The Impact of an Early Career Shock on Intergenerational Mobility*

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Abstract

Children's incomes are highly correlated with their parents' incomes. Differences in the first job explain part of this intergenerational persistence in incomes, but little is known about how subsequent labor market shocks might contribute to intergenerational mobility. In this paper, we focus on a consequential early career shock, job loss. We document three results. First, those born to lower-income parents suffer more from job loss. After an exogenous job loss, adult children born to parents in the bottom 20% of the income distribution have double the unemployment compared with those born in the top 20%, with 118% higher earnings losses. Second, this causes the rank-rank correlation, a measure of persistence of incomes, to increase by 34% for those impacted and country-level rank-rank correlations to increase as children age. Third, direct interventions by parents after their child loses a job and earlier life investments both explain our main results.

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1 Introduction

Parents' and children's incomes are highly correlated (Martínez, 2021; Chetty *et al.*, 2014b; Corak, 2013; Björklund and Jäntti, 1997; Solon, 1992). Before even reaching the labor market children born into disadvantaged families experience many more challenges compared with children who are born advantaged (Black and Devereux, 2010). Much of the existing intergenerational mobility literature focuses on how these challenges in childhood translate to lower paying jobs to explain the correlation between parent and child incomes. In contrast, little is known about the role early career shocks might play in determining intergenerational persistence in incomes.

In this paper we show that focusing only on what happens in childhood to explain intergenerational persistence in incomes misses part of the story. We find that the effects of early career shocks can depend a great deal on parental background. This in turn causes intergenerational mobility to decrease as children progress in their early careers. To show this we use Finnish administrative data to link parents' and their adult children's incomes. We focus on a consequential labor market shock: job loss. Prior research indicates job loss has large and long-term impacts on future employment and earnings (Couch and Placzek, 2010; Jacobson *et al.*, 1993). This approach connects the intergenerational mobility literature to what happens within firms once the children are adults and have entered the labor market.

We present three new findings. First, we show that even 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. To do so we use an event study approach and exogenous separations due to plant closures to capture the causal impacts of job loss separately for those born to low- versus high-income parents. We find that those with parents in the top 20% of the income distribution have almost half the unemployment and their earnings rebound faster following a layoff relative to adult children of parents in the bottom 20%. These effects are persistent, with significant differences remaining in all 6 years following job loss for employment and 3 years for earnings. The earnings gap is large: The net present discounted value (PDV) of earnings losses are 118% higher for adult children born into the bottom 20% relative to the top 20%.

Large gaps in the impacts of job loss remain even conditional on similar pre-displacement incomes for adult children born to low- versus high-income parents. This suggests that the disparate impacts of job loss by parental background are not just due to children of richer parents themselves enjoying higher incomes prior to job loss. Even when children born to low-income parents obtain high-paying jobs, they still experience a larger fall in income if they lose these jobs relative to their peers with similarly high-paying jobs but who were instead born to higher-income parents.

Second, we examine the extent to which the disparate impacts of job loss we document reduce intergenerational mobility. We estimate an extension to the calculation of the correlation between the rank of the parent and the rank of the child from Chetty *et al.* (2014a) where we allow the rank-rank regression coefficient to vary with job loss.[1] Using this approach, we find that the rank-rank coefficient in the 6 years following the layoff is 34% higher for those impacted. To put this number in context, Pekkarinen *et al.* (2009) find that a major education reform in the 1970s in Finland reduced intergenerational income elasticity by 23%. Chetty and Hendren (2016) find that moving to a better neighborhood causes children's incomes to converge to their higher income peers at a rate of 4% per year in the United States.

To extend these results to country-level rank-rank measures, we run a simulation where we take all individuals at age 30 and estimate how their earnings would change from age 30 to age 40 either with no job loss in the economy, or with the impacts of job loss. We use ages 30 to 40 (as opposed to earlier ages) because in Nordic countries the rank-rank correlations do not tend to stabilize until the late 30s and many people do not join the labor market until their mid 20s (Landersø and Heckman, 2017). Our simulation captures two ways job loss impacts country-level rank-rank correlations. First, the impact of job loss depends on parental background, as discussed above. Second, the incidence of job loss is also unequal in the data, with children born into the bottom income decile almost twice as likely to experience unemployment compared with children born to the top decile.

[1] 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. We estimate the impact of job loss on intergenerational mobility using the rank-rank specification. We use the rank-rank measure of intergenerational mobility as it overcomes issues with zero earnings, which are particularly relevant when considering impacts of job loss on mobility.

We find that the overall rank-rank correlation at age 40 for the population of Finland is 3.9% higher due to the disparate impacts and incidence of job loss. This is the first paper we know of to estimate the contribution of an early career shock to a country's rank-rank correlation. Despite the prolific literature on the impacts of job loss, fortunately it is relatively uncommon to lose one's job. In our data, 6% of adult children born to the bottom decile transition into unemployment. This number decreases monotonically ending at 3.5% for the top decile. Thus, it would be implausible if job loss alone accounted for a large portion of country-level rank-rank correlations, even with the large differences in the impacts we document.

However, even if job loss is somewhat rare, it is only one of many possible labor market shocks. For example, other labor market shocks such as recessions (Kahn, 2010; Oreopoulos *et al.*, 2012), trade shocks (David *et al.*, 2013), disability (Kostol and Mogstad, 2014), and even the arrival of the internet (Bhuller *et al.*, 2021) all have large impacts on careers and could impact those born poor versus rich differently. The fact that job loss alone causes the rank-rank correlation to be 3.9% higher by age 40 provides prima facie evidence that differences in how those born poor versus rich experience their early careers beyond just the first job helps determine rank-rank correlations. Our results demonstrate that even after entering the labor force, adult children of low-income parents have a more precarious perch on the job ladder compared with children of high-income parents, with important implications for intergenerational mobility.

Third, we investigate mechanisms. There are many possible ways high-income parents could provide advantages to their children that change how their children respond to labor market shocks, from direct interventions at the time of job loss to investments in childhood. While controlling for these possible ways high-income parents might advantage their children would understate the full differences across parental income groups and thus be incorrect for the main analysis, in the last part of the paper we show how higher-income parents mitigate the impacts of job loss on their children.

To set ideas we first provide a conceptual framework. We write a model extending the canonical theoretical framework from Becker and Tomes (1979, 1986) to include shocks to adult children in the labor market and ways parents might mitigate these shocks. The model incorporates interventions by parents at the time of job loss as well as prior human capital investments, both of which we then explore empirically. First, we test whether parents intervene at the time of job loss. Parents might step in by providing housing, jobs, or cash transfers.[2] We focus on the first two since do not observe cash transfers in our data. We show that adult children born to lower-income parents are more likely to live with their parents, consistent with Kaplan (2012). We also find very small impacts of job loss on the probability of living with one's parents and no statistically significant differences in the impacts between those born poor versus rich.

Turning to jobs, children of high-income parents might bounce back faster because they are hired by their father's firm after a layoff. We initially find that children of high-income parents are less likely to work at the same firm as their father after a layoff (children of low-income parents are unaffected). However, we show that this result is mechanical: Children born to high-income parents are more likely to work in the same firm as their fathers before job loss, consistent with Staiger (2020) and Corak and Piraino (2011), meaning that when the firm closes both father and child lose their jobs and no longer work together. When we address this issue, we find that children of high-income parents are actually more likely to work in the same firm as their fathers following job loss. As such, our paper demonstrates that higher-income parents intervene more forcefully to help their children retain their higher perches in the income distribution well into adulthood. It is difficult to justify this sort of nepotism on efficiency grounds, and eradicating it could lead to greater mobility.

High-income parents could also invest more in childhood (or provide genetic advantages). These investments in the child's human capital could both help their kids land better initial jobs and also make their children more resilient to labor market shocks. Thus, we examine the role of education.[3] 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

[2]Parents might also provide information on social safety nets (Dahl *et al.*, 2014).

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

the assumptions required for such an exercise to hold. We find that approximately 28% (46%) of the difference between the two groups in employment (earnings) job loss scars is explained by observable differences in education.

The results from this paper contribute to our understanding of how inequality transmits across generations. As such this paper is most closely related to the intergenerational mobility literature (Black and Devereux, 2010; Corak, 2013; Jäntti and Jenkins, 2015; Cholli and Durlauf, 2022). Much of this literature focuses on quantifying the amount of intergenerational mobility across time and space (Davis and Mazumder, 2022; Jäntti and Jenkins, 2015; Chetty *et al.*, 2014a; Corak *et al.*, 2014; Aaronson and Mazumder, 2008), and measurement issues (Jácome *et al.*, 2021; Ward, 2021; Deutscher and Mazumder, 2021; Nybom and Stuhler, 2017). Relative to these papers it is worth noting that overall intergenerational mobility in Finland, as measured by the rank-rank correlation, is two-thirds the size of the same figure for the United States.[4] Thus even in Nordic countries where mobility is higher this is still an important phenomenon.

Our contribution is more closely related to a smaller set of papers examining what contributes to this intergenerational persistence in incomes. These papers have focused on what happens in childhood. For example, geographic location during childhood plays a role in determining intergenerational mobility (Chyn, 2018; Chetty *et al.*, 2016, 2014a; Ludwig *et al.*, 2013; Katz *et al.*, 2001). Black *et al.* (2019) find that environmental factors in early life explain much more of intergenerational wealth transmission compared with inherent talent. Carneiro *et al.* (2021) show that not only do the total investments in childhood matter for intergenerational transmission of incomes, but the timing of these investments during childhood is important.

We show that the importance of parental background and parental investments follow children well into their careers. The impact of labor market shocks during adulthood is determined in part by parental income and investments, leading to lower mobility and a vicious cycle. These results have two implications for the broader literature. First, our results indicate the importance of focusing on the contributions of early career shocks in adulthood to overall intergenerational mobility, whereas much of the prior literature has focused on the relative contributions of differ-

[4]We find the rank-rank correlation is 0.19 in the full sample. For comparison, the equivalent estimate for the United States in Chetty *et al.* (2014a) is 0.287 (see Table 1 row 7 of that paper).

ent childhood experiences.[5] Second, our results contribute to a rich debate on when in the adult child's life these correlations should be calculated and what you might capture at different ages. Our results suggest that while measuring intergenerational mobility correlations when children are in their twenties or early thirties is interesting[6], these measures will not fully capture lifetime mobility for substantive reasons, and not just due to measurement error.[7]

We also contribute to the job loss literature. Many papers have documented that layoffs lead to long-term losses in both employment and earnings (Lachowska *et al.*, 2020; Couch and Placzek, 2010; Jacobson *et al.*, 1993).[8] We extend this literature in two ways. First, we show that job loss causes worse outcomes for those born to lower-income parents, even conditional on similar pre-displacement earnings. While a number of papers explore the reverse direction, i.e. the impacts of a parent losing their job on their child's outcomes (Willage and Willén, 2020; Huttunen and Riukula, 2019; Lindo, 2011; Rege *et al.*, 2011; Oreopoulos *et al.*, 2008), this is the first paper to ask whether adult children might benefit from having wealthier parents when they experience job loss. By showing disparate impacts by parental income, we contribute to a broader literature examining who suffers the most from job loss. For example, Hoynes *et al.* (2012) show that men, Black and Hispanic workers, and low educated workers are more affected by job loss. More importantly, we show that these differences in the impacts of job loss have important implications for intergenerational mobility. Our results suggest that early career shocks like job loss play a role in explaining intergenerational persistence in incomes. Second, we provide a methodological extension of the Blinder-Oaxaca decomposition to analyze mechanisms that can easily be used in other applications.

[5]Related is a discussion of the dynamics of labor market earnings across income groups. For example, Halvorsen *et al.* (2021) find that children of wealthier parents are more likely to pursue high-risk, high-reward jobs.

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

[7]The notion that the time at which income is measured might matter is consistent with the idea that current income may not accurately capture long-run income. For example, Haider and Solon (2006) state that "the association between parents' and children's long-run income is susceptible to dramatic underestimation when current income variables are used as proxies for long-run income." The evidence in our paper shows a substantive reason why this may be the case beyond just measurement error: Labor market shocks can differentially impact permanent incomes. Related to the results in this paper, Bütikofer *et al.* (2018) find that a large positive economic shock (the Norwegian oil boom) in adulthood has positive impacts on mobility.

[8]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).

2 Data and Institutional Context

2.1 Data and Measurement of Income Ranks

We use Finnish linked employer-employee data (known as FLEED), which covers all Finnish residents between the ages of 16 and 70 years in the period 1988–2016.[9] The unique person identification codes allow us to follow individuals over time and link to their parents' incomes. Unique firm and plant codes allow us to identify each worker's employer and observe job separations.

We restrict to those aged 25-35 to form our "adult children" sample. We restrict to ages 25-35 for two reasons. First, the earnings data is only available from 1988 onward and we need to calculate their parents' earnings before their parents reach retirement age, which is only possible for adult children at younger ages. More substantively, we are interested in early career shocks. We focus on the early career given that age-wage profiles show that wages increase rapidly in the beginning of the career, peaking in the forties, and thereafter decline (Johnson and Neumark, 1996). Moreover, rank-rank correlations tend to stabilize after the early career (in Nordic countries in the late 30s). Together, these statistical facts suggest that one's early career plays a disproportionate role in determining lifetime incomes.

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.[10] Parental earnings, like child earnings, come from FLEED, administrative data covering all Finnish residents. We are able to match biological parents to children using unique identifiers established at birth. We measure parental earnings by taking the average of total labor market earnings of both parents from 1988 until the year of the displacement of their adult child. We rank the resulting average earnings to assign each child a parental income rank comparing to other parents within the child's birth cohort. For the first set of results we will focus on adult children in the bottom and top 20% in terms of parental income rank. Table B.1 provides summary statistics for these estimation

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

[10] We restrict to heterosexual parents as it is more straightforward to build earnings panels for these parents. This excludes a very small number of same-sex parent households. We do not alter parental earnings calculations in response to family breakup, and use biological parents throughout.

samples of adult children.[11] We find that our results are robust to many alternative ways to define the parental income rank, both in terms of when the income of the parents is measured as well as what we include in parental income. For example, we show our results are robust to including taxable benefits in addition to labor market earnings when defining parental income groups, and are similarly robust to only using the years 1988-1990 to calculate the average earnings of parents. We have also replicated the results using only the earnings of the father at age 55.[12]

We do not use lifetime earnings for the parents to calculate ranks because we do not observe them in our data. Instead, as described above, we take average earnings over a number of years to assign the rank of the parents within child-birth cohorts. Many papers in the intergenerational mobility literature do not observe lifetime incomes of parents (and in some cases don't observe any incomes for parents and instead impute them). Instead, "the ideal data set should contain several years of income for both parents and children, preferably measured around the middle of their careers" (Mogstad and Torsvik, 2021, p. 13). For parents this is what we do, as we are using several years of incomes for the parents in their middle to late careers.

For the adult children, we also do not observe lifetime earnings. However, one of the main questions this paper seeks to answer is whether adult child ranks might change substantially in their early careers precisely because early life shocks have persistently different impacts on incomes of children of low- versus high-income parents. If we wish to capture the impact of early career shocks on rank-rank correlations as they happen, one way to do so is to observe how an adult child's income rank within their own birth cohort changes over time before and after a shock. This is precisely what we do. Generally, our approach in terms of measurement of rank of parent and child is consistent with Chetty *et al.* (2014a), although we differ slightly in timing.[13]

[11]Descriptive statistics for growth years (recession years) appear in Appendix Table B.2 (Appendix Table B.3).

[12]While measurement in this literature is taken very seriously, for example see Jácome *et al.* (2021), Ward (2021), and Deutscher and Mazumder (2021) for discussions of some of these issues, we find that our results are robust to all alternative measurement approaches we are able to implement.

