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Unlucky Labor Market Entry and Resilience in Subsequent Shocks

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Abstract

This study investigates how labor market conditions at graduation affect individual's labor market outcomes when facing employment shocks in later career, specifically due to plant closures. We focus on university graduates and vocational school graduates as two distinct groups. Our findings reveal that the long-term earnings loss following a plant closure is 175% higher for those university graduates who entered the labor market during periods of high regional unemployment. Additionally, these unlucky university graduates are more likely to work in lower quality firms. Among vocational school graduates, we do not find a similar additional negative effect on earnings or employment quality for unlucky graduates. Instead, our results suggest higher labor market activity compared to the luckiest graduates.

Keywords: Displacement, Plant closure, Business cycle, Recession, Graduation

JEL Classification: J21 , J24 , J65 , E32

1 Introduction

The period immediately following graduation can be a critical time in a person's career trajectory. This early career period is characterized by a number of transitions, including the transition from education to the labor market, the acquisition of new skills and work experience, and the development of professional networks. Research has shown that the experiences of early career can have a lasting impact on an individual's career path and long-term earnings potential (Altonji et al, 2016). For this reason, understanding the factors that shape the outcomes of early career, and in particular the role of macroeconomic cycles, has become an important area of inquiry in labor economics.

Several studies have investigated the impact of luck in the labor market entry timing, with a particular focus on university graduates. According to Kahn (2010), unlucky university graduates, who graduate during a tight labor market, start in lower-level occupations and, even when controlling for occupation, experience lower earnings. This is consistent with the results of Oreopoulos et al (2012), who find that unlucky graduates start at poorer quality firms, from which the more advantaged graduates move towards better firms. Using Norwegian data, Liu et al (2016) find that mismatch in the first employment is one of the main drivers behind persistent career losses. Additionally, Arellano-Bover (2020) suggest that skill development is hindered for unlucky entrants, as they are often matched with smaller firms and therefore have fewer opportunities for on-the-job learning.

Despite the relatively large literature on the effects of graduating during adverse economic conditions, which typically focuses on the initial shock of unlucky graduation timing, it is important to analyze the longer-term consequences as highlighted by Schwandt and von Wachter (2019).

We extend this research agenda by investigating how adverse conditions at labor market entry impact individuals' resilience in future labor market shocks. Specifically, we study individuals who are displaced in a plant closure and compare the costs of job loss across workers with different labor market conditions at labor market entry. The main hypothesis of this paper is that unlucky individuals face more difficulties recovering from a plant closure. The lower resilience can be due to lower human capital accumulation through unemployment or being employed in lower quality firms (Gibbons and Waldman, 2006). However, there is also a case to be made for higher resilience, which could be driven by, for example, having more experience of job-search (Gonzalez and Shi, 2010), lower relative wages (Schmieder and von Wachter, 2010) or seeking higher education when opportunity costs are low (van den Berge, 2018).

Our empirical results support the main hypothesis for university graduates. We find that the unlucky face a larger initial shock but also have significantly lower earnings in the long-term, which is driven by the quality of employment rather than the probability of employment. We do not find a similar effect among the vocational school graduates. Instead, we find zero or slightly better recovery from a plant closure for the unlucky, which is associated with higher labor market activity.

Examining the differences in the costs of job loss in a plant closure links this paper to the literature examining the costs of displacement. Since the seminal paper by Jacobson et al (1993), this well-established literature examines the effects of mass layoffs and plant closures on earnings and other labor market outcomes, and finds significant and persistent earnings losses. Stevens (1997), while reporting slightly lower estimates, emphasizes the influence of subsequent shocks in driving substantial and persistent earnings declines. Huttunen et al (2011), using data from Norwegian manufacturing plants, discover an increased likelihood of exiting the workforce and earnings losses among those transitioning between firms after displacement. Fackler et al (2021) emphasize the role of lost wage premiums and firm size. To develop a better understanding of the mechanisms at play, recent papers have focused on heterogeneous effects of job loss.

Our paper is most closely related to other studies examining the heterogeneous effects of plant closures. Schmieder et al (2023) highlight the role of recessions, and similar to Verho (2020), find larger earnings losses in displacements taking place during a recession. Other studies focus more on occupation and individual-specific differences. For example, Dauth et al (2021) examine the role of industry-specific import competition, and find that mass-layoff in high-wage plants leave scarring effects to the displaced workers. Blien et al (2021) find that individuals in routine occupations face larger earnings losses, while Izadi and Tuhkuri (n.d.) examine the role of psychological traits. We add to the literature by examining the differences in the recovery from the plant closure by different labor market conditions at graduation.

In the empirical analysis, we examine how the variation in regional unemployment at graduation affects one's recovery from a plant closure. We employ an event-study model with three-way interactions, where regional labor market conditions are divided into four groups, which allows for non-linear effects. In addition, this accounts for the development between lucky and unlucky non-displaced workers. To prevent potential selection issues of the unlucky being more likely to participate in mass layoffs, we focus on plant closure, a labor market shock that we consider more plausibly exogenous to the initial labor market conditions. To mitigate the risks of results being driven by direct immediate effects of graduation at different times, we restrict the analysis to plant closures at a minimum of 5 years from graduation. Finally, we control for differences in potential experience, graduation year, graduation region, and displacement year to examine the effect of unluckiness on recovery from a plant closure.

We can summarize our results as follows. We find that displaced unlucky university graduates face a larger and more permanent shock than their lucky counterparts. Ten years after the plant closure the displacement effect on annual incomes for the unluckiest quartile is -8.0% compared to -2.9% for the luckiest quartile. The long-run lower incomes are associated with lower employment quality, but not lower labor market activity. For vocational school graduates, we do not find a similar additional negative effect on employment, earnings, or employment quality for the unlucky. Instead, the estimates suggest higher labor market activity compared to the luckiest group, consistent with a smaller negative effect on employment. Our overall results concerning the effects of job loss align with the existing literature focusing on mass layoffs in Nordic countries. Moreover, echoing findings from studies such as Huttunen and Kellokumpu (2016) and Blien et al (2021), we observe that the initial shock is particularly pronounced among individuals with lower levels of education.

The rest of the paper is organized into four sections. Section 2 describes the data, identification, and sample construction. Section 3 outlines the methodology used to study resilience in future shocks. Results of our analysis are presented in Section 4. After displaying the estimates for the overall costs of job loss, we examine the results by initial labor market conditions and by early career characteristics. Finally, Section 5 concludes.

2 Data and variables

In our analysis, we use several high-quality register-based firm- and individual-level data sets from Statistics Finland. The core data set for our analysis is the matched employer-employee data (FOLK Employment Relationship Data). Using the employer and employee identifiers, we are able to link this data set to a large set of background characteristics from different registers.

Individual-level outcomes and information on background characteristics are from modules FOLK Basic and FOLK Income, of which the former includes individual-level demographics (age, gender, region, education, etc.) and the latter various annual income measures (e.g. taxable labor and capital income, transfers, taxes paid, etc.). In our analysis all nominal incomes are CPI-adjusted to 2019 euros and winsorized at 1%-level. We focus on market incomes, that include labor and capital incomes capturing a wide range of earnings from employment or self-employment.[1]

Firm-level information is based on firms' annual reports from 1986 to 2020. This data set provides us with information on firm's number of employees, value added and paid wages, which we use to construct measures of employer quality (See Appendix A for more details). Together with information from FOLK Employment Relationship Data enables us to identify plant closures and the affected individuals. Similar to individual nominal incomes, all firm-level outcomes in euros are CPI-adjusted to 2019 euros.

