(0.269)	(0.370)	(0.423)	(0.427)	(0.346)	(0.545)
4	-3.629	-2.777	-5.379	-5.036	-2.501	-1.239
	(0.274)	(0.373)	(0.444)	(0.450)	(0.346)	(0.543)
5	-3.048	-2.417	-4.920	-4.546	-1.853	-0.973
	(0.282)	(0.426)	(0.449)	(0.491)	(0.361)	(0.630)
6	-2.661	-1.933	-4.648	-4.381	-1.436	-0.302
	(0.300)	(0.460)	(0.508)	(0.554)	(0.373)	(0.673)
N	2,709,160	2,941,413	811,012	1,047,279	1,898,148	1,894,134

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.11: 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	0.001	0.000	0.002	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
-2	0.000	-0.000	-0.001	0.000	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	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
1	-0.005	-0.035	-0.004	-0.044	-0.005	-0.029
	(0.002)	(0.004)	(0.002)	(0.006)	(0.002)	(0.004)
2	-0.003	-0.033	-0.003	-0.037	-0.003	-0.030
	(0.002)	(0.004)	(0.002)	(0.006)	(0.002)	(0.005)
3	-0.003	-0.029	-0.003	-0.032	-0.002	-0.027
	(0.002)	(0.004)	(0.002)	(0.006)	(0.002)	(0.005)
4	-0.003	-0.025	-0.003	-0.029	-0.003	-0.023
	(0.002)	(0.004)	(0.002)	(0.006)	(0.002)	(0.005)
5	-0.002	-0.022	0.001	-0.024	-0.003	-0.020
	(0.002)	(0.004)	(0.003)	(0.006)	(0.002)	(0.005)
6	-0.002	-0.020	0.000	-0.023	-0.004	-0.019
	(0.002)	(0.004)	(0.003)	(0.006)	(0.002)	(0.005)
N	2,709,160	2,941,413	811,012	1,047,279	1,898,148	1,894,134

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

Table A.12: The Effect of Job Loss Working for Any of Father's Prior Industries

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

	All		Recession		Growth	
Time (1)	Bottom (2)	Top (3)	Bottom (4)	Top (5)	Bottom (6)	Top (7)
-3	0.000	0.004	0.003	0.000	-0.001	0.007
	(0.001)	(0.003)	(0.002)	(0.004)	(0.002)	(0.003)
-2	-0.001	0.004	-0.001	0.003	-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	0.000	-0.006	-0.001	-0.002
	(0.001)	(0.002)	(0.001)	(0.004)	(0.001)	(0.003)
1	-0.003	-0.024	-0.003	-0.044	-0.004	-0.010
	(0.002)	(0.004)	(0.003)	(0.007)	(0.002)	(0.005)
2	0.000	-0.017	0.001	-0.032	-0.000	-0.006
	(0.002)	(0.004)	(0.003)	(0.007)	(0.003)	(0.005)
3	0.001	-0.011	0.003	-0.026	-0.000	-0.001
	(0.002)	(0.004)	(0.003)	(0.007)	(0.003)	(0.005)
4	0.002	-0.004	0.002	-0.023	0.002	0.008
	(0.002)	(0.004)	(0.003)	(0.007)	(0.003)	(0.005)
5	0.002	0.000	0.007	-0.018	-0.001	0.013
	(0.002)	(0.004)	(0.003)	(0.007)	(0.003)	(0.005)
6	0.004	0.004	0.009	-0.017	0.001	0.018
	(0.002)	(0.004)	(0.003)	(0.007)	(0.003)	(0.006)
N	2,709,160	2,941,413	811,012	1,047,279	1,898,148	1,894,134

Notes: The table shows event time coefficients underlying Figure 11 Panel D (which shows results from columns 2 and 3). We obtain the estimates from Equation (1) for adult children of top and bottom 20% separately. The outcome variable is whether the child works in 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: 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)		-1.127	1.034	0.764
		(0.132)	(0.126)	(0.269)
Post (β_6)			-3.791	-5.585
			(0.031)	(0.045)
Displaced $\times$ Post (β_7)			-3.607	-5.071
			(0.117)	(0.245)
Family rank $\times$ Displaced $\times$ Post (β_2)				0.027
				(0.004)
Family rank $\times$ Displaced (β_3)				0.006
				(0.005)
Family rank $\times$ Post $\times$ (β_4)				0.035
				(0.001)
N	15,058,295	15,058,295	15,058,295	15,058,295