[13]Chetty *et al.* (2014a) measure child earnings primarily for ages 21-22 or 31-32, whereas we focus on child earnings up to age 40 and examine how the child's rank changes due to the job loss shock, for the reasons described in the text. According to Chetty *et al.* (2014a) earnings stabilize in the early 30s in the United States. This implies that labor market shocks might not matter as much for rank-rank correlations in later ages, and is consistent with our focus on early career shocks. We include up to age 40 (and do not stop in the early 30s) because people enter the labor market later and earnings stabilize at older ages in Nordic countries compared with the United States. Chetty *et al.* (2014a) measure parents' incomes as the mean income when the children are between the ages of 15 and 20. We

2.2 Job Loss and Plant Closures

Consistent with much of the literature on job loss, to identify causal impacts of job loss we focus on adult children who are displaced. Displaced workers are defined as individuals who involuntarily separate from their jobs due to an exogenous shock, specifically a plant closure.[14] A plant closure is likely an exogenous shock to a worker's career since it results in separation of all the plant's workers and is not related to the worker's own job performance. To define plant closures, we observe all (Finnish) private sector plants from 1988 to 2016. A plant is a production unit (for goods or services) that is owned by one firm (or enterprise), is located on one site, and operates within one industry. A plant is defined as closing in year t if it is in the data in year t but is no longer there in year $t + 1$ or in any of the years after $t + 1$. We also confirm that these are real plant closures. Those plant closures for which 70% or more of the workforce is working in a single new plant in the following year are not included.[15]

We label workers "displaced" if their plant closed down during t and $t+1$, or if they separated from a plant during t and $t + 1$ that closed down the next year between $t + 1$ and $t + 2$ and that reduced its workforce by more than 30% between t and $t+1$ ("early leavers"), similar to Huttunen and Kellokumpu (2016) and Huttunen *et al.* (2018) . We focus on people working in Finland in the years 1991–2010. We label these years "base years," b. 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 three or more years of tenure in base year b. We relax this assumption to only 1 year of tenure in a robustness check and results are identical.

As with prior papers on job loss, our control group of non-displaced workers consists of all workers who were not displaced between years t and $t + 1$ and meet the same tenure and plant size restrictions as the displaced workers. Importantly, we allow workers in the control group to

calculate mean income for parents over a longer period and do not restrict to specific child ages. However, we do not believe this will cause substantial differences in parent ranks given that when we use father's income only at age 55 or just the years 1988-1990 we get similar results. We only include labor market earnings in the main specification, but results are unchanged if we also include benefits, which we discuss in the text. We refer the interested reader to Section IV.B of Chetty *et al.* (2014a) for a lengthy discussion of measurement in this literature.

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

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

separate for reasons other than displacement, including voluntary job changes and sickness. In robustness checks we also use the matching procedure from Schmieder *et al.* (2018) to construct the control group and find that the results are identical.

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 20 base-year samples for the years 1991-2010 into a panel spanning the years 1988–2016.

Our analysis in Section 4 of the impacts of job loss considers three outcomes for the adult children. First, we look at an individual's employment status as measured at the end of the calendar year. Second, we construct an individual's relative earnings by comparing that individual's labor and entrepreneurial earnings each year with his average annual labor and entrepreneur earnings in the 3 years before the layoff. For this measure all earnings are deflated to 2013 euros using the consumer price index. This earnings measure gives a relative interpretation of magnitudes while still allowing us to include those who have zero earnings. Third, we estimate impacts on the adult child's earnings rank. We construct the individual's yearly earnings rank by comparing an individual's labor earnings relative to the full population of individuals in Finland in the same birth cohort.

2.3 Institutional Context

It is useful to first characterize the relationship between parent and child income in Finland for the full population and also for our estimation sample prior to the job loss shock. In Figure 1 Panel A we show the percentage of working adult children (our estimation sample) in each earnings quintile in early adulthood, separately for those born to parents in different earnings quintiles as specified on the x-axis.[16] Notably, almost none of the children born into the bottom 20% who have jobs (a necessary precursor to job loss) remain in the bottom 20% as adults. Over 80% of these children have moved out of the bottom two quintiles by their mid-thirties.[17] This

[16]Figure 1 restricts to adult children from our estimation sample as described in Section 3. The figure would look different if we were to include the full population. In particular, restricting to those who are employed (a necessary precursor to job loss) is a major reason why so few adult children are in the bottom 20%.

[17]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

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

Next, consider Figure 1 Panel B, which graphs the rank-rank correlation as in Chetty *et al.* (2014a) for our estimation sample and the full population. The overall rank-rank correlation we estimate of 0.190 for the full population in Finland is two-thirds the size of the equivalent correlation in the United States,[18] and thus indicates a substantial role for parental incomes in determining the child's income in Finland. The correlation between the rank of the parents and the rank of the child for the estimation sample of 0.122 is far from 0, suggesting parental income still plays a role in determining the child's future income, even conditional on obtaining a job.

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

Since we focus on the effects of job loss as our labor market shock in this paper, it is also useful 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. 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

other Nordic countries experience more intergenerational mobility than the United States.

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

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.[19] GDP dropped by 5.9% in 1991 and by 0.7% further in 1993.[20] Starting in 1994, Finland went through a recovery phase that lasted until the first years of the 2000s. During the recovery period, 1994–2007, the Finnish growth rate averaged 4%, higher than the European Union average. The unemployment rate stayed at a higher rate than before the depression and reached its lowest point (6.4%) in 2008, after which it started growing again. In that year, Finland was hit by the global crisis, and in 2009 GDP dropped by 8.1%, the largest annual drop since 1918 and the Finnish Civil War. The unemployment rate rose to 8.5% in 2010. In our analysis we will look at all years for our main results, but will also estimate the effects separately for growth and recession years.

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

3 Empirical Strategy to Identify Impacts of Job Loss

Figure 2 presents descriptive results on the impact of job loss due to plant closures for adult children born to parents in the top 20% of the income distribution versus adult children born in the bottom 20%. Plant closures are unlikely to be related to individual worker productivity and thus

[19]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`.

[20]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`.

capture quasi-random job loss. Figure 2 also shows the evolution of labor market outcomes for the control group of adult children not displaced by layoffs due to plant closures. The figure shows that adult children whose parents are in the bottom 20% of the income distribution experience much larger and longer-term decreases in employment and earnings following a displacement. However, these results, while evocative, are merely descriptive.

To formally identify the labor market effects of job loss, and how these might differ between children of low- and high-income parents, we use an event-study-style fixed effects regression:

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

where Y_{ibt} is the outcome variable for worker i in base-year sample b at time t. The variables $D_{b,t+j}$ indicate whether an individual was displaced in year $t+j$, t being the observation year. The parameters of interest are the δ_js that measure, for example, the earnings differentials of displaced workers relative to non-displaced workers in pre- and post-displacement years $j \in [-3, ..., 6]$. The period $t-1$ is used as the baseline and thus the displacement dummy for this year is dropped. To identify the impact for children of low- and high-income parents, equation 1 is estimated separately for individuals whose parents belong to the bottom and top 20% of the earnings distribution.

The specification also includes year dummies, γ_t, and base year fixed effects, π_b, to ensure a comparison between the earnings of displaced and non-displaced workers in the same base-year sample and with the same distance to the base year (-3 to 6 years).[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 current-year age fixed effects. Standard errors are clustered by individual i to allow for the correlation of the error terms, ϵ_{ibt}, across different time periods t and base years b for individual i.

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

Our key identifying assumption is that displaced and non-displaced individuals' outcomes would have similar trends in the absence of plant closure. We provide visual evidence that the outcomes for displaced and non-displaced groups were evolving very similarly before the displacement shock, suggesting that they would have followed similar trajectories had the plant closure not taken place. We also show that estimates are identical when we use alternative control groups in robustness checks, such as using matching as in Schmieder *et al.* (2018).

The event study estimates based on equation 1 are the main estimates of interest, but difference-in-difference (DiD) estimates are also reported for each specification in the graphs (detailed estimates reported in Appendix Tables B.4-B.8). The DiD estimates are based on differences between displaced and non-displaced workers after versus before the layoff. These estimates are reported throughout the paper as an alternative measure of the disparate impacts. A recent literature suggests that event study estimates may be severely biased if the timing of the treatment is staggered and treatment effects are heterogeneous or evolve over time (Sun and Abraham, 2020; Goodman-Bacon, 2018). To ensure staggered treatment is not a problem in this application, the data is constructed so that comparisons always occur between treated and never-treated individuals.

In addition to using matching as a robustness check (Schmieder *et al.*, 2018), we also add base-year characteristics X_{ibt} such as gender, tenure, education level, and industry, and individual fixed effects are removed.[22] The results are unchanged with these robustness exercises (see Appendix Figure C.5).

This approach recovers the causal impacts of job loss separately for those born to low- versus high-income parents. In Section 5 we present our empirical strategy to use these estimates to understand the impacts of this early career shock on intergenerational mobility.

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

4 Impacts of Job Loss

4.1 Employment and Earnings

Figure 3 shows the impact of a layoff on employment and earnings in the next 6 years for individuals with low- versus high-income parents. The figures show a complete absence of pre-trends, an affirmation that the no-anticipation assumption necessary for the event study to identify the effects holds in this setting. While the absence of pre-trends is mechanical for employment, that is not the case for earnings. Moreover, when we do not impose the assumption of 3 years of employment prior to the layoff in Appendix Figure C.6, we still see a complete absence of pre-trends. Those who are laid off experience an immediate and large negative effect on employment and earnings. These effects are persistent, lasting at least six years.

However, the impact is much more pronounced for individuals with parents in the bottom 20% of the income distribution compared to those in the top 20%. Individuals with low-income parents have almost double the non-employment compared with individuals with high-income parents. This result is not necessarily obvious a priori. A standard job search model where children of the top 20% and the bottom 20% are similar except that the top 20% have access to a stronger safety net could predict that the top 20% 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. The differences are significant at the 95% level in the first three years post layoff for earnings and for at least six years post layoff for employment.

The impact is large in absolute terms as well. In the first year post layoff 20.7% of adult children of low-income parents are still not employed relative to the control group. The comparable number for adult children of high-income parents is 11.4%. In the second year post layoff, those with low-income parents have an 18.4% drop in earnings relative to their average earnings in the 3 years preceding the layoff compared with an 8.9% drop in earnings for those with high-income parents (see also Table B.10). These results indicate a key way in which intergenerational mobility might be reduced. If adult children of lower-income parents have a looser grip on the job ladder leading to greater scarring following a labor market shock such as job loss, then this will exacerbate intergenerational inequality. We explore this in more detail in Section 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 these estimates show that those with parents in the bottom 20% experience a 10 percentage point average drop in employment (relative to the control group) versus a 4.9 percentage point average drop for the top 20%. This represents a 104% larger increase in non-employment for those with parents in the bottom versus the top group, and the difference is statistically significant. The reduction in earnings in the six years post layoff is 112% higher for those whose parents are in the bottom versus the top income group, and again, this difference is statistically significant.[23]

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%. The overall takeaway is consistent: adult children of lower-income parents experience larger impacts of layoffs in terms of both employment and earnings no matter the income cutoffs.

Motivated by the finding in the job loss literature that the impact of job loss varies with underlying 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 when 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.[24]

Figure 6 documents an interesting pattern between the state of the economy when the displacement occurred and the disparate impact of job loss.[25] 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 dif-

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

[24]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 do no include the 2012–2014 recession years.

[25]Appendix Figures C.1-C.2 show yearly event studies.

ferences between adult children of low- versus high-income parents are much more pronounced in growth years compared with recession years, as demonstrated by both the event study graphs and the DiD estimates. The DiD estimates show that the employment drop is 3 times larger for low-income children compared with high-income children in growth years. In contrast, in recession years the employment drop is 1.5 times higher for low-income children compared with high income children. When it comes to earnings, the earnings drop is 3.4 times larger for low-income children in growth years, and 1.6 times larger for low-income children in recession years. These heterogeneous results are consistent with the possibility that during recession years, it is simply much more difficult to find a new job, much less a well-paying new job, compared with growth years. Thus, it may be that in recession years there is only so much that family connections and other advantages can do for children of high-income parents.[26]

4.2 Earnings Inequality

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

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

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

For these results we use a slightly different estimation strategy. We match each displaced individual to a counterfactual non-displaced individual following a two-step matching estimator, similar to Schmieder *et al.* (2018). In the first step, we restrict the pool of potential matches to be consistent with the main analysis–for example, they must have 3 years of tenure in a private sector firm 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. We then estimate event-

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

study or DiD results using the displaced individual and their counterfactual matched control. This alternative matching approach yields identical results (see Appendix Figure C.5), but is necessary if we want to recover counterfactual earnings streams which we use below and are reported in column 3 of Table 1.

Table 1, column 1, presents estimates of the PDV for children of parents in the bottom versus the top 20%. In the 6 years post layoff, the estimates show that adult children with parents in the bottom 20% experience a PDV of job loss of €17,667 compared with a PDV of €8,096 for children with parents in the top 20%. Thus, the bottom 20% experiences 118% higher PDV earnings losses compared with the top 20%. As an alternative way to interpret the scale of these results, we next scale the PDV losses using average earnings for the two groups in the 3 years before the layoff. Column 2 shows that those with parents in the top 20% lose just under a fourth of a year's pre-layoff earnings, while those with parents in the bottom 20% lose almost two thirds a year's pre-layoff earnings. These numbers correspond to PDV earnings losses that are 159% higher for adult children in the bottom 20% in terms of pre-layoff earnings.

Next, we estimate the impact on earnings inequality. First, we estimate equation 3 for those who lose their jobs. Then we use the matched counterfactual earnings (Schmieder *et al.*, 2018) and estimate equation 3 had each person not lost their job. Formally, we estimate:

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

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

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

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

4.3 Ranks

Figure 7 plots the results of event studies showing how the percentile rank changes after a layoff for adult children of parents in the bottom versus top 20%. The percentile rank is defined as one's rank in the distribution of income for one's birth cohort. The figure shows that while both groups experience a drop in percentile rank following a layoff, the effects are larger for adult children of parents in the bottom 20%, and the difference is statistically significant in all 6 years post layoff.

An interesting question is whether we still see different impacts of job loss on income ranks for those born to lower- versus higher-income parents even when they have similar pre-displacement income ranks. If there were no differences conditional on pre-displacement rank, then the overall impact on the rank we found in Figure 7 would primarily be a "composition" effect, i.e., it could be fully explained by the observable differences in pre-displacement ranks across the two groups. While pre-layoff income rank is potentially a treatment effect of having higher-income parents and as such should not be controlled for in the main analysis, it is informative to see if the costs of job loss differ even when we compare those with similar ranks themselves (but born to different parental income groups) prior to displacement.

To address this question, we again estimate the impact of job loss on one's own income rank, but this time condition on the rank of the child before job loss. We show these results in Figure 8. We find that in every case there is a gap in the job scar conditional on pre-displacement rank, and this is especially stark (and significant) at the top two thirds of the pre-displacement income rank distribution. Thus, these results suggest that there is a "level" effect in the sense that even among those in the same pre-displacement rank there is still a difference in the impact of job loss depending on if you are born poor versus rich.

We further explore these ideas in Table 2, which presents a five-by-five grid of parent by child ranks. In the five columns are the parent's quintile of income from the bottom 20% to the top 20%

for all quintiles (and not just the bottom and top 20%). In rows are the child's pre-displacement income rank. For example, the top left entry is the DiD estimate for children born into the bottom 20% who themselves are in the bottom 20% prior to displacement, while in the bottom left corner are children born into the bottom 20% who are themselves in the top 20% prior to displacement. Each entry in the table is a separate DiD estimate of the impact of job loss on the rank of the child within their birth cohort in the six years post layoff for the specified parental income group and child pre-displacement income group.