2.1 Identifying Labor Market Conditions at Graduation

The main objective of this paper is to examine how experiencing adverse labor market conditions at the time of graduation affects recovery from subsequent economic shocks, such as plant closures. To achieve this, we need to identify the relevant labor market conditions at the time of graduation.

[1] As a robustness check, we have also considered a more narrow income measure focusing on labor earnings. See Appendix G.2.2 for details.

We obtain graduation timing from the register data on Completed Degrees (FOLK Education) based on the first completed degree (separately for university and vocational school degrees) and graduation region based on the region of residence from FOLK Basic. We then match the time and region of graduation with labor market conditions, measured by annual regional unemployment rates.[2] We compute these rates based on the region of residence and primary activity information from the FOLK Basic dataset (See Figure 1 for an illustration).[3] It is important to note that this measure assigns the overall regional unemployment rate for all graduates within a calendar year, irrespective of their field of study. As a robustness check, we also consider unemployment rates specific to education fields and regions, which yield similar results (see Appendix G.1.1 for more details).

Finally, for analysis, we categorize the labor market conditions into four groups based on severity. Given that our data end in 2018 and we require five years of potential labor market experience before any layoff events, the last included graduates are from 2013. Therefore, our sample covers individuals who graduated between 1987 and 2013. Figure 1 illustrates how these 27 years are divided into quartiles based on the severity of regional unemployment rates at the time of graduation. The first quartile includes those who graduated during the seven years with the lowest regional unemployment rates, followed by six years in the second quartile, seven years in the third quartile, and seven years in the fourth quartile.

[2]We acknowledge that individuals might attempt to time their graduation according to the prevailing labor market conditions. We investigate this potential source of endogeneity in Appendix G.1.2.

[3]Annual regional unemployment rates are computed at the NUTS3 level. See Appendix B for more information.

2.2 Identification of plant closures

To effectively investigate the recovery process following plant closures, it is essential to establish clear criteria for identifying individuals impacted by these closures. Our approach involves implementing several key restrictions. Firstly, our focus is specifically on private firms. Secondly, we narrow down the range of eligible plant sizes, opting for those with 5 to 1000 employees in main employment, as derived from employment spells register data. This selection balances the exclusion of smaller firms and family-owned businesses while also mitigating the influence of outliers. A plant closure is identified when a plant observed at year b, referred as a base year, exits the register data at year b+1. To ensure we capture genuine closures and not just firm restructurings, we refrain from defining a closure in cases where 70% or more of the workers transition to a single new plant, a practice consistent with prior research. Additionally, we account for early leavers, considering situations where over 30% of workers depart from a plant in the year preceding its closure. Ultimately, an individual is deemed affected by a closure if they were employed in the plant at year b, which subsequently closes at year b+1.[4]

Establishments that fulfill the same criteria but do not exit the data at year b+1 form a universe of workplaces for non-displaced individuals. Similarly to the displaced, only individuals employed in these non-closure workplaces at year b are defined as non-displaced. These stringent criteria provide a solid foundation for our analysis, allowing us to explore the impact of plant closures on individuals' labor market outcomes with confidence. While our main interest is to examine the differences following a plant closure, the inclusion of non-displaced individuals is key to account for the labor market trajectories of non-displaced workers.

[4]For early leavers, we denote the last year they were employed at the plant as year b, even though the plant continues to operate in the following year.

2.3 Sample construction

The sample used in our main analysis consists of pooled event-study datasets, one for each base year b. Each base year sample consists of individuals for whom we observe the initial labor market conditions at the time of graduation and who are employed in a plant that closes down or at a counterfactual establishment. Similar to earlier literature on the effects of plant closures and mass-layoffs, we restrict the sample to workers with high attachment to the labor force.

More specifically, the following procedure is conducted to build the estimation sample. First, we start with panel datasets, one for each education group. We focus on university and vocational school graduates as they are common endpoints for the two educational tracks of secondary education.[5] These panel datasets consist of individuals for whom we observe the first graduation from 1987 and 2013 and region of residence at the time of graduation. We are then able to match the individuals with the local labor market conditions at the time of graduation.

Second, we build a separate event-study window for each base year b by including the individuals who were employed in a plant closure or a counterfactual establishment, as discussed in Section 2.2, at base year b. Each base year sample extends 5 years before and up to 10 years after the base year. We restrict the analysis to workers who at base year have at least 5 years of potential experience since graduation. This helps us to mitigate the risks of the results being affected from the direct effects of graduating in adverse economic conditions. This limits the earliest base year to be examined to 1992. We allow for unbalanced panel after the base year, and hence the last base year to be included is 2018.

[5] See Appendix C for more details about the Finnish education system.

Third, we restrict each base year sample to include workers with high attachment to the labor force. We include workers who are up to 50 years old at base year. We require an individual to be working in a plant closure or a counterfactual firm during base year b and b-1, to have been employed for 4 years, and to not have been working in a plant that closed down in b-3, b-2, or b-1. Finally, the base year–specific datasets are pooled together to form the estimation samples, one for each educational group.

2.4 Descriptive statistics

The identification of those affected by a plant closure, and the categorization into four groups based on initial labor market conditions at graduation, result in eight groups for our analysis. To examine the differential recovery from a plant closure by initial labor market conditions, the most important groups are the displaced groups with different initial labor market conditions, while the non-displaced control for between-group trends.

Table 1 panels (a) and (b) present the summary statistics for University and Vocational school graduates, respectively. Summary statistics columns 1 and 2 present the unconditional raw means for the non-displaced and displaced, respectively, while columns 3 to 6 present means among the displaced by increasing severity in initial labor market conditions.

In contrast to much of the literature on the effects of displacement, we choose not to match on observables between the displaced and non-displaced. The main reason is that the treatment of interest is the effects of initial labor market conditions on subsequent shocks. Essentially, everything observed at the base year or the pre-trend period can already be considered an outcome of the differences in initial labor market conditions. Additionally, matching becomes relatively cumbersome with more than two separate groups, as the interest is not solely on the effects of the displacement in a plant closure. This increases the risks of external validity if the sample becomes overly restricted. Instead, we choose to control for differences in potential experience, graduation year, graduation region, and the base year. Hence, we do not expect the different groups to be identical in terms of the unconditional characteristics.

Table 1 columns 1 and 2 indicate that in our sample, on average, the displaced are slightly younger and relatively as often married. Unconditionally, the displaced also seem to be negatively selected in labor market characteristics at the base year. They have lower tenure in a firm, experience more time in unemployment, have changed firms more often since graduation, and received more benefits in the base year. Also for vocational school graduates, we find that the displaced have lower incomes. Among university graduates, the unconditional average annual earnings since graduation are slightly higher. The summary statistics do not reveal differences in terms of changes in education between displaced and the non-displaced.