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.14: Simulation Results

	Baseline Simulation	**Job Loss Simulation**
Age (1)	Rank-Rank Correlation (2)	Rank-Rank Correlation (3)
30	0.1234	0.1251 (0.0001)
31	0.1307	0.1358 (0.0001)
32	0.1382	0.1455 (0.0001)
33	0.1454	0.1539 (0.0002)
34	0.1512	0.1604 (0.0002)
35	0.1567	0.1667 (0.0001)
36	0.1632	0.1722 (0.0001)
37	0.1688	0.1769 (0.0001)
38	0.1739	0.1816 (0.0001)
39	0.1782	0.1855 (0.0001)
40	0.1823	0.1895 (0.0001)

Notes: This table displays the estimates from the simulation exercise described in Section 5.1 and shown in Figure 9. Column 1 reports the age at which the rank-rank correlation is calculated. Column 2 reports results from a simulation where the earnings of the adult children at age 30 are equal to the earnings in the data, and the earnings from age 31 to age 40 are simulated using the age-decile-specific wage growth calculations represented in Appendix Figure 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.15. 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.15: Unemployment Transition Probabilities

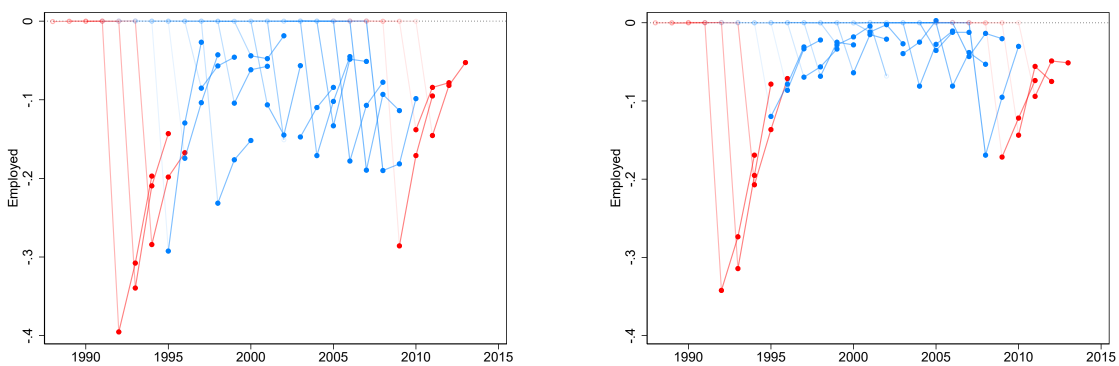
Parental Income Decile (1)	**P(Unemployed$_{t+1}$| Employed$_t$)** (2)
1 (Bottom Decile)	5.96
2	5.67
3	5.52
4	5.33
5	5.00
6	4.80
7	4.55
8	4.28
9	3.98
10 (Top Decile)	3.51

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 5.1 and shown in Figure 9 and Appendix Table A.14.