This table illustrates two main facts. First, it is striking that within each row when we move from the left to the right the DiD estimates tend to decrease. While this this is not true for 100% of cases, the pattern is clear. These results show that even when we keep the child's pre-displacement quintile fixed, as we move from children born to poorer parents towards children born to richer parents the impacts of job loss decrease. Thus, our results are not simply capturing the fact that children who are born to lower-income parents are themselves more likely to obtain lower-paying first jobs as adults, with anyone who is in a lower-paying job experiencing larger impacts of job loss. Even conditional on similar pre-displacement incomes, we still see that those who are born to higher-income parents suffer less following job loss.

Second, we see that within each column as we move down the column, the impact of job loss increases. This suggests that within a given parental income quintile, those who have higher-paying jobs prior to displacement experience larger negative impacts on their ranks post-displacement. These results indicate that those with higher paying jobs have more to lose from displacement, and this appears to be generally true across parental income quintiles.

4.4 Robustness

We perform several robustness checks of our results, which can be found in the Appendix. Figure C.3 shows that the results are robust to alternative measures of earnings for the adult child such as real earnings as opposed to relative earnings. Figure C.4 shows that our results hold if we use alternative approaches to assign parental income ranks. Figure C.6 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. The latter restriction is standard in the job loss literature which is why we use it in our main estimates, but relaxing this assumption is particularly relevant in this context where there might be less attachment to the labor force among adult children from low-income backgrounds. Together, these robustness checks suggest that no matter how we approach the data, we always find similarly sized gaps in the impacts of job loss on employment and earnings between adult children of low- versus high-income parents.

Figure C.7 depicts the overall job loss scar without separating into low- versus high-income parents. We present estimates for those between 25–35 (as in our main results, where the younger ages are necessary to link to parental incomes) but also for all ages. We find significant scarring and much more persistent earnings losses when we expand to all ages. This result is consistent with earlier work showing that older workers suffer more following a displacement (see, e.g., Chan and Huff Stevens 2001).

5 Impacts on Intergenerational Mobility

5.1 Impacts of Job Loss on the Rank-Rank Correlation

What are the implications of our estimates for intergenerational mobility? While the figures described in Subsection 4.3 were revealing, we can estimate the impact of the differential impacts of job loss on intergenerational mobility directly within a rank-rank regression framework and expand the analysis to consider all parental income ranks jointly. 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:

$$R_C = \alpha + \beta_1 R_P + \beta_2 R_P D_C Post + \beta_3 R_P D_C + \beta_4 R_P Post + \beta_5 D_C + \beta_6 Post + \beta_7 D_C Post + \varepsilon_i. \quad (7)$$

This exercise is similar 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. Using ranks addresses issues with zero earnings, which is particularly relevant in the context of job loss. Rank-rank correlations are also a better measure if parental and child earnings are not measured at the same age, as is this case in this context (Nybom and Stuhler, 2017).

Table 3 reports results from this exercise.[27] We first note that as in previous work, there is a large and significant positive correlation between the income rank of parents and that of their child captured by β_1 which is equal to 0.094. Note that this estimate is lower than for the full population estimate of 0.190 as seen in Figure 1, which is two-thirds the size of the equivalent estimate in the United States.[28] The differences arise because our estimation sample restricts to those who work (a necessary pre-condition to experience job loss) and we focus on labor market earnings only. If we instead include all income the coefficient increases to 0.122 for our estimation sample (see Figure 1). As discussed in Section 2, the lower estimates of rank-rank correlations for our estimation sample compared with the full population suggest that obtaining a job serves as something of an equalizer, although there is still intergenerational persistence in incomes.

[27] The higher number of observations compared with Table B.1 is because each displaced and non-displaced individual appears each year as a separate observation and we include adult children from all parental income quintiles.

[28] See Table 1 row 7 of Chetty *et al.* (2014a) which reports the equivalent estimate for the United States of 0.287.

Presumably negative labor market shocks reduce everyone's upward mobility. To that end, we next find that a layoff leads to very large, negative, and significant impacts on the adult child's rank, captured by β_7. This is consistent with our earlier results but extends the analysis to the full population.

In this paper we investigate whether those who come from lower-income backgrounds, conditional on entering the labor market and achieving a good degree of upward mobility as a result, are as secure in their positions when labor market shocks hit. If they aren't, then what is the impact on intergenerational mobility? The answer to this question is captured by the main regression coefficient of interest, 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). β_2 is 0.032 and is statistically significant. The fact that it is positive means that layoffs are experienced differently by adult children of low- and high-income parents, and as a result there is an increase in the correlation between the percentile income rank of the parents and the percentile rank of the child. Conceptually, this effect is equivalent to job loss causing the slope of the line representing the relationship between parents and child rank to grow steeper. Compared to the overall rank-rank correlation of 0.094, our results suggest that intergenerational mobility decreases by 34%[29] as a result of job loss.

The results from Table 3 show the overall impact of job loss on intergenerational mobility. We might also be interested in the yearly effects because our main results show that the gaps in the impacts of job loss are largest in the first few years after job loss and then grow smaller. A natural question based on this is if we are identifying a transitory impact on intergenerational mobility or a permanent impact on intergenerational mobility? To assess this question, we estimate the following regression:

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

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

where "Year" stands for year fixed effects.

We present the estimates of the main coefficients of interest, $\beta_{2,t}$, in Figure 9. We find that there are no pre-trends, which is expected if the job loss is quasi-random. We show that immediately following the layoff there is large jump in the Displacement x Rank x Time coefficient β_2, which increases to approximately 0.06 by the second year after the layoff. The coefficient then decreases over time and is around 0.02 six years after the layoff but still statistically significant.

Given that much of the intergenerational mobility literature is interested in lifetime mobility, it is perhaps more interesting that we find that the disparate responses to job loss lead to long-term changes in the rank-rank correlation. Our finding that disparate impacts of a negative labor market shock affect rank-rank correlations long term suggests that it is not quite right to think of a permanent and fixed rank-rank correlation for a given parent-child distribution. Our results demonstrate 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.

Next, we consider the extent to which including benefits might mitigate the effects documented in Figure 9, given the generous social welfare system that exists in Finland. Of course, labor supply decisions may also be endogenous to the existing welfare system, which is beyond the scope of this paper to examine. In Figure 10 we re-estimate equation 8, but instead of using labor market earnings as the measure used to calculate ranks, we use total taxable income (which also includes taxable benefits) to calculate the income rank for both parents and children. We also replicate the results from Table 3 using total income instead in Appendix Table B.14.

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 Figure 10. 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, specifically job loss, play a role in determining intergenerational mobility and perpetuating inequality.

5.2 Contribution of Job Loss 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 evidence on the extent to which this phenomenon explains overall rank-rank correlations in the full population. For the purpose of this exercise, we include not only the disparate impacts of job loss, but also the disparate incidence of job loss which we can identify from the data.

We start with the earnings of all individuals aged 30 in 2000-2019. We divide individuals into deciles according to their parents' earnings, where parental earnings are calculated as described in Section 2. To run the simulation, we assign the starting earnings at age 30 to be equal to each person's actual earnings in the data. For each person we then draw from a uniform distribution. If the resulting number is greater than the unemployment transition probability for that decile (see Table 4), we assign the person to remain employed. In this case we add the age-decile-specific wage growth absent job loss. The age-decile-specific wage growth is calculated as the average growth in wages for working individuals within the specified age and decile group who do not become unemployed (see Figure 11).

Alternatively, if the individual becomes unemployed, they receive the earnings growth as before, but also incur the job loss penalty. The job loss penalty is calculated separately for each decile as described in Section 3 for six years following a layoff. After the six years are complete, we assume the person becomes employed. 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 likely cause us to understate the true contribution of job loss to rank-rank correlations.

The decile-specific probabilities of transitioning from employment to unemployment in Table 4 are calculated from the data. We include all unemployment when calculating these transition probabilities. Thus we include fires and quits, in addition to layoffs. Ideally, we would only include firings and layoffs for this analysis. Unfortunately, the data does not allow us to distinguish between quits that result in unemployment and firings/layoffs. However, if individuals quit and immediately start a new job they will not enter our unemployment transition probabilities. We find that the risk of falling into unemployment is highest for those born to parents in the bottom income decile, at 5.97%, and decrease monotonically until the risk is only 3.54% for those born to parents in the top income decile. These estimates demonstrate the disparate incidence of job loss by parental background.

We continue this process for each age until the full population is 40. We then take the simulated earnings at each age and convert them into ranks, in order to estimate the rank-rank correlation. We call this the "Job Loss Simulation". In addition, we run an alternative simulation where we do not allow for unemployment. We call this the "Baseline Simulation".

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

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

Where y_t refers to earnings in period t and y_{t+1} refer to earnings the following year. "$losses_{decile,t}$" 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 we estimate earnings losses for adult children separately for each parental income decile. The time subscript refers to the fact that the estimated cost of job loss changes in each year following the job loss. "$growth_{age,decile}$" refers to the age- and parental-income-decile-specific earnings growth accumulated between year t and $t+1$ in the absence of job loss. We calculate these values directly from the data as described above, and report them in Figure 11. Last, we calculate the resulting rank-rank correlations for each age within birth cohorts.[30]

We graph the rank-rank correlation for each age as the shocks accumulate according to this process in Figure 12.[31] We find that the rank-rank correlation is increasing as the child ages, but that the increase is larger when there is job loss included. Based on our estimates, absent job loss the rank-rank correlation would grow from 0.1232 at age 30 to 0.1928 at age 40. With job loss, the rank-rank correlation grows from 0.1250 at age 30 to 0.2003 at age 40. The simulation results imply that the increase in the intergenerational rank-rank correlation from age 30 to age

[30]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.

[31]The estimates are also reported in Appendix Table B.15

40 is 8.19%[32] higher due to the disparate incidence and impacts of job loss. An alternative way to frame these results is in terms of the rank-rank correlation at age 40. We find that the rank-rank correlation is 3.9%[33] higher at age 40 when we take into account the disparate incidence and impact of job loss.

Note that our simulation takes into account not only the disparate impacts of job loss, but also the disparate incidence of job loss. We find that those in the bottom deciles are more likely to transition into unemployment compared with individuals in the top deciles (see Table 4 which shows, for example, that the probability of unemployment is 68.6% 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.

This is the first paper to estimate the impact of an early career shock on the country-level rank-rank correlation. As such there are not other estimates with which to compare our 3.9% result. On the one hand, it would be implausible for the number to be much larger. Despite the massive literature on job loss it is still relatively rare, even for the adult children of lower-income parents who we find experience it more often. Thus, although the differences in impacts are large, we cannot expect job loss alone to explain a large portion of the total rank-rank correlation.

That being said, there are two reasons we view this as a substantive number. First, it is unlikely that any one thing explains the majority of country-level rank-rank correlations. Rather, rank-rank correlations are explained by a multitude of different factors which research must uncover one by one. Second, there are many other shocks to early careers that could also contribute to a country's rank-rank correlation, such as recessions (Kahn, 2010; Oreopoulos *et al.*, 2012), trade

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

[33] 0.2003/0.1928=1.0389. Note that .0057 ((0.2003-0.1250)-(0.1928-0.1232)), or 2.8%, of the overall .2003 rank-rank correlation at age 40 is explained by the disparate incidence and impact of job loss.

shocks (David *et al.*, 2013), disability (Kostol and Mogstad, 2014), and more. The fact that loss alone causes the country's rank-rank correlation to be 3.9% higher suggests that by combining estimates of the impacts of all early career shocks might explain quite a bit of overall rank-rank correlations. Thus, while this paper provides a first step, more research is needed to uncover the causal impacts of these other early career shocks on country-level rank-rank correlations.

6 Mechanisms

6.1 Conceptual Framework

What explains the starkly different impacts in job loss we have documented? To set ideas we provide a simple conceptual framework adapted from the canonical models in Becker and Tomes (1979) and Becker and Tomes (1986), as presented in Mogstad and Torsvik (2021). Relative to their framework, we explicitly account for labor market shocks to children's incomes and how parents can mitigate their impacts.

Formally, consider a simple two-period model of child income. In the first period the child's income is equal to their wage w_t, which depends on their human capital, f. Human capital depends on genetics endowed by the parents, A, and investments made in childhood by the parents, I_t. In addition to their earnings, the child receives cash transfers from their parents, X_t. As in prior models of intergenerational mobility (Becker and Tomes, 1979, 1986; Mogstad and Torsvik, 2021), this collapses everything that happens in childhood and the resulting earnings accrued by the child in the first job into one period. As Carneiro *et al.* (2021) document in their paper, this misses a lot of important dynamics in childhood. In this paper rather than focus on the possibility of more important dynamics in childhood, we focus on and demonstrate that there are also important dynamics in intergenerational mobility in adulthood, i.e. adult children experience their early careers differently based on parental background. To formalize this in the model, we add a second period of child earnings.

Turning to the second period, for simplicity we omit wage growth[34], so the child's wage

[34]It is straightforward to include wage growth that depends on past human capital, which would replicate the fact that in the data wage growth varies by parental decile, see Figure 11.

remains the same if they remain employed. Alternatively, if they lose their job they will be re-employed but experience a negative shock to their income given by $\sigma_{t+1} \in [0,1]$. σ_{t+1} takes as inputs human capital, given by $f(I_t, A)$, and investments by parents to address the job loss shock, I_{t+1}. In the second period children can also receive cash transfers from parents, X_{t+1}. ϵ_t represents random luck in the income process for children.

Parents wish to maximize their utility in each period. Utility depends on their own consumption and the income stream of their child. We assume parents' incomes are equal to some value Y_t^{Parent} in every period t. The formal model is thus written as:

$$\max_{C_t, I_t, C_{t+1}, I_{t+1}} u\left(C_t, Y_t^{child}\right) + \beta u\left(C_{t+1}, Y_{t+1}^{child}\right) \tag{9}$$

subject to:

$$Y_t^{Parent} = C_t + X_t + I_t \tag{10}$$

$$Y_{t+1}^{Parent} = C_{t+1} + X_{t+1} + I_{t+1} \tag{11}$$

$$Y_t^{Child} = w_t f\left(I_t, A\right) + X_t + \epsilon_t \tag{12}$$

$$Y_{t+1}^{Child} = \left\{ \begin{array}{ll} \Big(1 - \sigma_{t+1}\Big(f\left(I_t, A\right), I_{t+1}\Big)\Big) w_t f\left(I_t, A\right) + X_{t+1} + \epsilon_{t+1}, & \text{if job loss} \\ w_t f\left(I_t, A\right) + X_{t+1} + \epsilon_{t+1}, & \text{otherwise} \end{array} \right\} \tag{13}$$

With a borrowing constraint each period for the parents:

$$X_t \geq 0, X_{t+1} \geq 0. \tag{14}$$

And investments in the child must be non-negative each period:

$$I_t \geq 0, I_{t+1} \geq 0. \tag{15}$$

The model provides four links between parent and child incomes, and four ways higher-income parents might reduce the impact of the job loss shock on total child income. First, if higher income parents have better genetic endowments (Black *et al.*, 2005), given by A, this increases child human capital which increases wages in the first and second periods and decreases the impact of job loss in the second period. Second, parents with higher incomes can invest more (given borrowing constraints) in education in childhood, with these investments given by I_t. Higher education increases wages in both periods and can also reduces the job loss shock, σ_{t+1}. Third, if their kids experience job loss, higher-income parents can provide direct investments (I_{t+1}) to decrease σ_{t+1}. Fourth, parents can provide cash transfers, X_t and X_{t+1}. All of these possible links represent potential benefits from having high-income parents, which is why we do not control for them in the main analysis. However, understanding which are relevant could help guide policy to reduce these disparities.