Columns 3 to 6 present the unconditional means among the displaced for our four groups based on initial labor market conditions. We find that these groups are relatively similar in terms of gender, tenure, and unemployment months. Overall, we find that a higher share of the unluckier cohorts have continued their education to a different field. Unsurprisingly, attaining higher education is more likely among vocational school graduates, while the differences between groups of initial labor market conditions are mixed. The lower share among the 2nd and 3rd quartiles could be related to these groups being, on average, younger and having lower potential experience. In the model, we include various fixed effects to control for level differences (See Section 3 for more details).

The differences in base year unconditional income levels between groups with different initial labor market conditions are apparent from Table 1. For example, market income is higher among the unluckiest quartile of university graduates (Column 6). In our empirical model, we control for differences in potential experience, graduation year, graduation region, and the base year, and thus we gain further insights on the income differences conditional on these outcomes. After controlling for these differences, the luckiest university quartile has 2-4% higher incomes than other quartiles in b-1. However, the income levels do not statistically significantly differ between the luckiest and unluckiest quartiles. For vocational school graduates, there are no significant differences in income levels in b-1 (except non-displaced 2nd luckiest quartile has 1% higher incomes than the non-displaced luckiest quartile).

Due to the pooled construction of our sample, an individual can participate in one or more base years, either as non-displaced or displaced, i.e., we allow individuals to be multiple times in the analysis. The last row of each panel in Table 1 indicates the number of unique individuals in each sample. As a robustness check, we have conducted the main analysis using a sub-sample, where each individual is allowed to participate in the base year samples until their first plant closure experience. The results of this robustness check, detailed in the Appendix G.1.3, align with our main findings.

3 Methods

Our study is methodologically divided into two main parts. First, we examine the effects of plant closure to establish a baseline of the effects of displacement. Second, we compare the effect of a plant closure between the unlucky and the lucky labor market entrants to examine the differences in recovery to the shock. We then replicate the latter part of the analysis by subgroups and for a range of alternative outcomes to gain a more nuanced understanding of the mechanisms.

As a methodology, event studies are utilized across various research fields, particularly in displacement studies, due to their capability to explore dynamics over time. These studies are prevalent in displacement research, where comprehending the dynamics of labor market adjustments following significant events like plant closures or layoffs is essential. In the main specification, the incorporation of various interaction terms aids in controlling for between-group trajectories characterized by different initial labor market conditions at graduation.

We start by estimating the event-study model in Equation 1 to examine the effects of plant closure. We conduct this for two main reasons: 1) to establish a baseline for the effect of displacement through plant closure, and 2) The baseline allows us to compare the results with our sample restrictions to a wide literature on the effects of displacement using relatively similar specification. Hence, we estimate the following event-study specification:

$$Y_{ikb} = \gamma_{bk} + D_{ib} + \sum_{\substack{k=-5,\\ k\neq -1}}^{10} \beta_k D_i \times I_k + \phi_c + \theta_r + \mu_e + \epsilon_{ikb}. \tag{1}$$

The main outcomes Y_{ikb} are employment status and log earnings of individual i at time k relative to the event in base year b.[6] The term γ_{bk} are fixed effects for base year $\times$ event-time and capture the base year–specific development of the non-displaced. The level differences between displaced and non-displaced at the reference point ($k = -1$) are captured by a displacement-dummy D_i, which indicates whether an individual was effected by a plant closure between

[6]Before taking logs, we first calculate the cell mean of each outcome, where a cell is based on graduation year and region, time relative to the event, base-year and displacement status (d). See Appendix D for more details.

$0 < k < 1$. We also include fixed-effects for graduation cohort (ϕ_c), graduation region (θ_r) and potential experience (μ_e).[7] Standard errors are clustered at the level of our main treatment, graduation year and region, to account for correlation of the error terms. The sum of interaction terms $D_i \times I_k$ includes a displacement dummy and an indicator for event time I_k. We follow the individuals 5 years before and up to 10 years after the plant closure and omit event time $k = -1$ as a reference point. The coefficients of interest are β_k, capturing the effect of plant closure at time k relative to the event.

Our main objective is to examine how the recovery of the plant closure varies between individuals with different labor market conditions at graduation, i.e. luckiness. To examine this, we extend the model in Equation 1 by including the measure of luckiness (L_{cr}), which is categorized into 4 groups based on the severity of the regional unemployment rate at the time of graduation, and the relevant interaction terms. The group with the most favorable conditions ($l = 1$) is held as a reference group. Hence, we estimate an event-study model with triple difference-in-differences:

$$Y_{ikb} = \gamma_{bk} + D_{ib} + \sum_{l=2}^{4} (\omega_l L_{cr} + \omega_{lD} D_{ib} \times L_{cr}) + \sum_{\substack{k=-5,\\ k\neq -1}}^{10} \beta_k D_{ib} \times I_k$$

$$+ \sum_{\substack{k=-5,\\ k\neq -1}}^{10} \sum_{l=2}^{4} [\gamma_{kl} I_k \times L_{cr} + \delta_{kl} D_{ib} \times I_k \times L_{cr}) + \theta_r + \phi_c + \mu_e + \epsilon_{ikb}. \quad (2)$$

In this specification, coefficients γ_{kl} pick up differences in the development for different luckiness-quartiles ($l = 2, 3, 4$) relative to the base year–specific

[7] Our results are robust to including either displacement firm or graduation field fixed effects. See Appendix G.2.1 for details.

development of the non-displaced luckiest quartile (γ_{bk}). The main coefficients of interest are δ_{kl}, which capture differences in the development of the luckiness-quartile l, who experienced a plant closure, at time-to-event k in addition to the development of the displaced reference group (β_k). To evaluate the differences in the recovery of luckiness-quartiles, we base the evaluation on the coefficient δ_{kl}. To analyze the recovery relative to the non-displaced, we instead use the sum of β_k and δ_{kl}.

The main coefficients of interest are the δ_{kl}, which capture the difference in the development of the luckiness-quartile l at time-to-event k relative to the development for the reference group, non-displaced luckiness-quartiles and the non-displaced luckiness quartile, captured by β_k, γ_{kl} and γ_{bk}, respectively.

An obvious caveat in our research setup is that our treatment of interest, the labor market conditions at the time of graduation, takes place in the past. Hence, everything can be considered part of the outcome. By taking into account differences in the between-group trajectories and including controls, our aim is to compare conditionally similar individuals. The dynamic methodology allows us to examine pre-trends, indicating that at least for the sample of university graduates, the displaced groups develop similarly before plant closure. For a sample of vocational school graduates, some pre-trend coefficients are concerning. Especially for earlier periods, where employment is not required.

4 Results

4.1 Effect of displacement in a plant closure

Figure 2 reports the findings from our baseline estimation (Equation 1), where we examine the effects of being displaced in a plant closure. We find that a plant closure event has a significant impact on both university and vocational school graduates, leading to persistently lower employment rates and incomes. Specifically, compared to the non-displaced, the university graduates face a 7.4% decrease in employment initially, which reduces to 1.2% after ten years. Their incomes initially drop by 7%, and this effect persists with a 4.9% decrease observed at the ten-year mark.