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

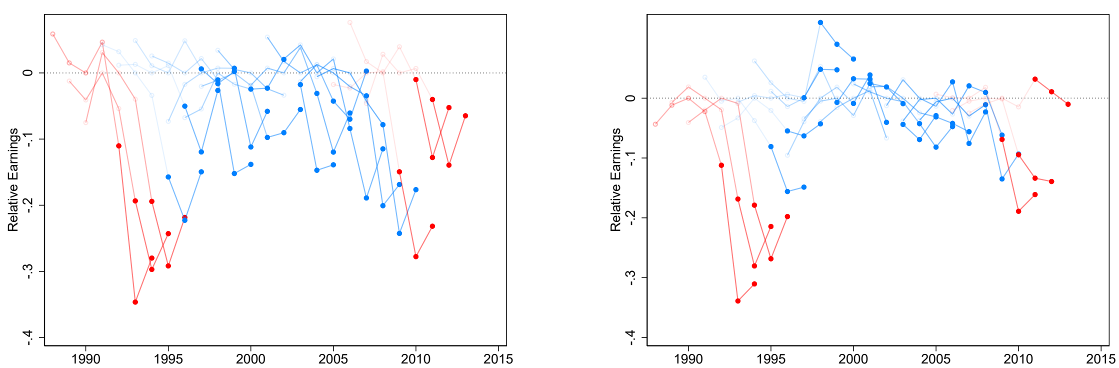
(a) Bottom 20% (b) Top 20%



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

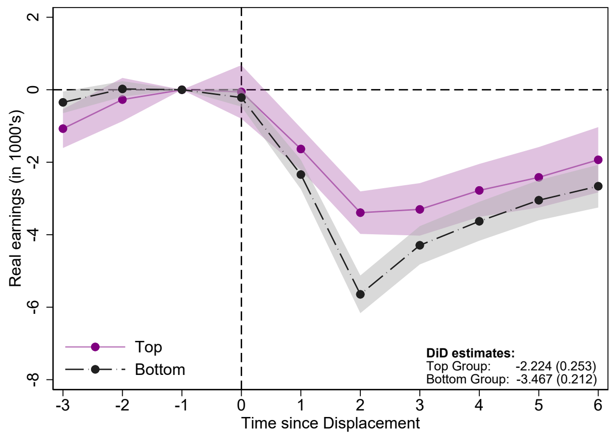
(a) Bottom 20% (b) Top 20%



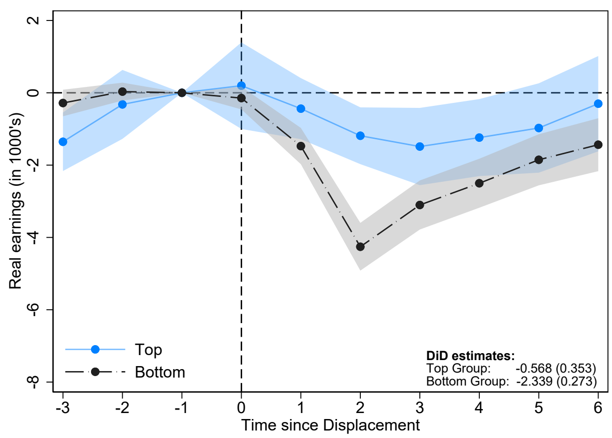
Note: Figures plot the estimates of δ_t obtained using equation 1 separately for different treatment waves. For presentation purposes, we only show the first three years after layoff. Panel A (B) shows the impact for individuals whose parents belong to the bottom (top) 20% of the income distribution.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