In what follows we empirically test whether the job loss shock is reduced by a) investments by parents at the time of job loss and b) education, i.e. we separately test if $\frac{\partial \sigma_{t+1}}{\partial I_{t+1}} < 0$, if $\frac{\partial \sigma_{t+1}}{\partial f} < 0$, and if I_{t+1} and/or $f\left(I_t, A\right)$ are larger for adult children of high-income parents.

6.2 Parental Investments after Job Loss: Cohabitation and Hiring in the Same Firm

We focus first on empirically testing the possibility that parents intervene in the second period by providing investments that reduce the impacts of job loss (I_{t+1}). Parents might also provide cash transfers (X_{t+1}) in the second period, but we do not observe these in the data so cannot test this possibility. In terms of investments after job loss, parents could allow their children to temporarily move in while the child searches for a new job. In Figure 13 Panel A we show that just over 12% of adult children of lower-income parents live with their parents prior to job loss, which is 4 percentage points higher than those born to higher-income parents. In Panel B when we look at the impact of job loss on whether the adult child lives with his or her parents, we find very small effects that are never statistically significantly different from each other for the top 20% and bottom 20%. While not significant, point estimates are slightly larger for the bottom 20% which suggest that if anything, this mechanism works in the opposite direction of our main results.[35] Thus, we conclude that this mechanism does not explain our main results.

Another possibility is that high-income parents use their connections to employ their children in their own firms or use broader connections to obtain jobs in the same industry after their adult child is laid off. Figure 14 explores this possible explanation with respect to fathers' current and past employers and shows that the opposite is true.[36] Panel B shows a statistically significant negative effect of job loss on working with one's father for children of parents in the top 20% and no significant effect for children in the bottom 20%.

However, this result could be misleading. Panel A of Figure 14 shows that high-income fathers are at least eight times more likely than low-income fathers to work in the same firm as their children prior to job loss. This strong income gradient in the intergenerational transmission of employers is consistent with results from Corak and Piraino (2011) in Canada and Staiger (2020) in the United States. Due to this, the results shown in Panel B could be largely mechanical: The 8% of adult children born to higher-income parents and working with their parents before job loss share the same firm closure with their fathers, making them much less likely to work together post job loss. In contrast, the job loss shock is almost never shared between father and child for those born to lower-income parents since less than 1% work with their fathers prior to job loss. Thus, these pre-layoff gaps could entirely explain the post layoff differences in Panel B.

To address this concern, Figure 15 repeats the same exercise but presents results separately for those who work with their fathers prior to job loss versus those who do not. A very different picture emerges. Those whose parents are in the top 20% are more likely to work for one of the father's employers post layoff in both cases. For those who do not work with their father prior to job loss, those born to high-income parents are almost 5 times more likely to work with their fathers post job loss (Panel A of Figure 15). Point estimates indicate large gaps for all six years post job loss, and the gap is significant the first year post job loss. For those who do work with their fathers prior to job loss, given the shared plant closure both groups are mechanically less

[35] Overall DiD estimates suggest very small but significantly larger effects on the bottom 20%.

[36] For this exercise we identify all firms in which the father worked between 1988 and the event year t. Then we define an indicator variable that takes the value 1 if a child's employer at the time t is among the set of his or her father's employers, and 0 otherwise. Regression results are reported in Appendix Table B.12 for Panel B. Appendix Figure C.8 shows the equivalent results for father's industry.

likely to work with their fathers post job loss. However, the negative effect is smaller for those born into the top 20%, and this gap is significant the first year post job loss.

Thus higher-income parents intervene directly to help their children get jobs by hiring them into their own firm. This network effect is consistent with the models in Calvo-Armengol and Jackson (2004) and Jackson (2021). Conditional on not working with one's father prior to job loss (which is the case for 92% of the top 20% and 99% of the bottom 20%), our DiD estimates indicate a 0.5 percentage point increase in the probability of working in the same firm as one's father for the top 20% in the next 5 years, and no significant impact for the bottom 20%. The overall employment gap is 9.3 percentage points from our main results (See Table B.9), our estimates indicate that this mechanism could possibly explain just over 5% of the employment gaps we documented earlier, if those who are employed by their fathers would otherwise remain unemployed. Moreover, this explanation could play an even larger role if we expanded our analysis to consider all possible networks, with those born to higher-income parents benefiting from better connected siblings, aunts and uncles, school friends, and more. In summary, this evidences suggests that $I_{t+1}^{Top20} > I_{t+1}^{Bottom20}$ and $\frac{\partial \sigma_{t+1}}{\partial I_{t+1}} < 0$.

6.3 Education

Next we turn to the education link, i.e. the role of $f(I_t, A)$ in explaining our main results. Figure 16 Panel A (B) shows how the individual-level job loss scars in employment (earnings) vary with education level separately for those born in the top versus bottom 20%. Earnings and employment job scars are one half to one third as large for those with a tertiary degree compared with those who only have basic education. This suggests that $\frac{\partial \sigma_{t+1}}{\partial f} < 0$. Yet even within the same educational groups, the impacts of job loss still differ for adult children of low- and high-income parents. For employment, the two groups always experience significantly different job loss scars. For earnings, point estimates always suggest larger effects for the bottom 20%, but the difference is only significant for secondary school. The majority (55%) of those in the bottom 20% have only a secondary education and 40% of those in the top 20% have only a secondary education (see Table B.1).

These figures suggest that a) education appears to play a role in reducing the impacts of job loss but b) differences on this margin alone cannot fully explain our main results. To formally estimate the role education plays in explaining our main results, 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 the canonical Blinder-Oaxaca decomposition, but we introduce a methodological extension 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 using the matched counterfactual from Schmieder *et al.* (2018) and described in detail in Section 4.2. We then estimate the following regression to decompose the overall job loss scar into the explained and unexplained portions:

$$\hat{\Delta}_t = \underbrace{\Sigma_k \left(\hat{\beta}_k^H - \hat{\beta}_k^*\right) E\left[X_{kit}^H\right] + \Sigma_k \left(\hat{\beta}_k^* - \hat{\beta}_k^L\right) E\left[X_{kit}^L\right]}_{\text{Unexplained}} + \underbrace{\Sigma_k \hat{\beta}_k^* \left(E\left[X_{kit}^H\right] - E\left[X_{kit}^L\right]\right)}_{\text{Explained by difference in pre-determined endowments}}, \tag{16}$$

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 16 is the "unexplained" part, while the second term is the "explained" part (Fortin *et al.*, 2011).[37] We outline conditions under

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

which this approach is valid in Appendix A. Thus approach could easily be used in other settings to recover a decomposition of an estimated object. For example, this approach could be used to decompose child penalties.

The conceptual model suggests that observable differences in education across the two groups could be due to differences in childhood investments by parental income. This is why we do not control for education in the main results and instead view it 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.

Table 5 reports results. Observable differences in the education of adult children of low- versus high-income parents accounts for 28% of the employment and 46% of the earnings differences in the impacts of job loss. These results are different for growth and recession years. In growth years, education gaps account for only 23% of employment gaps and 46% of earnings gaps in the impacts of job loss. In recession years, 43% of employment gaps and 55% of earnings gaps are explained by education. Thus we conclude that education reduces the size of the job loss shock overall ($\frac{\partial \sigma_{t+1}}{\partial f} < 0$), particularly in recession years, and more so for children born to high-income parents who obtain more education.

7 Conclusion

This paper documents three new findings. First, while getting a job can be a great source of mobility, those who were born into lower-income families have a more precarious perch on the job ladder, and when they fall off, they struggle more to recover. There are large, significant, and sustained gaps in the employment (and to a lesser extent, earnings) job loss scars experienced by adult children of low- versus high-income parents, with adult children of low-income parents experiencing greater losses following a layoff. These gaps remain even conditional on similar pre-displacement incomes.

it can inadvertently put a bit too much weight on the explained portion.

Second, these disparate impacts of job loss translate to significant effects on intergenerational mobility. Specifically, job loss causes a 34% increase in the rank-rank correlation, which implies substantial decreases in intergenerational mobility. We also find that the impact on intergenerational mobility is still significant even 6 years after the job loss. In a simulation, we show that the overall rank-rank correlation at age 40 is 3.9% higher due to the disparate impacts and incidence of job loss in the preceding decade.

Third, we presented evidence on mechanisms. We introduced a straightforward methodological extension to the Blinder-Oaxaca decomposition to our setting and show that differences in educational attainment play an important role in explaining the disparate impacts of job loss in adulthood. Thus, the larger investments higher-income parents make in childhood continue to advantage their children well into adulthood by allowing them to better respond to shocks. Additionally, we show that parents also intervene at the time of job loss by providing jobs, and more so for higher-income parents. Thus, high-income parents continue to disproportionately invest in their children's perch on the job ladder well into adulthood.

These results deepen our understanding of the many ways in which parental poverty leads to intergenerational impacts. While much of the previous literature on intergenerational mobility has focused on quantifying the amount of mobility, and early life causes, this paper shows the importance of labor market shocks to measures of intergenerational mobility. As such, this paper fills a key gap in the literature and increases our understanding of how inequality transmits across generations.

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

	PDV_{Loss}	PDV_{Loss} in years of average pre-layoff earnings	$PDV_{Earnings}$ without job loss	$PDV_{Earnings}$ with job loss	Change in 80:20 inequality
	(1)	(2)	(3)	(4)	(5)
Top 20	€8,096	0.232	€209,107	€201,011	1.080
Bottom 20	€17,667	0.603	€160,368	€142,702	

Notes: Top 20 refers to adult children who were born into the top 20% based on their parent's income (equivalently for Bottom 20). Column 1 shows estimates of the PDV of job loss in the 6 years following the layoff derived by Equation (2) for adult children who lost their jobs but were born in the top 20% versus bottom 20%. Column 3 shows estimates of the PDV of earnings over 6 years for those not laid off (using the matching exercise described in Section 6.3), 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 Euros accounting for inflation in columns 1, 3, and 4.

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

		Parent Quintile				
		1	2	3	4	5
Child Quintile	1	-4.526	-4.424	-3.832	-4.040	-2.288
		(0.665)	(0.625)	(0.644)	(0.618)	(0.816)
	2	-5.763	-6.605	-4.870	-5.377	-4.098
		(0.632)	(0.648)	(0.605)	(0.661)	(0.827)
	2	-5.977	-6.067	-5.052	-5.519	-3.881
		(0.793)	(0.739)	(0.661)	(0.685)	(0.769)
	4	-6.733	-6.759	-5.427	-5.987	-3.230
		(0.797)	(0.712)	(0.661)	(0.642)	(0.593)
	5	-5.687	-5.380	-6.202	-5.112	-3.001
		(0.843)	(0.724)	(0.657)	(0.583)	(0.446)

Notes: Table reports difference-in-difference estimates using an adjusted version of Equation (1), in which we collapse the event study dummies into a single displacement indicator. The outcome is the income rank of the adult child within their birth cohort. Columns indicate parental income quintile. Rows indicate the child's income quintile pre-displacement. For example, the top left indicates a child who was born into the bottom 20% in terms of parental income, and the child is also in the bottom 20% before they lose their job based on their own income. Bottom left indicates a child born into the bottom 20% who is in the top 20% of the income distribution within their birth cohort based on their pre-displacement income.

Table 3: Impacts of Job Loss on Intergenerational Mobility

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

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

Table 4: Unemployment Transition Probabilities

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

Notes: This table displays the probability of transitioning from employment to unemployment, with separate estimates reported for the adult children of parents in each parental earnings decile. Calculations include all possible forms of unemployment the adult children might experience, including firings and quits in addition to plant closings. These estimates are used to produce the simulations described in Section 5.2 and shown in Figure 12 and Appendix Table B.15.

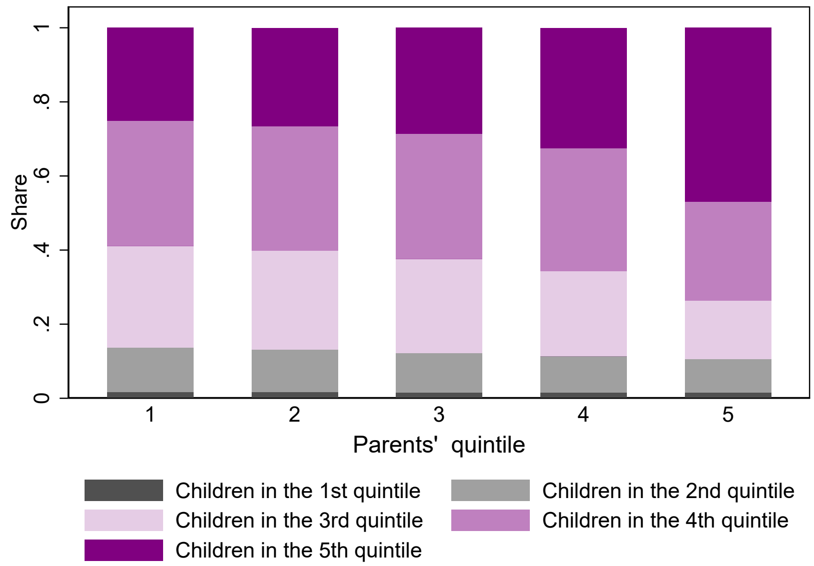
Table 5: Decomposition of Differences in Employment and Earnings Job Loss Scars

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

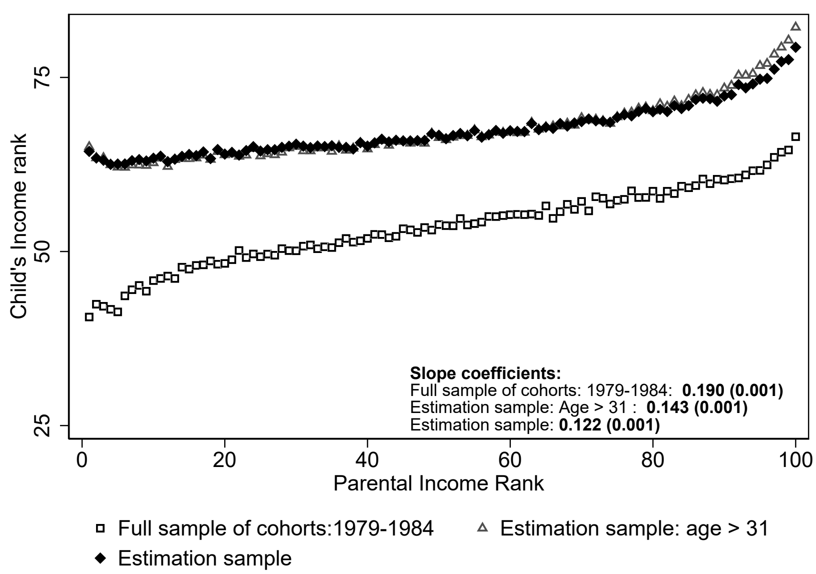
Notes: Table shows the decomposition of the differences in employment (Panel A) and earnings (Panel B) job loss scars between children of parents in the bottom 20% of the income distribution versus the top 20% into the explained and unexplained parts. Estimates are based on Equation (16) for all years, 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



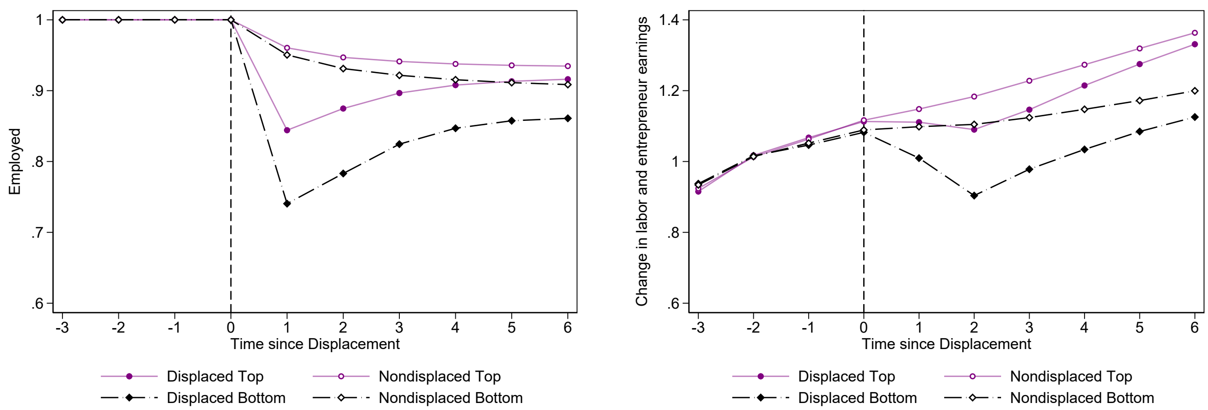
(b) Rank-Rank Correlation Using Full Population vs. Our Sample



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 time 0.