We find that vocational school graduates experience a severe initial shock, with a 15.2% decrease in employment and a 15.4% decrease in income compared to the non-displaced. After ten years, the employment rate is still 2.3% lower than the baseline, and incomes remain 4.1% lower. Differences in the estimates between different education groups suggests that the impact of the plant closure is more pronounced for vocational school graduates compared to their university counterparts. However, the long-lasting effects are relatively similar, especially for incomes.

Figure 2 underscores the advantages of employing event study models to investigate dynamics. The timing of the shock can vary significantly depending on the outcome under scrutiny. For instance, outcomes like employment clearly exhibit an immediate effect following the shock. However, when considering annual incomes, the impact may be contingent upon the timing of the plant closure. If the closure occurs towards the end of the year, individuals may have already earned a substantial portion of their annual income. Additional factors, such as severance payments and temporary transfers like earnings-related unemployment allowance, prevalent in the Finnish context, could also influence income dynamics.

Compared to the earlier literature on the effects of displacement through plant closure or mass layoff from other countries, our estimated effects are slightly smaller in magnitude. Both for the severity of the initial shock as well as for long-term effects. Recent papers estimating the effects of displacement in Germany find that a decline in earnings from 25% (Blien et al, 2021; Fackler et al, 2021) to 55% (Jarosch, 2023), and 10-15% in the longer term. Also for Germany, Schmieder et al (2023) find that earnings losses vary from 13% to 25% depending on the business cycle. The estimated earning losses from displacement are high in United States, where studies have found initial earning losses of 33-49% and 12-25% persistent losses in the long-term (Jacobson et al, 1993; Couch and Placzek, 2010; Lachowska et al, 2020).

While our results deviate from the estimated effect for Germany and United States, they are in line with the other studies estimating the effects in Finland and studies focusing on other Nordic countries. For Finland, Huttunen and Kellokumpu (2016) find a short-term effect of -23% and a long-term effect of -2.2%, with larger impacts observed for individuals with lower levels of education. The role of business cycle is emphasized in Verho (2020), who finds earning losses of -60% during the 1990s recession in Finland. Eliason and Storrie (2006) find 3.2% lower employment even 12 years after displacement using Swedish data. Huttunen et al (2011) find similar long-term effects of displacement using Norwegian data, while the short-term effects are relatively small. Taken together, our results seem to be well in line with the comparable studies using data of similar countries.

Based on the results of our basic model, we find intriguing disparities in the recovery process following a plant closure among different educational groups. However, it is important to acknowledge that not all individuals within a particular educational group are treated equally. Some individuals may have experienced a turbulent start to their careers, facing challenges that significantly impact their subsequent trajectories. There exists an extensive body of literature that has found that adverse initial labor market conditions has a negative effect on individuals' careers in both the short and long term (See e.g. Kahn, 2010; Oreopoulos et al, 2012; Liu et al, 2016; Arellano-Bover, 2020). This prompts us to delve deeper into the following question: How do adverse initial labor market conditions influence one's recovery process?

4.2 Effect of mass-layoff by Unluckiness

The primary focus of this study is to investigate the impact of adverse initial labor market conditions at graduation on one's recovery from a plant closure. To this end, we employ an extended event study model as expressed in Equation 2. The key estimates derived from our estimation are illustrated in Figure 3 for employment outcomes and Figure 4 for income measures. Panels (a) and (b) of the figures depict the overall effect of displacement for University and Vocational school graduates, while panels (c) and (d) present the estimated differences relative to the luckiest quartile, as captured by δ_{kl}.

Concerning employment outcomes, as depicted in panels (c) and (d) of Figure 3, unlucky university graduates experience a larger initial shock of 2 to 4 percentage points, representing a 33% to 66% increase compared to the reference group, and this effect is statistically significant. However, this additional harm diminishes by the 7th year. Conversely, for vocational school graduates, no such additional negative effect is observed. In fact, the estimated difference tends to favor the unluckier cohort, albeit not statistically significant for the majority of the years.

Regarding the effect on incomes, the story is relatively similar. Figure 4 reveals heterogeneous effects based on the initial labor market conditions. Among university graduates, graduating during a period of higher regional unemployment rate is associated with additional harm during future plant closures, as evidenced by statistically significant negative coefficients for the highest regional unemployment rate quartiles in most years. These effects are substantial in magnitude, with the luckiest quartile experiencing a 3.1% decrease in earnings at the 7th year, while the 3rd and 4th quartiles endure additional 7.1 and 4.1 percentage points lower earnings, respectively.[8] In contrast, among vocational school graduates, no similar additional negative effects on incomes are observed. On the contrary, the estimates for the differences tend to be positive and, at times, statistically significant, indicating a smaller negative shock and faster recovery for the unlucky graduates. However, the estimated statistically significant differences before the plant closure for vocational school graduates raises some concerns regarding parallel trends assumption.

Overall, our main results indicate that among university graduates, unluckier individuals—those who graduated during times of adverse labor market conditions—suffer larger losses from job loss in a plant closure compared to their luckier counterparts. While the lower employment appears to be temporary, with differences diminishing by the 7th year, income losses are relatively persistent. The unluckiest graduates face an 8.0% decrease in incomes 10 years after displacement, compared to a 2.9% decrease for the luckiest quartile. For vocational school graduates, the results do not indicate any negative effects of graduating in adverse economic conditions. Disparities between the effects on employment and incomes among university graduates, as well as between educational groups, encourage us to examine potential mechanisms behind these developments. In the following subsection, we explore various outcomes regarding labor market activity and the quality of employment to shed light on the plausible mechanisms explaining the different outcomes.

[8] As a robustness check, we have considered a more restricted measure for incomes. Using a similar model specification for labor earnings, we find an additional 3.8 and 2.3 percentage-points lower earnings over the -3% for the luckiest quartile at year 7.

4.3 Effects on labor market activity and quality of employment

We examine effects of labor market activity and quality of employment using the same extended dynamic model as specified in Equation 2. Table 2 summarizes the results for both initial and long-term effects on the main and alternative outcomes examined to reveal potential mechanisms. Initial effects refer to the coefficients at the peak of the shock, while long-term effects pertain to the estimated impact seven years after displacement. Figures presenting all estimated time-to-event coefficients are presented in Appendix (See Figures E3, E4 and E5).

Regarding labor market activity, we examine the effects on unemployment months, being outside of labor force, received benefits, and firm changes. As evident from coefficients β_1 and β_7 in Table 2 columns 3 to 6, for the reference group of the luckiest quartile, we find displacement effects that are approximately two-fold for the vocational school graduates compared to university graduates for time spent in unemployment and received benefits, and three-fold for probability of being outside of the labor force.

In terms of heterogeneity by initial labor market conditions, captured by $\delta_{k,l}$, we find that the unlucky university graduates spend more time in unemployment than the luckiest quartile. This is in contrast to the vocational school graduates, where the coefficients are negative. Results on the probability of being outside of labor force depict a similar story, that among university graduates unluckiness increases labor market inactivity. Again the differences among vocational school graduates are insignificant. For firm changes, we find that the unlucky vocational school graduates are more likely starting in a new firm immediately after the plant closure, indicating faster re-employment. For unlucky university graduates, we do not find a similar effect.