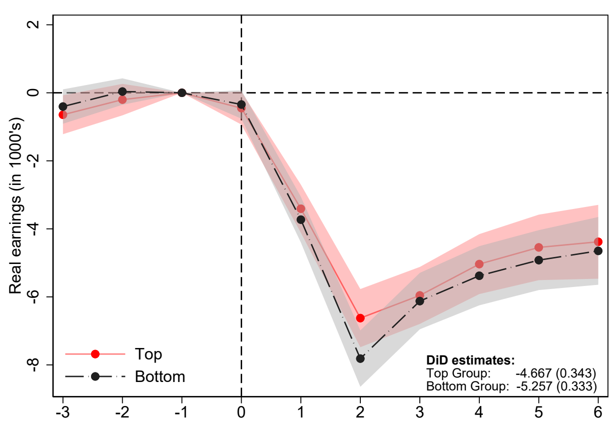
(a) All Years



(b) Growth Years



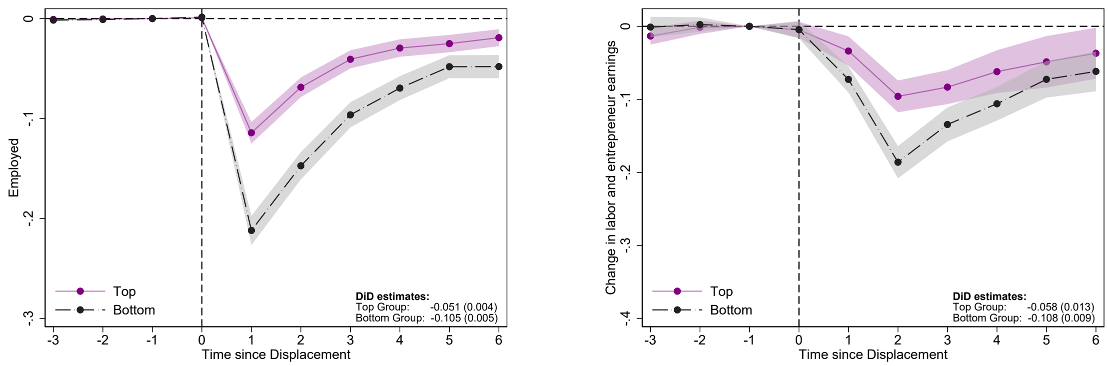
(c) Recession Years



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

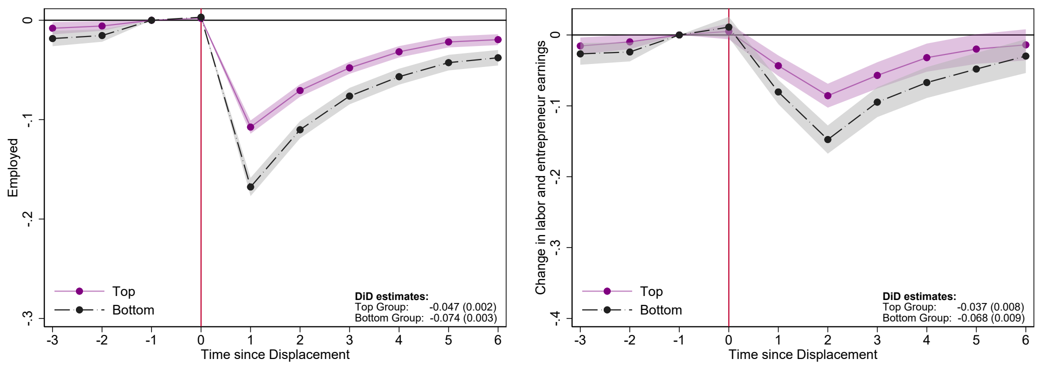
(a) Employment (b) Earnings Relative to Pre-mean



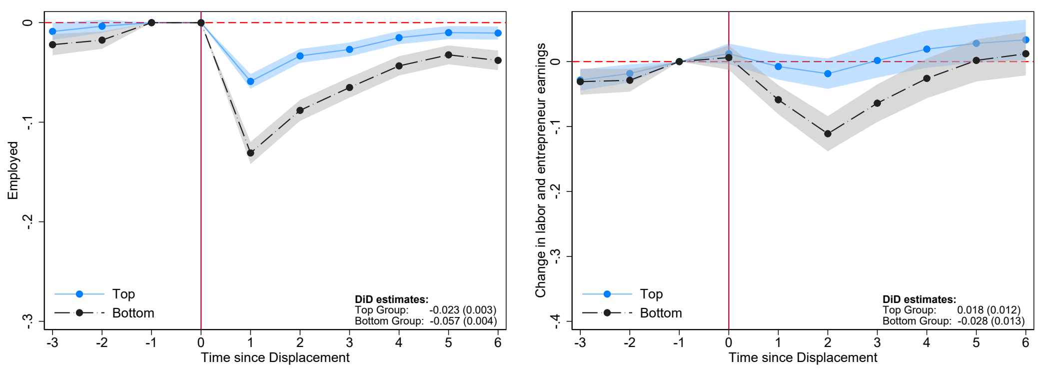
Note: Figures plot the estimated impacts of job loss on future employment and earnings and show that these results are robust to alternative approaches to defining parental income. Figures plot the estimates of δ_t obtained using Equation (1) separately for bottom and top parental income quintiles. In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

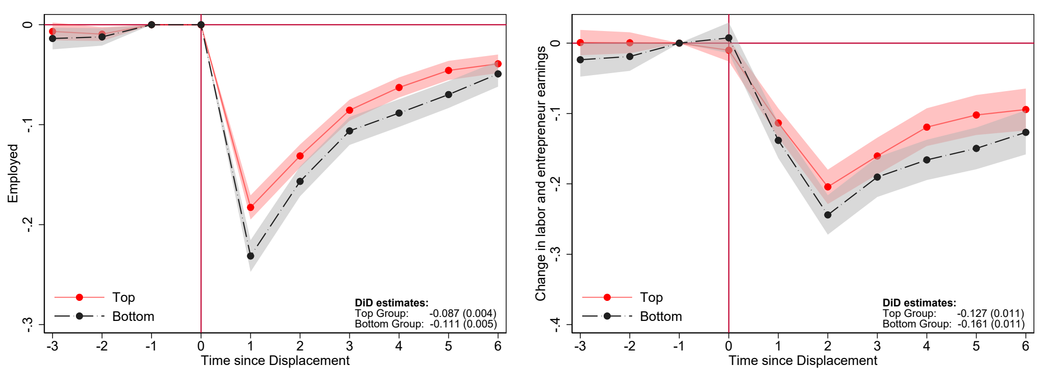
(a) Effects on Employment (Left) and Earnings (Right) for All Years