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

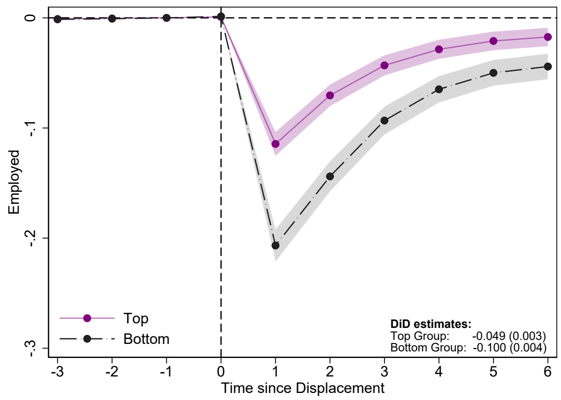
(a) Employment (b) Relative Earnings



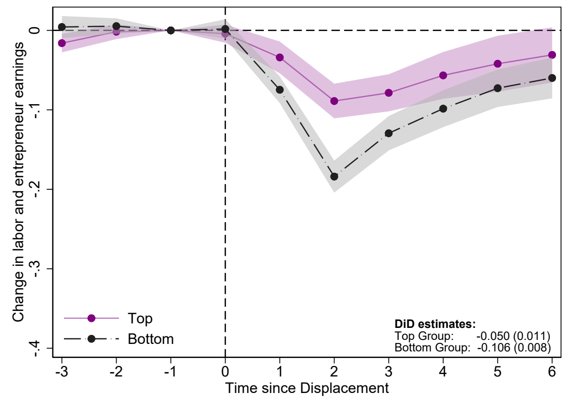
Note: Panel A (B) shows employment (relative earnings) of displaced and non-displaced individuals 3 years before and 6 years after the job loss by parental income group. Employment is measured at the end of the year. Relative earnings compare yearly earnings to the mean yearly earnings 1 to 3 years before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

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

(a) Employment



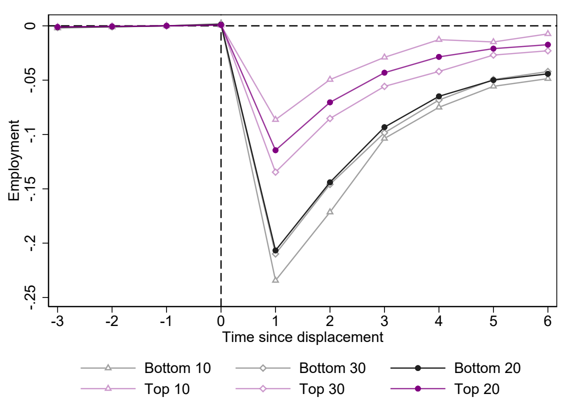
(b) Earnings Relative to Pre-mean



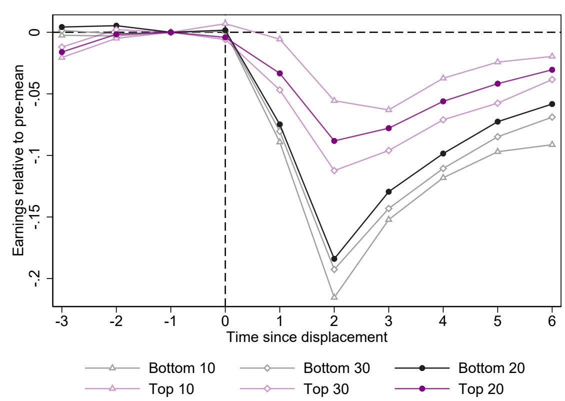
Note: Figures plot the estimates of δ_t obtained using Equation (1) separately for top and bottom parental income groups. In Panel A (B), the outcome is employment (relative earnings). Employment is measured at the end of the year. Relative earnings compare yearly labor and entrepreneurial earnings to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

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

(a) Employment

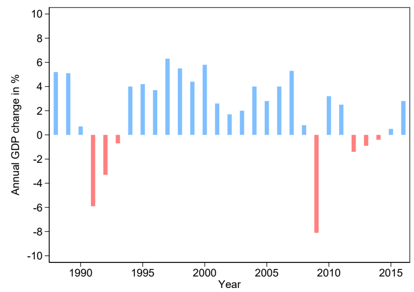


(b) Earnings Relative to Pre-mean



Note: Figures plot the estimates of δ_t obtained using Equation (1) separately for three pairs of top and bottom parental income groups. In Panel A (B), the outcome is employment (relative earnings). Employment is measured at the end of the year. Relative earnings compare yearly labor and entrepreneurial earnings to the mean of yearly earnings 1–3 years before displacement. Sample construction and data as defined in Section 2.1.

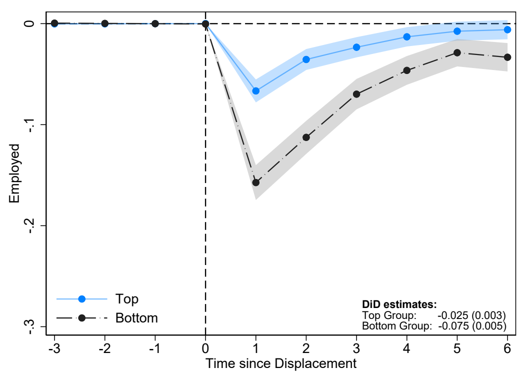
Figure 5: GDP Growth in Finland, 1988–2017



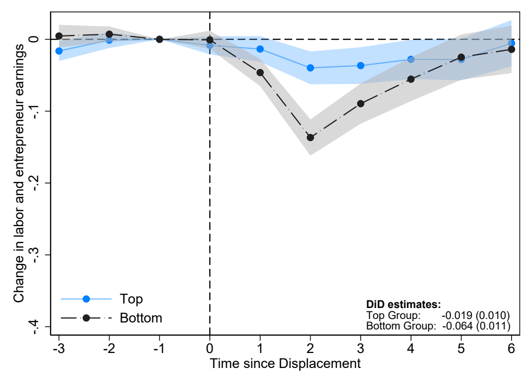
Note: The figure depicts years of growth (in blue) and recession (in red) in Finland used for the analysis.

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

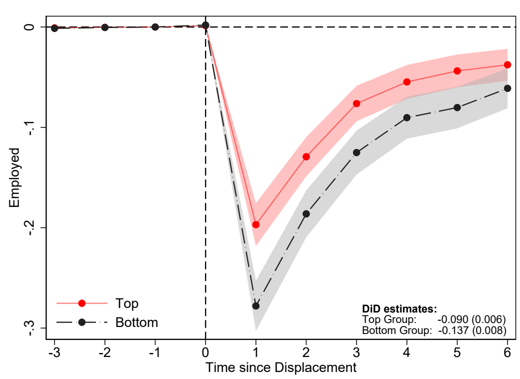
(a) Economy Growing: Employment



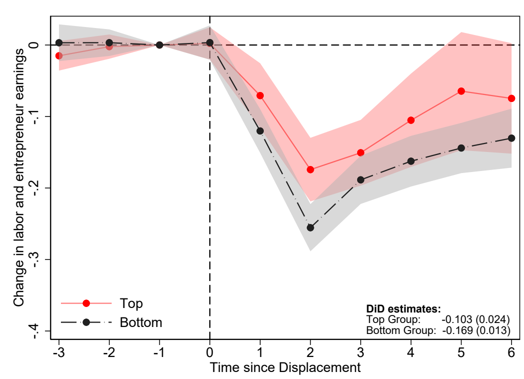
(b) Economy Growing: Relative Earnings



(c) Economy Shrinking: Employment

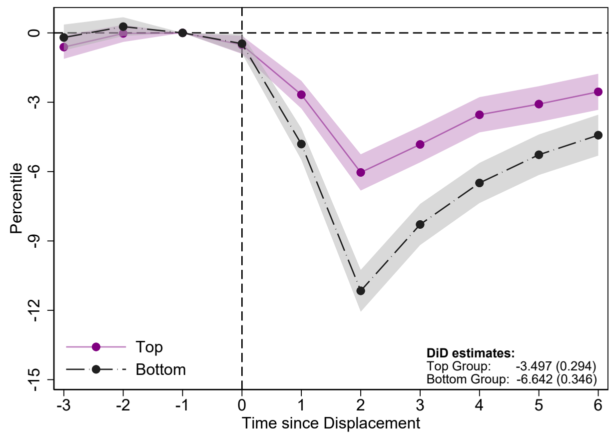


(d) Economy Shrinking: Relative Earnings



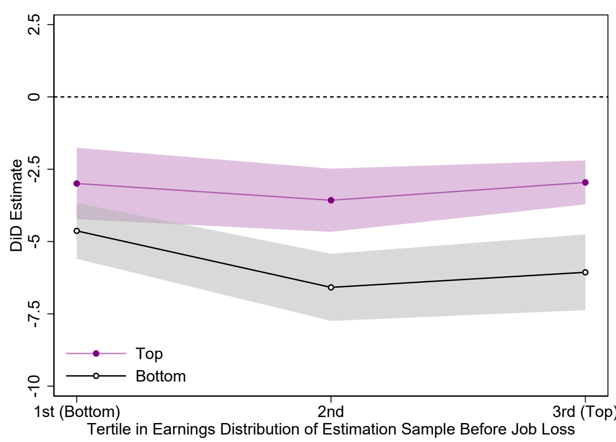
Note: Figures plot the estimates of δ_t obtained using Equation (1) separately for top and bottom 20% parental income groups. Panel A (C) shows the impact of job loss on employment when the economy is growing (shrinking). Panel B (D) shows the impact of job loss on relative earnings when the economy is growing (shrinking). Employment is measured at the end of the year. Relative earnings compare yearly labor and entrepreneurial earnings to the mean of yearly earnings 1–3 years before displacement. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level. DiD estimates are obtained using an alternative version of Equation (1) in which event study dummies are collapsed into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses. Sample construction and data as defined in Section 2.1.

Figure 7: Impacts of Job Loss on Percentile Rank by Parental Earnings Group, Bottom vs. Top 20%



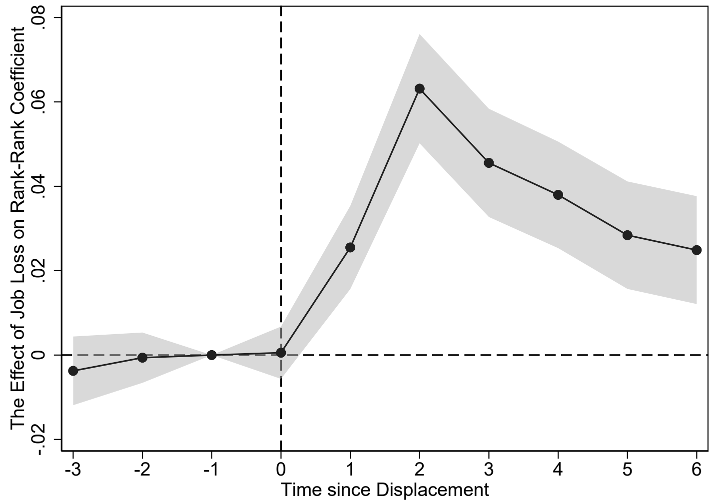
Note: Figure plots the estimates of δ_t obtained using Equation (1) separately for top and bottom parental income groups. The outcome is an individual's earnings rank within the birth cohort. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level. DiD estimates are obtained using an alternative version of Equation (1) in which event study dummies are collapsed into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses. Sample construction and data as defined in Section 2.1.

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



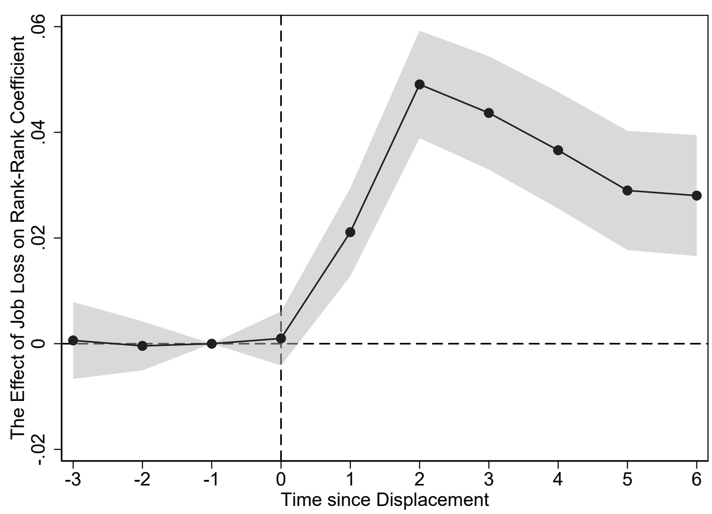
Note: Figure plots the DiD estimates obtained using an alternative version of Equation (1) in which event study dummies are collapsed into a single displacement indicator separately for top and bottom parental income groups, and for those in the bottom third, middle third, and top third of the pre-displacement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

Figure 9: Estimated Impacts of Job Loss on Intergenerational Mobility



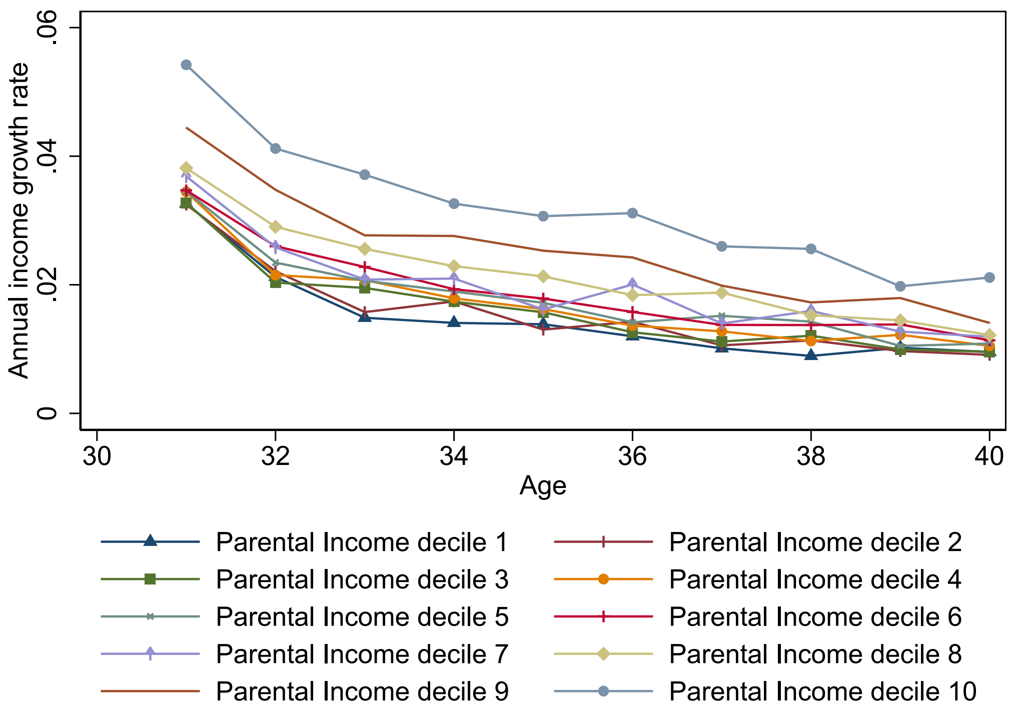
Note: Figure plots the estimates of β_{2t} obtained using equation (8) using all income groups. The outcome is a child's earnings rank within the birth cohort. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard errors are clustered at the individual level.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