In the long-term, there are no statistically significant differences between the unlucky quartiles and the luckiest quartile in labor market activity for university graduates, while among vocational school graduates the unlucky seem more active as they spend less time in unemployment and are less likely to be outside of labor force than the luckiest group at 7th year following the displacement.

We also investigate the differences in employment quality, where we examine probability of being employed in high productivity, high wage, or large firm. Column 7 of Table 2 reports the estimates on employment in a high productivity firm, which is defined as employment in a firm with above median productivity, where productivity is measured by firms' average value added per worker. This indicator receives value 1 if an individual is employed in a firm with above median productivity, and 0 otherwise.[9] The benefit of such measure is that the results are not conditional of employment. However, in the short-run effects are likely driven by the non-employment instead of individuals being actually employed in firms of different quality. For the long-term, we find that the displaced individuals in the luckiest quartile are more likely to be employed in a high productivity firm. As we do not observe statistically significant differences in the pre-displacement levels, we interpret this as creative destruction, in the form of plant closures, freeing labor resources to be employed in more productive firms.

Among the university graduates, we find that the unlucky fare worse in terms of being employed in a high productivity firm in the long-term. As is evident from the estimates on employment, this does not seem to be driven by non-employment. For vocational school graduates there are no significant

[9] First, we calculated the average annual value added per worker for each firm using all available years of data. This yielded a single value for each firm. We then computed the median from this cross-sectional distribution of firms. For an individual, this measure can change only when they leave their employer.

differences in the employer productivity between the lucky and unlucky graduates in short- or long-term. Hence, the unlucky displaced are similarly more likely to be employed in better firms seven years after a plant closure. The positive signs of being employed in better firms, does not however seem to be reflected in better income for the affected. One possible explanation for this is the reduced bargaining power of displaced individuals, although the relative importance of this channel is questioned by Jarosch (2023).

Column 8 in Table 2 presents the estimates for employment in a high wage firm. Similarly to productivity, this is an indicator variables based on the median.[10] We find that displaced vocational school graduates change to firms with higher average wages in the long-term, and this effect is more potent for the unluckiest group. For university graduates, the long-term effect of displacement on being employed in a high wage firm is not statistically significant for the luckiest quartile. The differences between the luckiness quartiles are also not statistically significant. However, the effect of displacement on the unluckiest university graduates, captured by $\beta_7 + \delta_{7,4}$, is negative and statistically significant.

Column 9 in Table 2 present the estimates for employment in a large firm. Results indicate that following a plant closure, the displaced find themselves in smaller firms in the long-run, in line with e.g. Lachowska et al (2020). For vocational school graduates, the displacement effect is less negative for those who graduated during periods of high regional unemployment. In contrast, among university graduates, the negative effect is more pronounced for these unlucky individuals.

To summarize, the results on labor market activity and employment quality provide additional insights that support our results on the effects of displacement, both between education groups and by initial labor market conditions

[10] See Appendix A for details.

at graduation. Among university graduates, the main results indicate that seven years after displacement, unluckiness has an additional negative effect on incomes but no statistically significant effect on employment. Analysis on unemployment months, labor force participation and received benefits supports this as we do not find statistically significant differences between groups with different initial labor market conditions. The results regarding employment quality suggest that unlucky university graduates are less likely to secure positions in large firms or in firms characterized by high productivity or wages, compared to those in the luckiest quartile. This is inline with the results on lower market incomes despite no additional effect on employment.

Among vocational school graduates, the main results do not indicate any additional negative effects of graduating at adverse economic conditions on the recovery from a plant closure. On the contrary, in the long-run, the coefficients are slightly positive but mostly not statistically significant. Examining the effects on other outcomes, we find that the unlucky vocational school graduates seem to be doing better in terms of labor market activity as they spend less time in unemployment and being outside of labor force. We do not find differences in the likelihood of being employed in highly productive firms. In fact, firm quality may even increase for unlucky graduates, as the data suggests they work in larger firms and firms with higher average wages. Overall, these results are inline with the main results, and highlight aspects, where the unlucky vocational school graduates fare better than their luckier counterparts.

Taken together, these results suggest that the income penalty associated with unfavorable labor market conditions at graduation may be linked to the quality of employers after displacement. This is inferred from the observation that university graduates experience this penalty, whereas vocational school graduates do not.

4.4 Role of early career characteristics

Earlier literature on the effects of unlucky graduation has found that adverse economic conditions at graduation affect one's decisions and early career development (see, for example, von Wachter, 2020). We draw from this literature to further explore plausible mechanisms explaining the observed differences in the recovery from a plant closure. To examine the mechanisms, we conduct a heterogeneity analysis examining the effects for various sub-groups. The results of this analysis are summarized in Tables 3 and 4 for employment and incomes, respectively. Figures F6 to F11 in Appendix present the estimated δ_{kl} coefficients for all periods. In Tables 3 and 4 panel (a) focuses on the university graduates, while panel (b) presents the results for the vocational school graduates.

We conduct the heterogeneity analysis by estimating Equation 2 for a subsample to avoid overly complicated dynamic models with 4-way interaction-terms. The sub-samples are derived from characteristics observed in the base year. It is important to note that, although these groups are formed based on pre-displacement characteristics, their composition is influenced by the primary variable of interest: the labor market conditions at the time of graduation. To examine how the decisions, that the unlucky are forced to make, affects the recovery from a plant closure, we compare the unlucky individuals with the specific early career characteristics to all individuals in the luckiest group.

4.4.1 Further Education

The opportunity cost of education tends to decrease during economic downturns when high-paying job opportunities are scarce. Consequently, some individuals graduating during a recession may opt to pursue a higher degree or an additional degree in a different field (See e.g., van den Berge, 2018). In this subgroup analysis, we delve into whether the disparities in displacement effects between lucky and unlucky individuals are linked to further educational attainment. We examine decisions to pursue further education at a higher level or in a different field separately.

When comparing the effects of displacement between individuals who have attained a higher degree and those who have not, it's important to acknowledge that for our sample of university graduates, attaining a higher degree implies getting a doctoral degree. This greatly reduces the number of observations and affects precision (Column 2 in Tables 3 and 4). Despite this caveat, our analysis unveils intriguing insights. Among university graduates, the additional initial shock in employment is primarily driven by individuals remaining at the tertiary degree level, while in the long term, a slight positive difference is observed for unlucky graduates who haven't changed their education level. Regarding incomes, although the estimates suggest larger negative effects for those with higher degrees in the long term, they are statistically insignificant due to the limited number of observations. Overall, the estimates from the main specification align with those from a subgroup with no change in the level of education.

This subgroup analysis provides valuable insights, particularly for vocational school graduates, where the hypothesis of individuals attaining higher degrees in response to adverse economic conditions at their initial graduation holds more weight. Short-term differences in employment effects between luckiness groups appear to be influenced by those who have attained higher degrees, among whom the unlucky graduates face a considerably smaller initial shock. While unlucky individuals with higher education also fare better in the long term, the differences are smaller, and also the unlucky with no higher degrees fare better than the reference group. Similarly, in terms of incomes, the less negative short-term effect for the unlucky is more pronounced among those who have attained higher education, and this trend persists in the long run. While the estimates for the unluckiness-effect are lower for a sample of individuals without higher degrees, it is important to note that the coefficients are still positive, implying that the non-negative effect among unlucky vocational school graduates is not solely driven by those with higher degrees. Overall, these results suggests that having attained higher education can be beneficial in the recovery from a plant closure for vocational school graduates. However, this could be driven by positive selection among vocational school graduates opting for higher education.