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



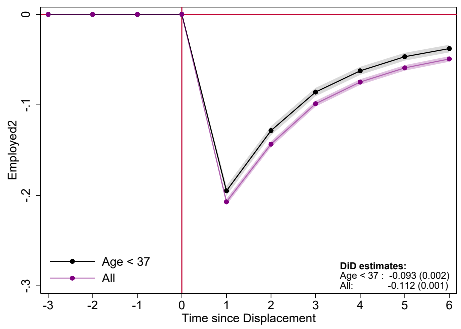
(c) Effects on Employment (Left) and Earnings (Right) for Recession Years



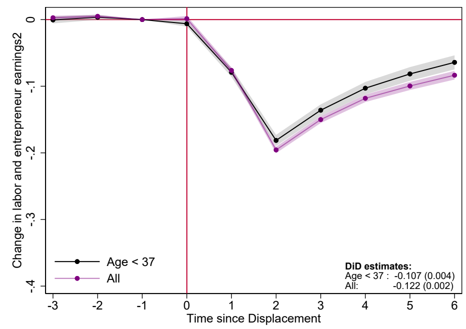
Note: Figures plot the estimated impacts of job loss on employment and earnings, and show that that these results are robust to only including 1 year of tenure before layoff as opposed to the 3 years in the main analysis. Figures plot the estimates of δ_t obtained using Equation (1) separately for bottom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