Figure 10: Estimated Impacts of Job Loss on Intergenerational Mobility Using Earnings Plus Taxable Benefits to Define Income Ranks



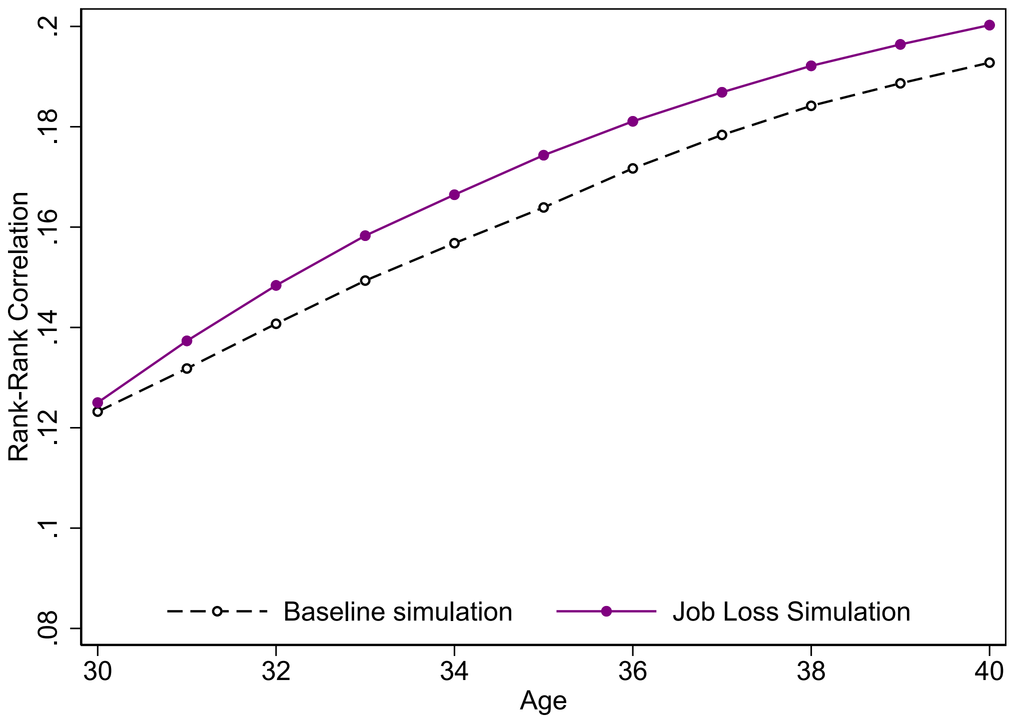
Note: Figures plot the estimates of β_{2t} obtained using equation 8 using all income groups. The outcome is a child's income rank (which includes earnings plus taxable benefits) within the birth cohort. Ninety-five percent confidence intervals appear as shaded bands around point estimates. Standard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

Figure 11: Income Growth Rates by Parental Income Groups



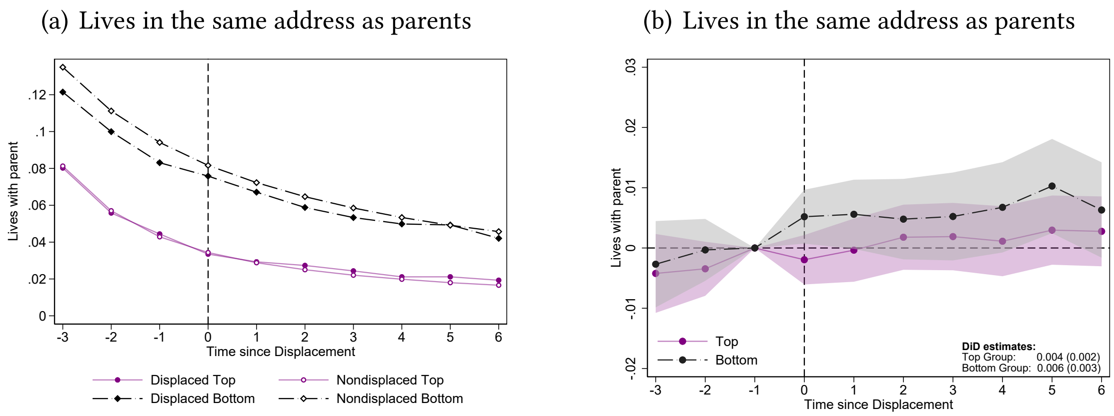
Note: This figure displays the age-decile-specific earnings growth rates. Earnings growth within each age and within each decile is calculated using the entire population. These estimated growth rates are used to produce the "Baseline Simulation" and "Job Loss Simulation" estimates as described in Section 5.2, with results reported in Figure 12 and Appendix Table B.15.

Figure 12: Simulation: Contribution of Disparate Impacts of Job Loss to Overall Intergenerational Mobility



Note: Figure plots the estimates from the simulation described in Section 5.2. The black dashed line represents the trajectory of the rank-rank correlation calculated separately for each age where the earnings at age 30 are equal to the earnings in the data, and the earnings from age 31 to age 40 are simulated using the age-decile-specific wage growth calculations represented in Figure 11. 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 Table 4. See Section 5.2 for more details. For point estimates, see Appendix Table B.15.

Figure 13: Impacts of Job Loss on Living in the Same Address as Parents, Bottom 20% vs. Top 20%

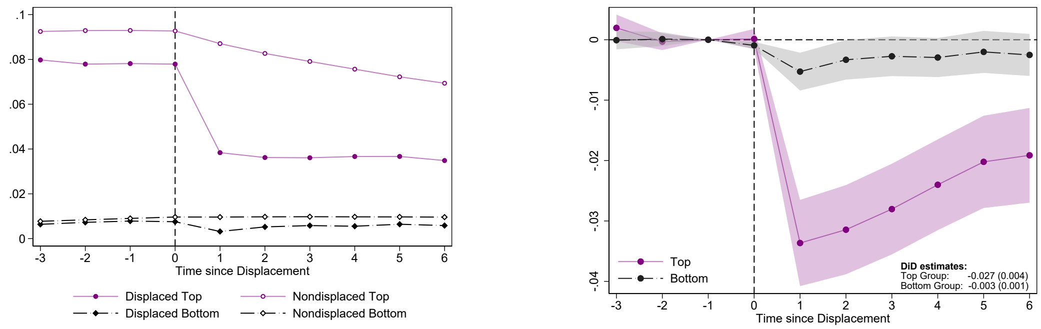


Note: Panel A shows the yearly probability of living in the same address as one of the parents. Panel B shows the estimates of δ_t obtained using Equation (1) separately for the top and bottom parental income groups. Ninety-five percent confidence intervals appear as shaded bands around point estimates. 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 14: Impacts of Job Loss on Working in the Same Firm as One's Father by Parental Income Group, Bottom vs. Top 20%

(a) Working for Any of Father's Employers

(b) Working for Any of Father's Employers

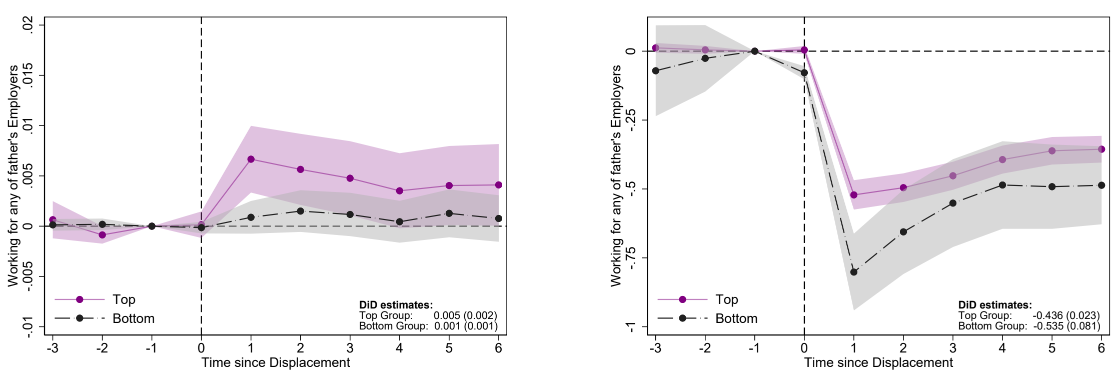


Note: Panel A shows the yearly probability of working for any of the father's employers for displaced and non-displaced individuals 3 years before and 6 years after the layoff by parental income group. The set of father's employers at year t contains all employers the father has had between years 1988 and t. Panel B shows the estimates of δ_t obtained using Equation (1) separately for the top and bottom parental income groups. Ninety-five percent confidence intervals appear in shaded bands around point estimates. Standard errors are clustered at the individual level. DiD estimates are obtained using an alternative version of Equation (1) in which event study dummies are collapsed into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses. Sample construction and data as defined in Section 2.1.

Figure 15: Impacts of Job Loss on Working in the Same Firm as One's Father by Parental Earnings Group, Separately by Whether a Child and Father Were Working in the Same Firm Before Displacement

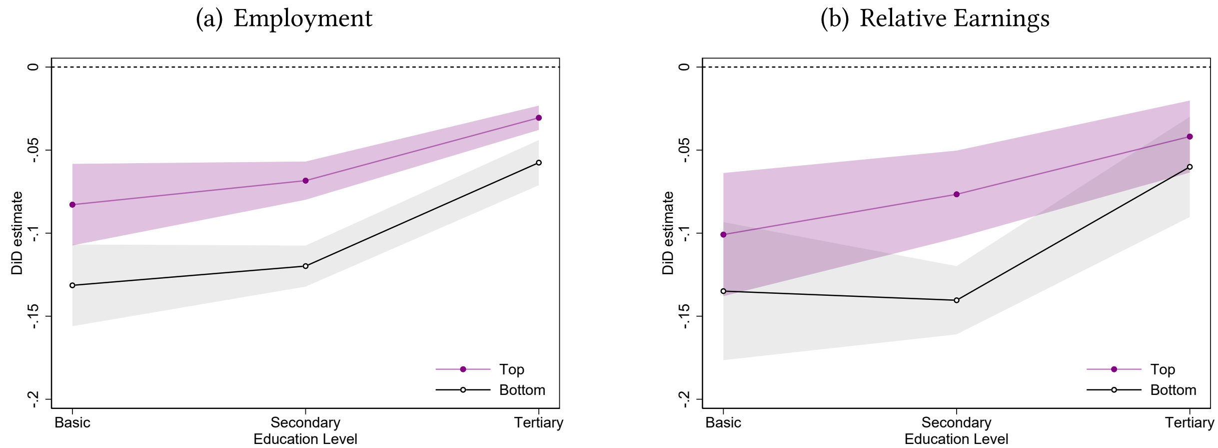
(a) Not working in the same firm as father at time 0

(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 16: 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. Results are based on DiD job scar estimates.

Online Appendix

A Decomposition Details

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

$$
\begin{aligned}
&E\left[\hat{\beta}_k^H, \hat{\beta}_k^L, \hat{\beta}_k^* | \hat{Y}_{it}^{No\,Layoff,H} - Y_{it}^{Layoff,H}, \hat{Y}_{it}^{No\,Layoff,L} - Y_{it}^{Layoff,L}\right] \\
-&E\left[\hat{\beta}_k^H, \hat{\beta}_k^L, \hat{\beta}_k^* | Y_{it}^{No\,Layoff,H} - Y_{it}^{Layoff,H}, Y_{it}^{No\,Layoff,L} - Y_{it}^{Layoff,L}\right] = 0,
\end{aligned} \tag{17}
$$

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:

$$
E\left[\hat{\beta}_k^H | \left(\left(\hat{Y}_{it}^{No\,Layoff,H} - Y_{it}^{Layoff,H}\right) | X_{kit}\right)\right] - E\left[\hat{\beta}_k^H | Y_{it}^{No\,Layoff,H} - Y_{it}^{Layoff,H}\right] = 0. \tag{18}
$$

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 C.5 shows that the estimated job loss scars when estimating counterfactual earnings in this way are almost identical to the main results, which is consistent with the underlying identification assumptions for this exercise.

B Additional Tables

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

	Displaced	Not displaced	P-value
Panel A: Adult Children Whose Parents Are in the Bottom 20%			
Age	30.698	30.665	0.521
Female	0.350	0.362	0.170
Number of children	0.892	0.911	0.325
Tenure, years	4.761	5.259	0.000
Plant size	89.795	103.133	0.000
Primary education only	0.160	0.149	0.081
Secondary education only	0.554	0.568	0.096
Tertiary education	0.284	0.279	0.545
Experience, years	10.335	10.406	0.474
Married	0.397	0.412	0.092
Real earnings in 1000s (€)	31.067	30.145	0.000
Real income in 1000s (€)	32.658	31.433	0.000
Observations	3,442	264,292	
Panel B: Adult Children Whose Parents Are in the Top 20%			
Age	30.843	30.909	0.139
Female	0.358	0.374	0.033
Number of children	0.783	0.845	0.000
Tenure, years	4.587	5.021	0.000
Plant size	97.494	116.080	0.000
Primary education only	0.105	0.092	0.006
Secondary education only	0.388	0.408	0.008
Tertiary education	0.506	0.496	0.206
Experience, years	9.176	9.135	0.672
Married	0.446	0.460	0.064
Real earnings in 1000s (€)	38.519	36.851	0.000
Real income in 1000s (€)	40.346	38.455	0.000
Observations	4,300	278,815	

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

	(1)	(2)	(3)	(4)
Top 20				
DiD Estimate	-0.027	-0.027	-0.027	-0.027
	(0.004)	(0.004)	(0.004)	(0.004)
Bottom 20				
DiD Estimate	-0.003	-0.003	-0.003	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)
Individual fixed effects	✓			
Base year fixed effects	✓	✓		
Year fixed effects	✓	✓	✓	
Displaced fixed effects		✓	✓	✓
Controls			✓	✓
Base year $\times$ time fixed effects				✓
N Top 20	2,819,839	2,819,839	2,819,839	2,819,839
N Bottom 20	2,671,751	2,671,751	2,671,751	2,671,751
Non-displaced mean Top 20	0.084	0.084	0.084	0.084
Non-displaced mean Bottom 20	0.009	0.009	0.009	0.009

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

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

	(1)	(2)	(3)	(4)
Top 20				
DiD Estimate	-0.009	-0.009	-0.009	-0.009
	(0.004)	(0.004)	(0.004)	(0.004)
Bottom 20				
DiD Estimate	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Individual fixed effects	✓			
Base year fixed effects	✓	✓		
Year fixed effects	✓	✓	✓	
Displaced fixed effects		✓	✓	✓
Controls			✓	✓
Base year $\times$ time fixed effects				✓
N Top 20	2,819,839	2,819,839	2,819,839	2,819,839
N Bottom 20	2,671,751	2,671,751	2,671,751	2,671,751
Non-displaced mean Top 20	0.085	0.085	0.085	0.085
Non-displaced mean Bottom 20	0.014	0.014	0.014	0.014

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

Table B.9: The Effect of Job Loss on Employment

Dependent variable: P(Employed)