Turning to the decisions of further education in a different field. A curious trend emerges, when examining the long-term effects of displacement on employment among university graduates: those who attained a degree in a different field seem to fare better, despite the possibility of experiencing a more severe initial shock, which is counter-intuitive. However, when delving into income outcomes, a more nuanced picture unfolds. Among those who did not change their field of education, negative long-term effects on incomes are observed for the unlucky group. For those who pursued a degree in a different field, the long-term results are mixed and lack statistical significance. An important caveat to note, is that the analysis of individuals changing their education field suffers from a limited number of observations.

Transitioning to vocational school graduates, the short-term effects of displacement on employment appear consistent across those who have changed their education field and those who have not. Similarly, this pattern persists in the long term. However, regarding incomes, an intriguing pattern emerges: among unlucky graduates who acquired a degree from a new field, the short-and long-term income losses mirror those who have not changed their education field. This suggests that additional education alone does not significantly impact how unlucky vocational school graduates react to displacement; rather, it is the individuals who pursue higher levels of education that tend to suffer less from displacements.

4.4.2 Job mobility

Oreopoulos et al (2012) have suggested that the adverse effects of graduating during unfavorable labor market conditions on earnings can be mitigated through gradual mobility to better firms. This concept may also be relevant for recovery from subsequent employment shocks for several reasons. Firstly, individuals might develop essential job search skills when compelled to seek better matches early in their careers (Gonzalez and Shi, 2010). Secondly, advancing up the job ladder and securing positions in larger firms may allow individuals to accumulate human capital which is advantageous when applying for future positions.

To investigate the role of firm changes in this context, we conducted a heterogeneity analysis by estimating the displacement effects separately for individuals with cumulative firm changes during the first five years of their careers that were above and below the sample median. The results on employment and income are depicted in Appendix in Figures F6 and F7, respectively. The last two columns in Tables 3 and 4 summarize these results for outcomes employment and log market incomes, respectively.

For university graduates, the short-term penalties on employment and income due to unfavorable labor market conditions at graduation are more pronounced for those who have changed firms less frequently in their early careers. In the long term, the income penalty for these less mobile individuals is slightly larger, though the employment penalty is non-existent for both groups. These findings suggest that early career mobility is associated with higher resilience to future shocks. According to the results by Gonzalez and Shi (2010) the individuals who end up selecting into lower mobility might be those who are discouraged by negative search outcomes. Thus, our results might reflect the differences in the initial labor market prospects.

An alternative explanation is that unlucky individuals who changed firms less frequently may have initially started in more prestigious firms and subsequently experienced a larger loss in the firm-specific wage component due to displacement, as suggested by Fackler et al (2021). However, our heterogeneity analysis (not reported here) does not support this explanation, as it indicates that the unluckiness penalty on the probability of working in a high-productivity firm is indeed larger for individuals who have changed employers less frequently.

For vocational school graduates, our findings indicate that the relatively faster recovery of the unlucky graduates, as observed in our main results, is primarily attributable to those who have changed employers more frequently in their early careers. However, it is important to note that in this sub-group analysis, the pre-trends of market income for vocational school graduates are not parallel.

5 Conclusion

This paper set out to investigate how adverse conditions at labor market entry impact individuals' resilience in future labor market shocks. The literature examining the development of income and employment primarily focuses on the initial shock of unlucky graduation timing. This study contributes to the existing literature by examining how early career experiences impact recovery in future plant closures.

Our results demonstrate that university graduates embarking on their careers during adverse economic conditions face larger earnings losses in the event of future plant closures. Among vocational school graduates, we observe significant and persistent earnings losses overall, but we do not find similar additional losses for unlucky vocational school graduates.

The results regarding labor market activity and employment quality provide insights into the underlying mechanisms at play. We find that unlucky university graduates tend to be employed in lower-quality firms than their luckier counterparts, which may partly explain their larger earnings losses. Especially, when results indicate no additional negative long-term effect on employment for the unlucky. Among vocational school graduates, we find that all displaced individuals change to higher-quality firms. However, employment in higher-quality firms does not seem to translate into better earnings development compared to the non-displaced group.

The findings regarding labor market activity shed light on an additional mechanism underlying the impact of unlucky labor market entry timing. For unlucky university graduates, the initial shock reveals a higher likelihood of spending time in unemployment or outside of the labor force compared to their luckier counterparts. However, these seem temporary as the long-term analysis suggests no significant difference in labor market activity. Conversely, vocational school graduates experience a more pronounced initial shock, yet the short- and long-term results indicate some positive effects on labor market activity for the unlucky cohort. This could be associated with more experience of job search paying off, in line with the results of early career mobility.

Taken together, our result highlight that graduation timing has long lasting effects, that are also reflected in decisions and reaction later in the career shocks. The results on the overall effects of displacement highlight the vulnerability of the vocational school graduates, which could benefit from targeted support programs. The results focusing on unlucky vocational school graduates who attained further education suggests that policies aimed at up-skilling could be beneficial in helping displaced workers transition to new industries or occupations.

This study has three limitations. First, this paper focuses on high-attached individuals who, despite the early career difficulties, have managed to find employment. Hence, we might not capture the impact for the most harmfully affected groups.

Second, our focus on two distinctive education groups leaves out potentially interesting phenomena regarding education or occupation-specific developments. For instance, Blien et al (2021) has found that workers displaced from more routine occupations face larger earnings losses. It is plausible that the stronger effect among vocational school graduates is related to the higher share of individuals in routine intensive occupations. Hence, this might not apply to all vocational school graduates working in different sectors.

Finally, while our results on university graduates highlight the role of employment quality, our analysis does not delve deeper into the mechanisms behind the reasons why unlucky university graduates transition to lower-quality firms after plant closures. Focusing on the mechanisms of human capital accumulation, the role of networks, differences in reservation wages, or general pessimism about the labor market are all potentially interesting avenues for future research.