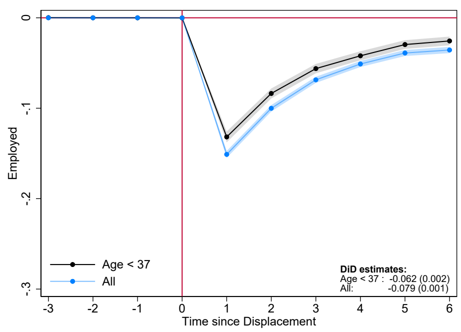
(a) Employment - All Years



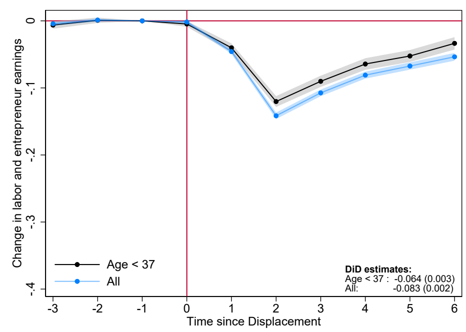
(b) Earnings - All Years



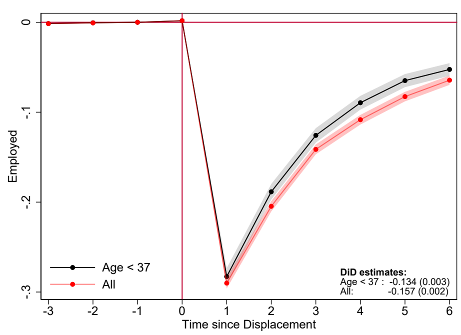
(c) Employment - Growth Years



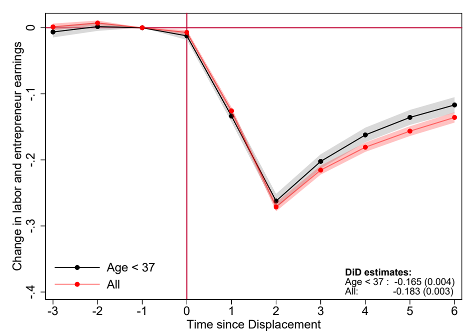
(d) Earnings - Growth Years



(e) Employment - Recession Years

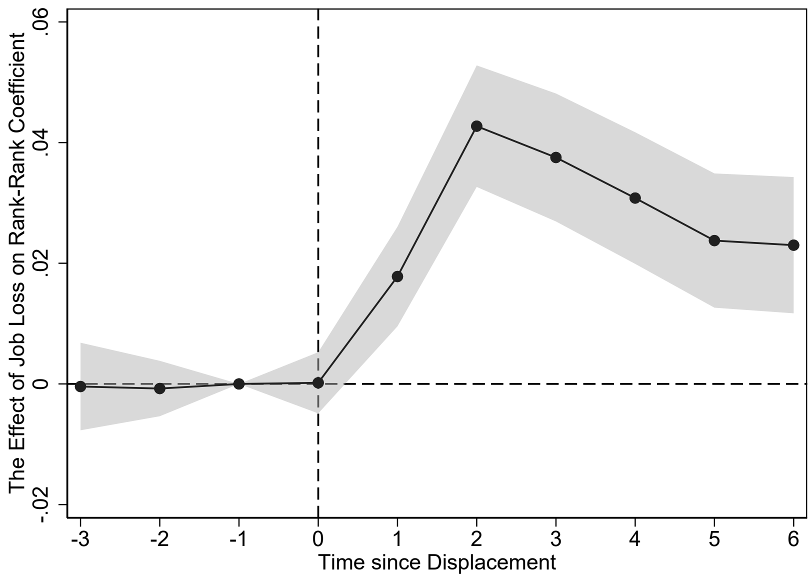


(f) Earnings - Recession Years



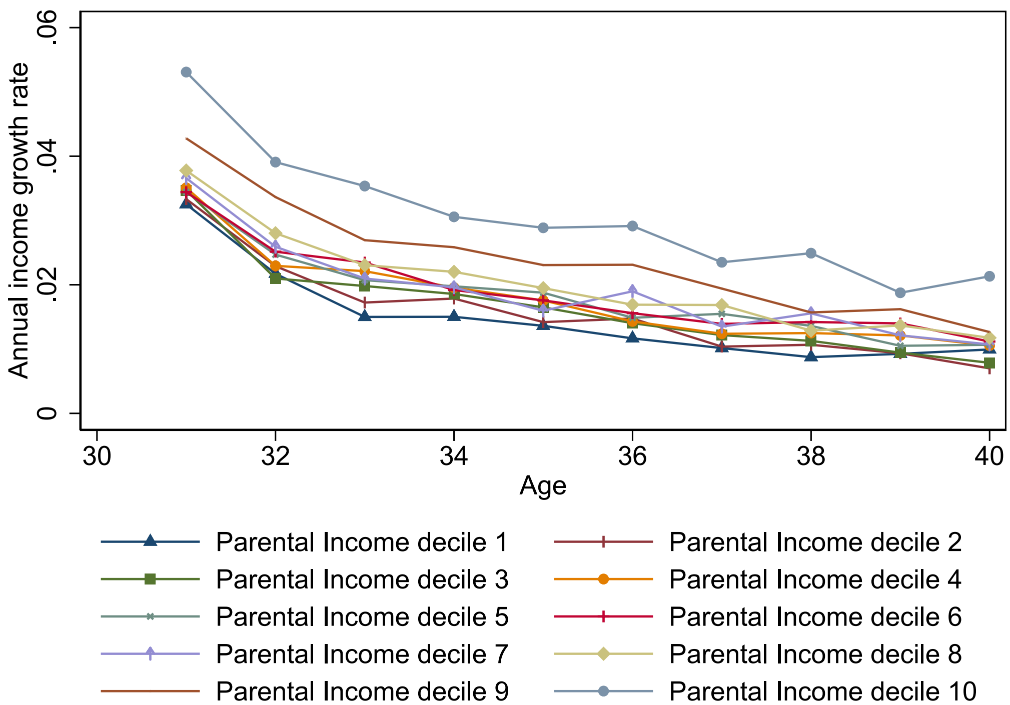
Note: Figure shows estimated impacts of job loss on future employment and earnings for the full population with all income groups for those aged 25–36 vs those aged 25–55. Panels A and B show results for layoffs in all years, Panels C and D for layoffs that occurs in growth years, and Panels E and F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