	All		**Recession**		**Growth**	
Time (1)	Bottom (2)	Top (3)	Bottom (4)	Top (5)	Bottom (6)	Top (7)
-3	-0.001	-0.001	-0.001	-0.001	0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
-2	-0.001	-0.000	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
-1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0	0.001	0.001	0.002	0.001	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1	-0.207	-0.114	-0.278	-0.197	-0.157	-0.067
	(0.007)	(0.006)	(0.013)	(0.011)	(0.009)	(0.006)
2	-0.144	-0.070	-0.186	-0.129	-0.113	-0.035
	(0.007)	(0.005)	(0.012)	(0.010)	(0.008)	(0.005)
3	-0.093	-0.043	-0.125	-0.076	-0.070	-0.023
	(0.006)	(0.005)	(0.011)	(0.009)	(0.008)	(0.005)
4	-0.065	-0.029	-0.090	-0.055	-0.046	-0.013
	(0.006)	(0.004)	(0.011)	(0.009)	(0.007)	(0.005)
5	-0.050	-0.021	-0.080	-0.044	-0.029	-0.007
	(0.006)	(0.004)	(0.011)	(0.008)	(0.007)	(0.005)
6	-0.044	-0.017	-0.061	-0.038	-0.033	-0.006
	(0.006)	(0.004)	(0.010)	(0.008)	(0.007)	(0.005)
N	2,671,751	2,819,839	823,051	894,679	1,848,700	1,925,160

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

Table B.10: The Effect of Job Loss on Relative Earnings

Dependent variable: Earnings relative to pre-displacement mean

	All		**Recession**		**Growth**	
Time (1)	Bottom (2)	Top (3)	Bottom (4)	Top (5)	Bottom (6)	Top (7)
-3	0.004	-0.016	0.003	-0.015	0.005	-0.016
	(0.007)	(0.006)	(0.013)	(0.011)	(0.008)	(0.007)
-2	0.005	-0.002	0.003	-0.002	0.007	-0.001
	(0.005)	(0.005)	(0.009)	(0.009)	(0.005)	(0.006)
-1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0	0.002	-0.004	0.003	0.002	-0.001	-0.008
	(0.006)	(0.006)	(0.012)	(0.011)	(0.006)	(0.006)
1	-0.075	-0.034	-0.120	-0.071	-0.046	-0.013
	(0.009)	(0.010)	(0.016)	(0.023)	(0.010)	(0.009)
2	-0.184	-0.089	-0.256	-0.174	-0.137	-0.040
	(0.010)	(0.011)	(0.017)	(0.023)	(0.013)	(0.012)
3	-0.129	-0.079	-0.189	-0.151	-0.089	-0.037
	(0.011)	(0.012)	(0.017)	(0.023)	(0.014)	(0.013)
4	-0.098	-0.057	-0.162	-0.105	-0.055	-0.028
	(0.012)	(0.015)	(0.018)	(0.033)	(0.016)	(0.014)
5	-0.073	-0.042	-0.144	-0.065	-0.025	-0.028
	(0.012)	(0.018)	(0.018)	(0.042)	(0.016)	(0.015)
6	-0.060	-0.031	-0.130	-0.075	-0.014	-0.005
	(0.013)	(0.018)	(0.021)	(0.039)	(0.017)	(0.016)
N	2,671,751	2,819,839	823,051	894,679	1,848,700	1,925,160

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

Table B.11: The Effect of Job Loss on Real Earnings

Dependent variable: Real earnings in thousands

	All		**Recession**		**Growth**	
Time (1)	Bottom (2)	Top (3)	Bottom (4)	Top (5)	Bottom (6)	Top (7)
-3	-0.289	-1.077	-0.360	-0.535	-0.208	-1.372
	(0.153)	(0.287)	(0.257)	(0.329)	(0.189)	(0.409)
-2	0.049	-0.291	0.046	-0.242	0.073	-0.320
	(0.111)	(0.322)	(0.198)	(0.268)	(0.129)	(0.481)
-1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0	-0.166	0.037	-0.352	-0.304	-0.054	0.224
	(0.128)	(0.398)	(0.211)	(0.281)	(0.160)	(0.604)
1	-2.300	-1.306	-3.747	-2.794	-1.350	-0.465
	(0.206)	(0.309)	(0.338)	(0.400)	(0.256)	(0.427)
2	-5.585	-2.938	-7.720	-5.958	-4.148	-1.212
	(0.266)	(0.311)	(0.418)	(0.487)	(0.340)	(0.399)
3	-4.188	-2.897	-5.964	-5.382	-2.975	-1.471
	(0.270)	(0.386)	(0.417)	(0.476)	(0.351)	(0.540)
4	-3.476	-2.442	-5.232	-4.668	-2.285	-1.171
	(0.274)	(0.389)	(0.440)	(0.502)	(0.348)	(0.538)
5	-2.889	-2.103	-4.790	-4.185	-1.612	-0.922
	(0.283)	(0.446)	(0.446)	(0.552)	(0.363)	(0.624)
6	-2.521	-1.680	-4.585	-4.232	-1.182	-0.265
	(0.301)	(0.482)	(0.504)	(0.626)	(0.375)	(0.665)
N	2,671,751	2,819,839	823,051	894,679	1,848,700	1,925,160

Notes: The table shows event time coefficients underlying Figure C.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 B.12: The Effect of Job Loss on Working for Any of Father's Prior Employers

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

	All		Recession		Growth	
Time (1)	Bottom (2)	Top (3)	Bottom (4)	Top (5)	Bottom (6)	Top (7)
-3	-0.000	0.002	0.000	0.002	-0.000	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
-2	0.000	-0.000	-0.001	0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
-1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0	-0.001	0.000	-0.000	0.001	-0.001	-0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
1	-0.005	-0.034	-0.005	-0.046	-0.005	-0.027
	(0.002)	(0.004)	(0.002)	(0.007)	(0.002)	(0.004)
2	-0.003	-0.031	-0.004	-0.039	-0.003	-0.027
	(0.002)	(0.004)	(0.002)	(0.007)	(0.002)	(0.005)
3	-0.003	-0.028	-0.003	-0.034	-0.002	-0.025
	(0.002)	(0.004)	(0.002)	(0.007)	(0.002)	(0.005)
4	-0.003	-0.024	-0.003	-0.030	-0.003	-0.020
	(0.002)	(0.004)	(0.002)	(0.007)	(0.002)	(0.005)
5	-0.002	-0.020	0.000	-0.025	-0.004	-0.017
	(0.002)	(0.004)	(0.003)	(0.007)	(0.002)	(0.005)
6	-0.003	-0.019	-0.000	-0.024	-0.004	-0.016
	(0.002)	(0.004)	(0.003)	(0.007)	(0.002)	(0.005)
N	2,671,751	2,819,839	823,051	894,679	1,848,700	1,925,160

Notes: The table shows event time coefficients underlying Figure 14 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 B.13: Effect of Job Loss on Working for Father's Industry at Time t

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

	All		Recession		Growth	
Time	Bottom	Top	Bottom	Top	Bottom	Top
(1)	(2)	(3)	(4)	(5)	(6)	(7)
-3	-0.000	0.004	0.002	-0.000	-0.002	0.007
	(0.002)	(0.003)	(0.002)	(0.005)	(0.002)	(0.003)
-2	-0.001	0.003	-0.001	0.002	-0.001	0.004
	(0.001)	(0.002)	(0.001)	(0.004)	(0.001)	(0.003)
-1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0	-0.001	-0.003	-0.001	-0.003	-0.001	-0.002
	(0.001)	(0.002)	(0.001)	(0.004)	(0.002)	(0.003)
1	-0.004	-0.022	-0.004	-0.042	-0.003	-0.010
	(0.002)	(0.004)	(0.003)	(0.007)	(0.002)	(0.005)
2	-0.001	-0.016	-0.002	-0.033	-0.001	-0.006
	(0.002)	(0.004)	(0.003)	(0.008)	(0.003)	(0.005)
3	0.001	-0.010	0.003	-0.027	-0.001	-0.000
	(0.002)	(0.004)	(0.003)	(0.008)	(0.003)	(0.005)
4	0.001	-0.003	0.002	-0.023	0.001	0.009
	(0.002)	(0.004)	(0.003)	(0.008)	(0.003)	(0.005)
5	0.002	0.002	0.007	-0.018	-0.001	0.014
	(0.002)	(0.004)	(0.003)	(0.008)	(0.003)	(0.005)
6	0.004	0.005	0.008	-0.018	0.002	0.018
	(0.002)	(0.004)	(0.003)	(0.008)	(0.003)	(0.005)
N	2,671,751	2,819,839	823,051	894,679	1,848,700	1,925,160

Notes: The table shows event time coefficients underlying Figure 14 Panel D (which shows results from columns 2 and 3). We obtain the estimates from Equation (1) for adult children of top and bottom 20% separately. The outcome variable is whether the child works in the father's industry. Each regression controls for base year fixed effects, age fixed effects, and individual fixed effects. Standard errors clustered at the individual level appear in parentheses.

Table B.14: Impacts of Job Loss on Intergenerational Mobility When Ranks Are Defined Using Income

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

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

Table B.15: Simulation Results

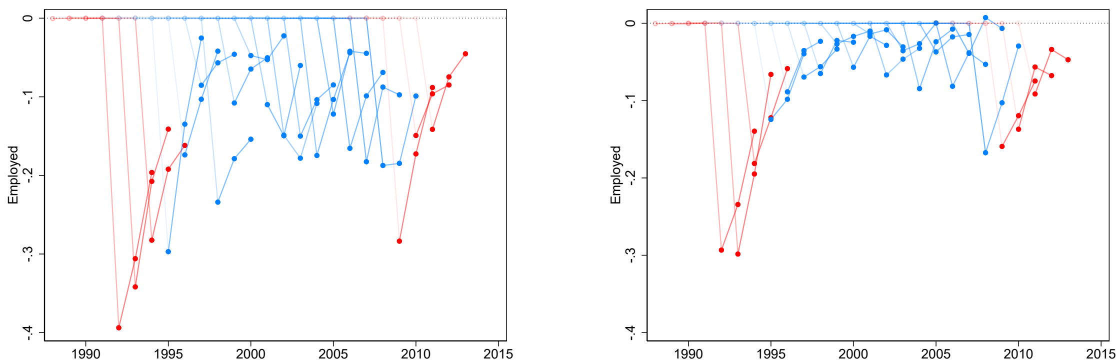
	Baseline Simulation	Job Loss Simulation
Age	Rank-Rank Correlation	Rank-Rank Correlation
(1)	(2)	(3)
30	0.1232	0.1250
		(0.0001)
31	0.1318	0.1373
		(0.0001)
32	0.1407	0.1484
		(0.0001)
33	0.1493	0.1583
		(0.0001)
34	0.1568	0.1665
		(0.0001)
35	0.1639	0.1743
		(0.0001)
36	0.1717	0.1811
		(0.0001)
37	0.1784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

Notes: This table displays the estimates from the simulation exercise described in Section 5.2 and shown in Figure 12. 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 11. 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 4. 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.

C Additional Figures

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

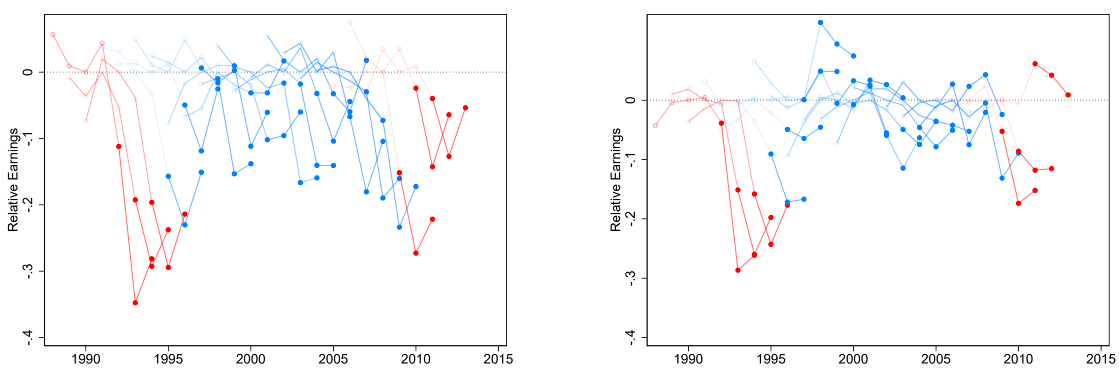
(a) Bottom 20% (b) Top 20%



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 C.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

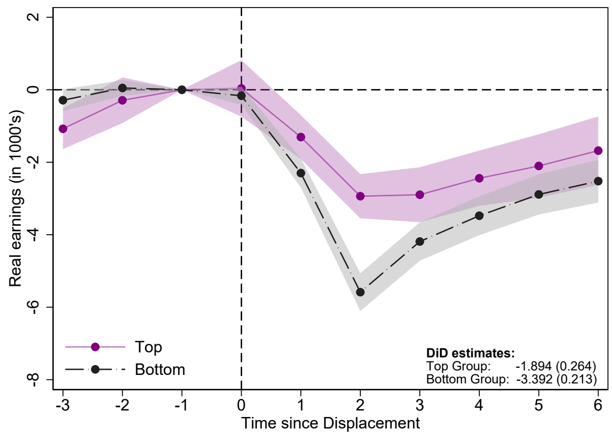
(a) Bottom 20% (b) Top 20%



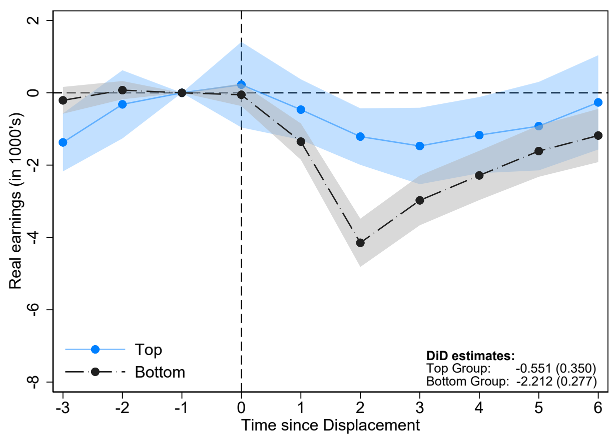
Note: Figures plot the estimates of δ_t obtained using equation 1 separately for different treatment waves. For presentation purposes, we only show the first three years after layoff. Panel A (B) shows the impact for individuals whose parents belong to the bottom (top) 20% of the income distribution. 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 C.3: Impacts of Job Loss on Real Earnings by Parental Earnings Groups, Bottom vs. Top 20%

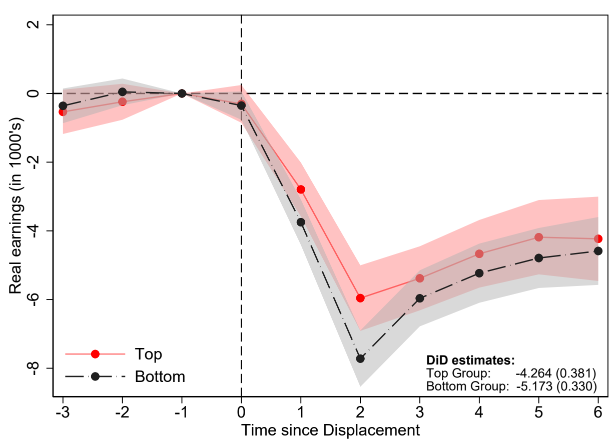
(a) All Years



(b) Growth Years



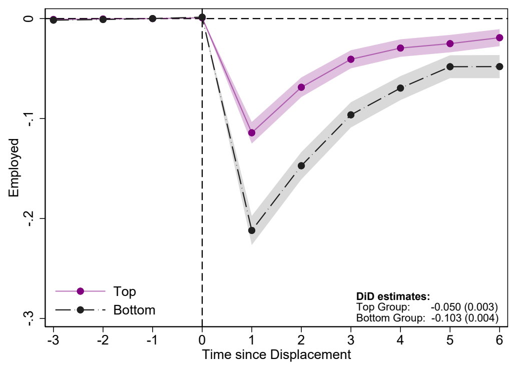
(c) Recession Years



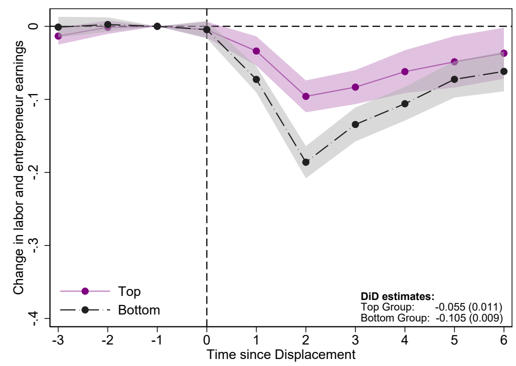
Note: Figures show that our results are robust to measuring child earnings in raw earnings as opposed to relative earnings. Figures plot the estimates of δ_t obtained using Equation (1) separately for bottom and top 20% parental income groups. Ninety-five percent confidence intervals appear as shaded 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 C.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