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Figures

Variation in regional unemployment rate

Fig. 1: Unemployment rate in Finnish regions from 1987 to 2013

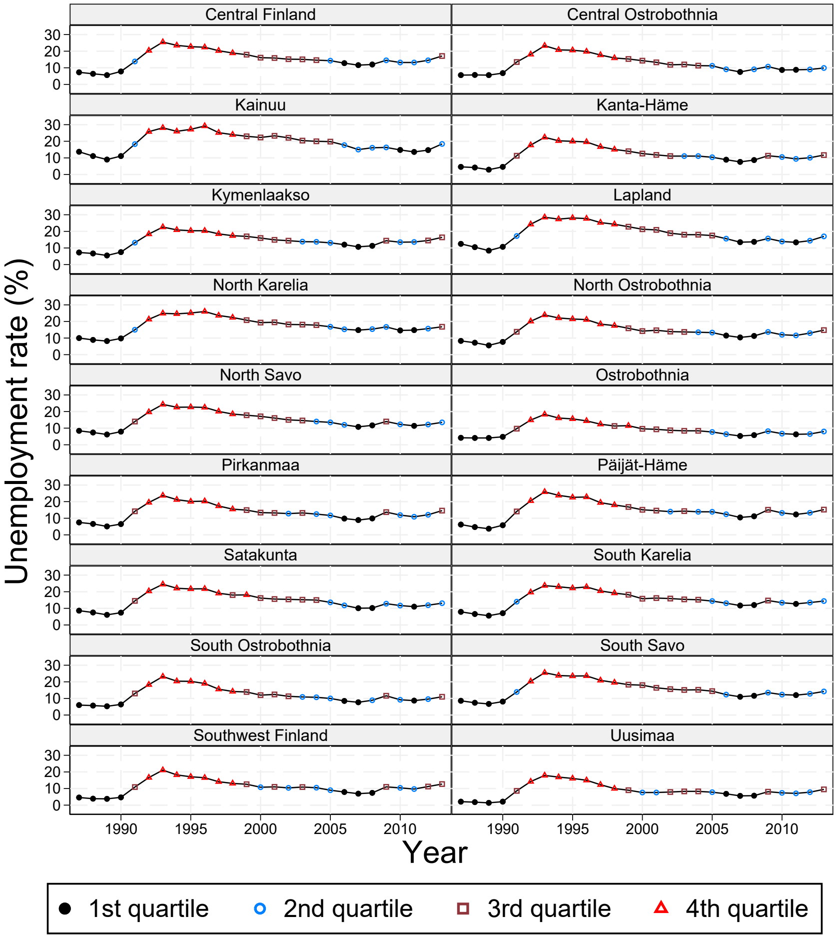
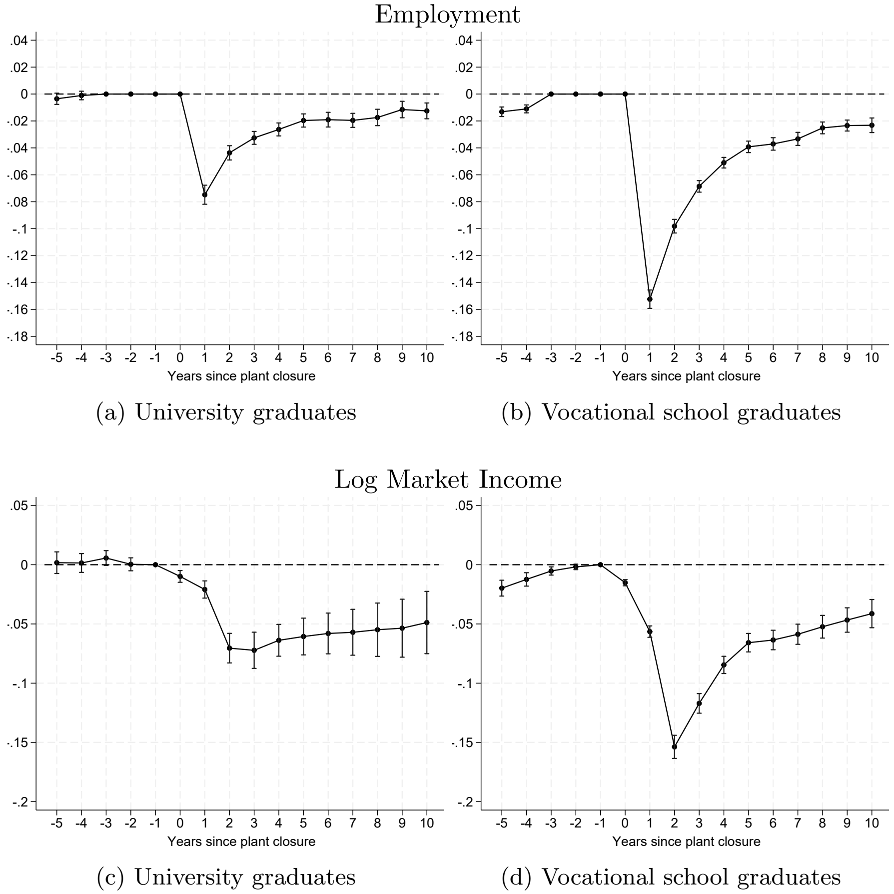


Figure 1 presents the unemployment rate in Finnish regions from 1987 to 2013. Observations with regional unemployment rates among the lowest 7 years are marked with black dots, those from 8 to 13 years are marked with hollow blue circles, those from 14 to 20 years are marked with maroon squares, and the 7 highest years are marked with red triangles.
Statistics: Mean 14.0%, Within region, std.dev: 4.9%
Source: Statistics Finland

Effect of displacement in a plant closure

Fig. 2: Effect of Displacement (β_k)



(a) University graduates (b) Vocational school graduates

(c) University graduates (d) Vocational school graduates

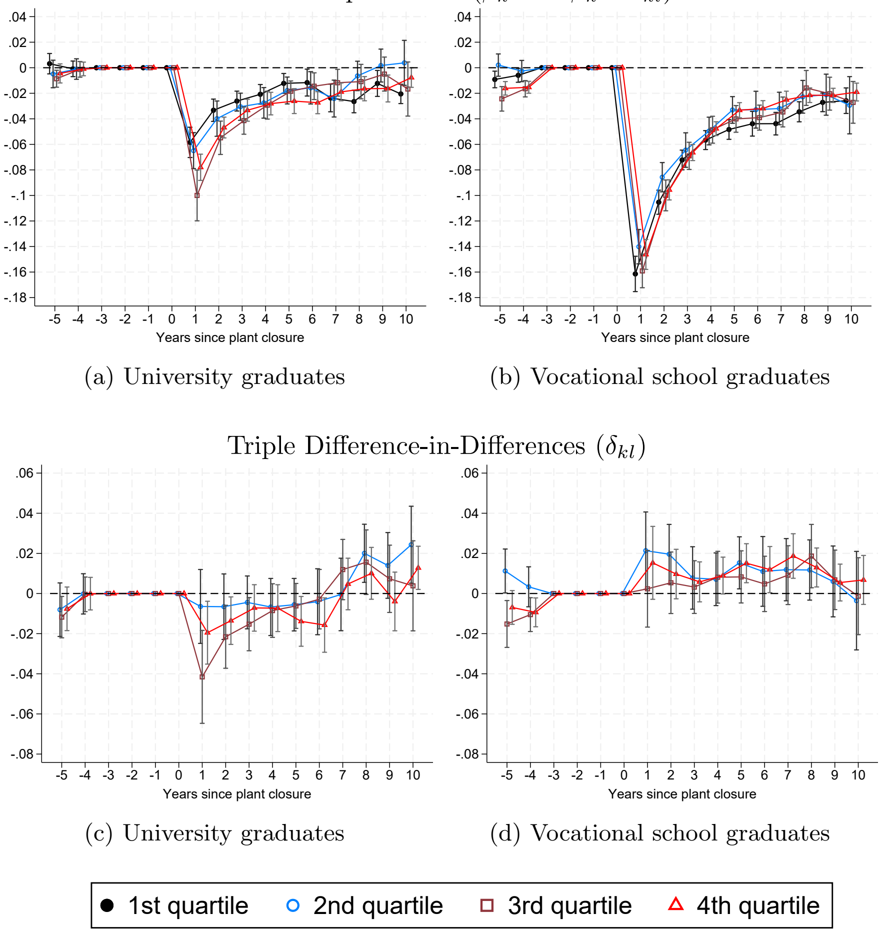
Figure 2 presents the coefficients β_k from estimating Equation 1, which captures the effect of displacement for individuals experiencing a plant closure during year 0. Panels (a) and (c) display the coefficient for outcomes employment and log market incomes, respectively, for the university sample. Panels (b) and (d) display the same for vocational school graduates. Reference category is omitted ($k = -1$ for incomes and $k \in [-3, 0]$ for employment). Standard errors are clustered at the level of graduation year and region.