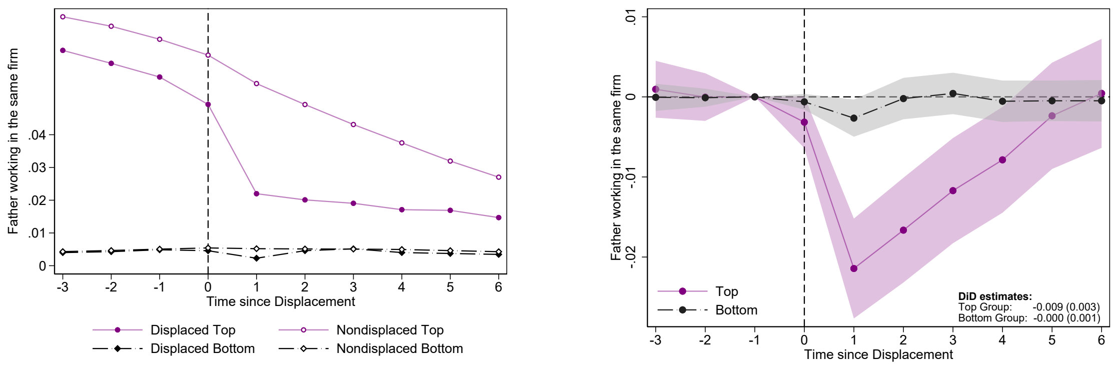


Note: This figure displays the age-decile-specific earnings growth rates. Earnings growth within each age and within each decile is calculated using the entire population. These estimated growth rates are used to produce the "Baseline Simulation" and "Job Loss Simulation" estimates as described in Section 5.1, with results reported in Figure 9 and Appendix Table A.14.

Figure B.9: 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

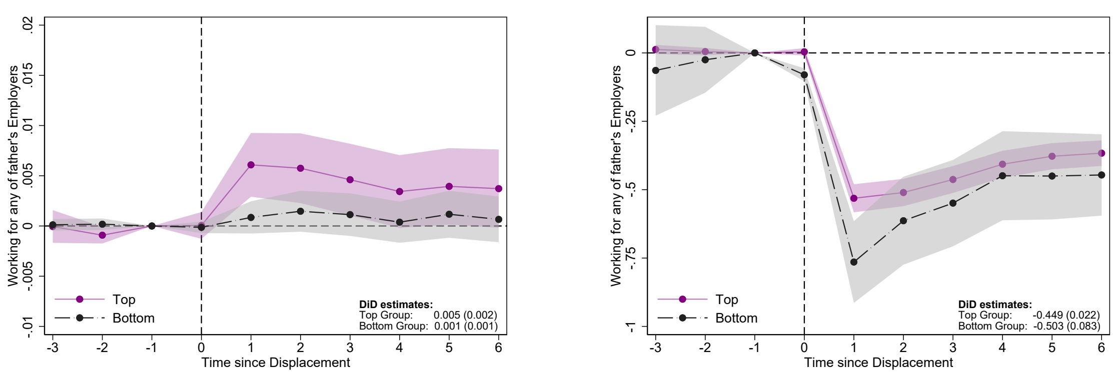


Note: Panel A shows the yearly probability of working in the same firm as the father. Panel B shows the estimates of δ_t obtained using Equation (1) separately for the top and bottom parental income groups. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard 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.10: 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

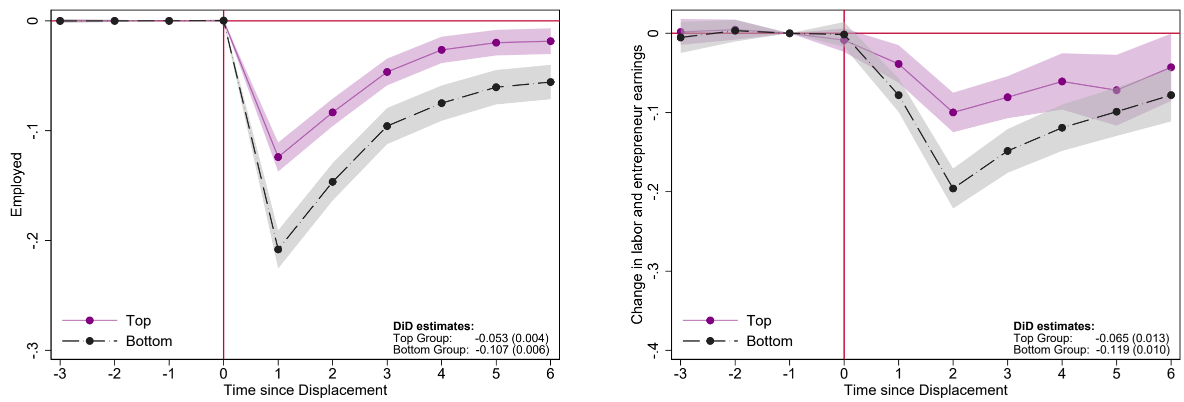


Note: Figures show the estimated impacts of job loss on the probability of working for any of the father's employers. The set of the father's employers at year t contains all employers the father has had between years 1988 and t. Estimates of δ_t obtained using Equation (1) separately for the top and 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.

Figure B.11: 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.