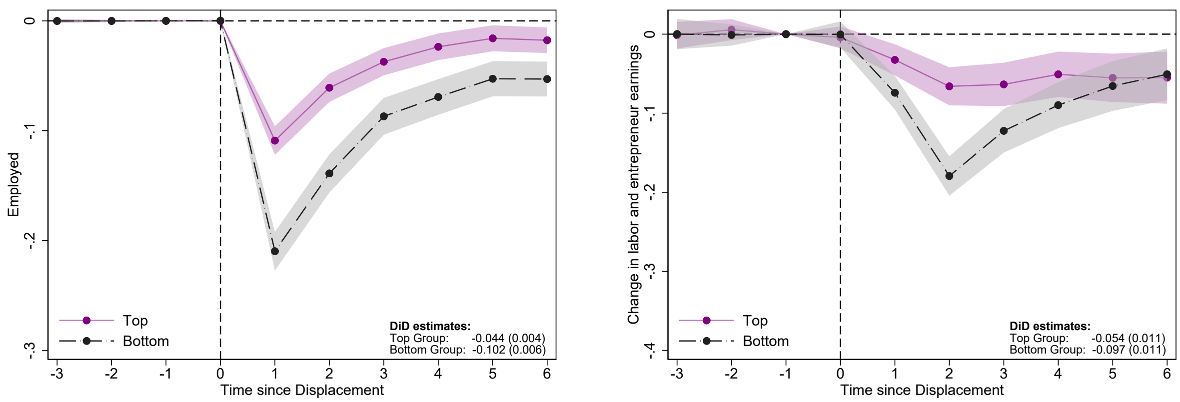
(b) Earnings Relative to Pre-mean



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 C.5: Impacts of Job Loss on Employment and Earnings Using the Matching Approach by Parental Earnings Groups, Bottom vs. Top 20%

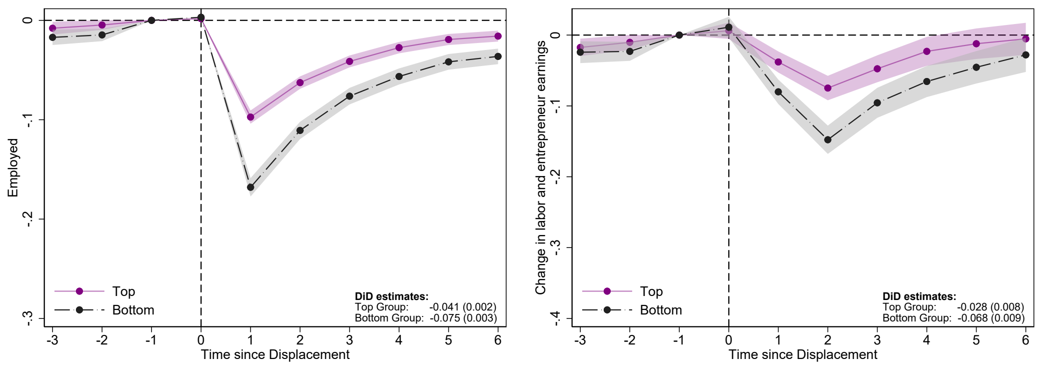
(a) Employment (b) Earnings Relative to Pre-Mean



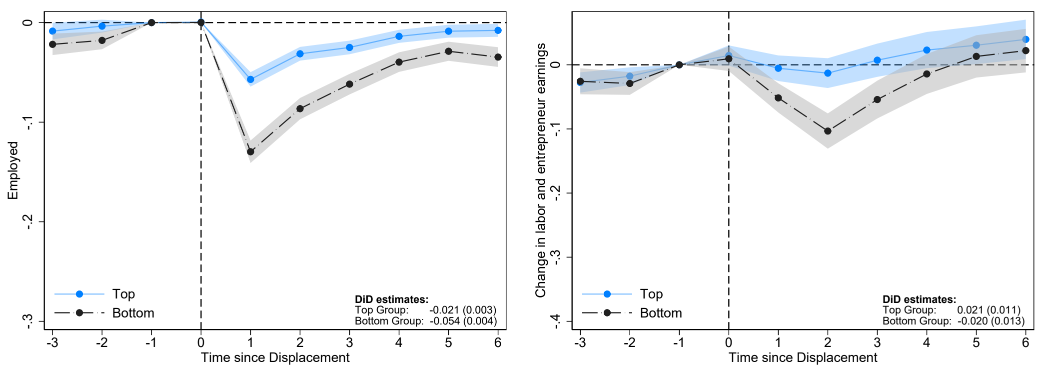
Note: Figures show the estimated impacts of job loss on future employment and earnings for the matched sample using the two-step matching estimator described in Section 6. In Panel A (B), the outcome is employment (relative earnings). Employment is measured at the end of the year. Relative earnings compare yearly labor and entrepreneurial earnings to the mean of yearly earnings 1–3 years before layoff. 95 percent confidence intervals appear as shaded bands around point estimates. DiD estimates are obtained by collapsing event study dummies into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses. Sample construction and data as defined in Section 2.1.

Figure C.6: Impacts of Job Loss by Parental Earnings Groups With Only 1 Year Tenure Required Instead of 3

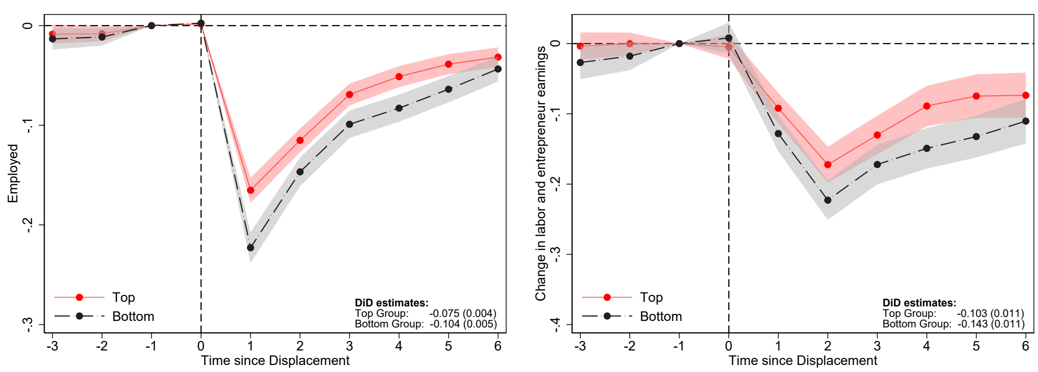
(a) Effects on Employment (Left) and Earnings (Right) for All Years



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

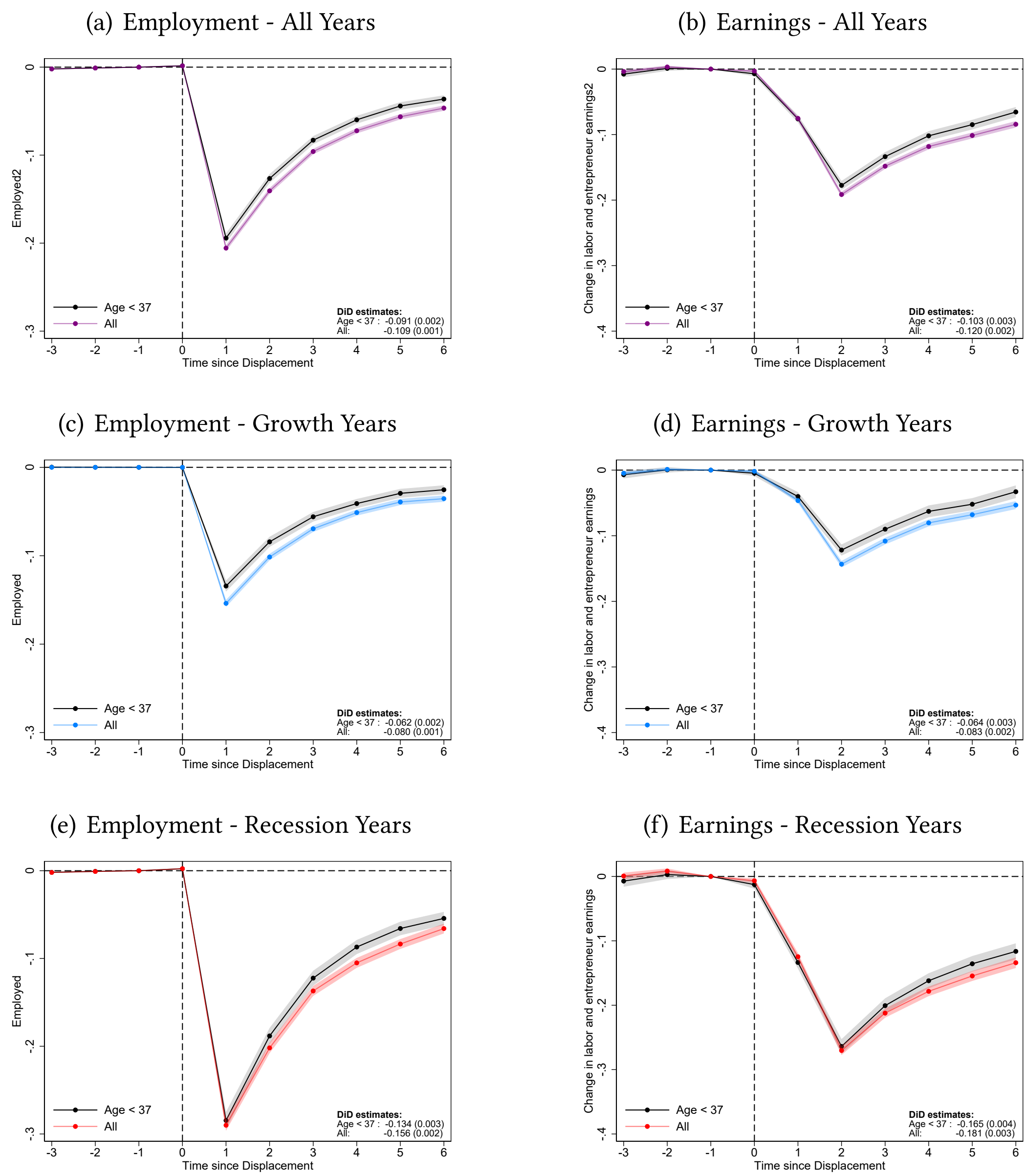


(c) Effects on Employment (Left) and Earnings (Right) for Recession Years



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.

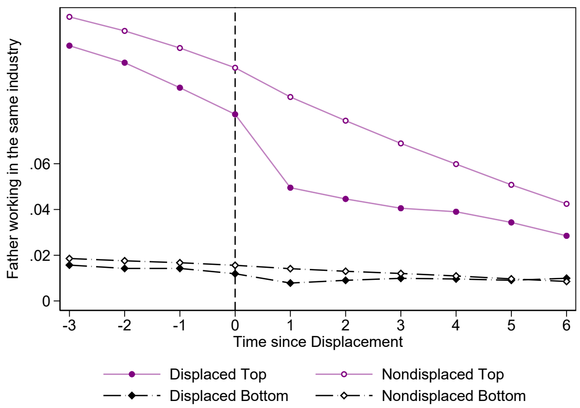
Figure C.7: Impacts of Job Loss on Employment (Left) and Earnings (Right) for the Full Population Aged 25–55 vs Those Aged 25–36



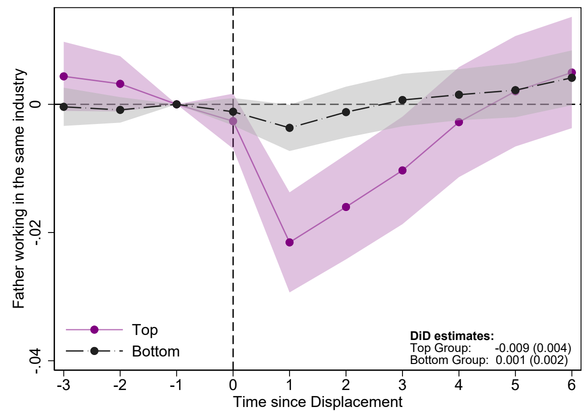
Note: Figure shows estimated impacts of job loss on future employment and earnings for the full population with all income groups for those aged 25–36 vs those aged 25–55. Panels A and B show results for layoffs in all years, Panels C and D for layoffs that occurs in growth years, and Panels E and F for recession years. Estimates derived using Equation (1). Ninety-five percent confidence intervals appear in shaded bands around point estimates. Standard errors are clustered at the individual level. DiD estimates are obtained using an alternative version of equation 1 in which event study dummies are collapsed into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses. Sample construction and data as defined in Section 2.1.

Figure C.8: Impacts of Job Loss on Working in the Same Industry as One's Father by Parental Income Group, Bottom vs. Top 20%

(a) Working in the same Industry as Father



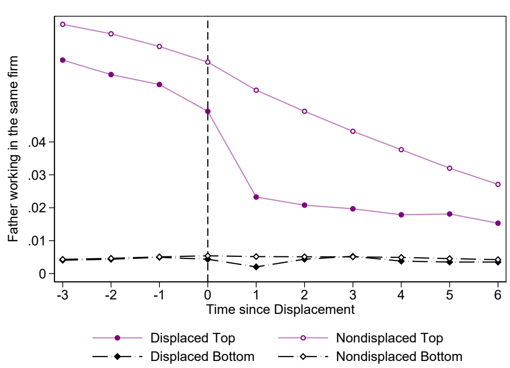
(b) Working in the same Industry as Father



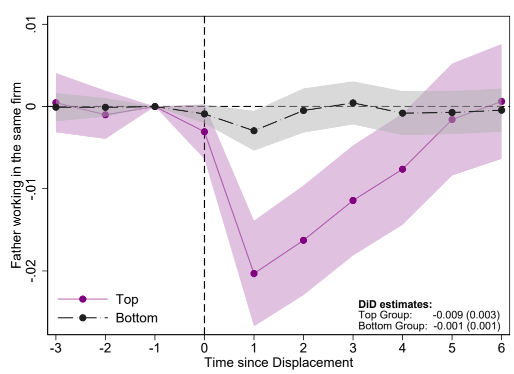
Note: Panel A shows the yearly probability of working for any of the father's industries for displaced and non-displaced individuals 3 years before and 6 years after the layoff by parental income group. The set of father's industries at year t contains all industries the father has had between years 1988 and t. Panel B shows the estimates of δ_t obtained using Equation (1) separately for the top and bottom parental income groups. Ninety-five percent confidence intervals appear in shaded bands around point estimates. Standard errors are clustered at the individual level. DiD estimates are obtained using an alternative version of Equation (1) in which event study dummies are collapsed into a single displacement indicator. Standard errors for the DiD estimates are shown in parentheses. Sample construction and data as defined in Section 2.1.

Figure C.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.