Differential recovery from a plant closure by Unluckyness

Fig. 3: Employment

Effect of Displacement (β_k and $\beta_k + \delta_{kl}$)

Triple Difference-in-Differences (δ_{kl})

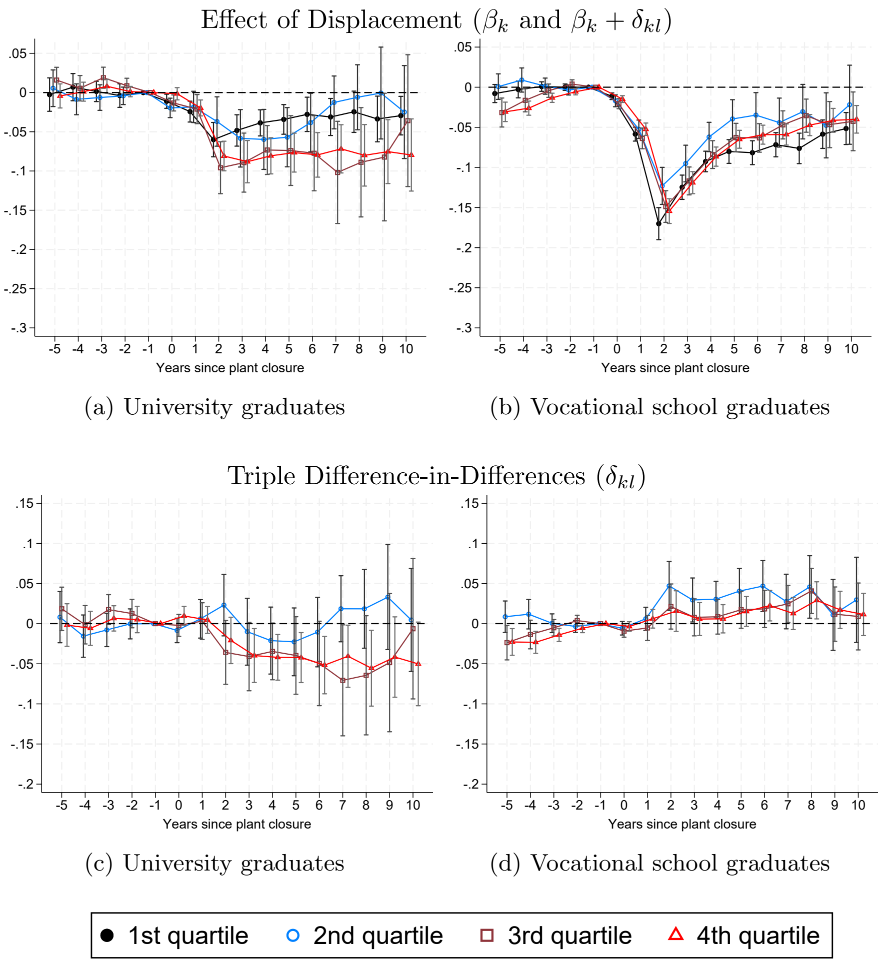


(a) University graduates (b) Vocational school graduates

(c) University graduates (d) Vocational school graduates

Figure 3 presents the coefficients from estimating Equation 2. The outcome used in the estimation is indicated in the caption. Panels (a) and (b) displays the coefficients β_k and $\beta_k + \delta_{kl}$ for university and vocational school graduates, respectively. Panels (c) and (d) display the triple difference-in-differences estimates δ_{kl}, which capture the differences in the recovery for the individuals graduating when regional unemployment was in the l^{th} quartile ($l = 2, 3, 4$). Event-time $k \in [-3, 0]$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

Fig. 4: Log Market Income



(a) University graduates

(b) Vocational school graduates

(c) University graduates

(d) Vocational school graduates

Figure 4 presents the coefficients from estimating Equation 2. The outcome used in the estimation is indicated in the caption. Panels (a) and (b) displays the coefficients β_k and $\beta_k + \delta_{kl}$ for university and vocational school graduates, respectively. Panels (c) and (d) display the triple difference-in-differences estimates δ_{kl}, which capture the differences in the recovery for the individuals graduating when regional unemployment was in the l^{th} quartile ($l = 2, 3, 4$). Event-time $k = -1$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

Tables

Table 1: Summary stats

	Non-displaced All (1)	Displaced All (2)	Displaced 1st (3)	Displaced 2nd (4)	Displaced 3rd (5)	Displaced 4th (6)
Panel (a) University graduates						
Age	39.61	38.79	38.49	37.17	38.25	40.22
Male	0.55	0.57	0.58	0.54	0.57	0.58
Married	0.68	0.67	0.66	0.67	0.67	0.68
Potential experience	12.13	11.37	11.11	9.48	10.79	12.94
Market income	62243	62284	60087	58496	62134	66150
Earnings	60164	60120	57925	56730	60109	63683
Received benefits	2120	2272	2097	2874	2463	1961
Tenure in a firm	6.53	5.81	5.72	5.64	5.90	5.93
Unemployment months	0.03	0.06	0.06	0.06	0.06	0.06
Firm changes	2.33	2.54	2.56	2.21	2.42	2.79
Average						
Market income	51367	52668	50950	52882	53828	53188
Earnings	50081	51357	49960	51831	52529	51479
Benefits	2082	1962	1540	2385	2110	1966
Changed						
Field of education	0.07	0.06	0.05	0.08	0.07	0.07
Level of education	0.07	0.06	0.05	0.06	0.05	0.07
Observations	850316	11898	3142	2260	2402	4094
Unique individuals	149410	11456	3012	2211	2320	3913
Panel (b) Vocational school graduates						
Age	34.06	33.21	35.29	30.70	31.39	33.43
Male	0.72	0.66	0.66	0.61	0.64	0.68
Married	0.41	0.38	0.40	0.32	0.33	0.41
Potential experience	14.14	13.18	15.41	9.86	10.97	13.81
Market income	36988	34265	34502	32693	33183	35245
Earnings	36677	34014	34210	32545	33016	34942
Received benefits	1454	1947	1707	2130	2222	1934
Tenure in a firm	6.83	5.88	6.38	5.29	5.42	5.93
Unemployment months	0.08	0.14	0.14	0.15	0.16	0.12
Firm changes	2.79	2.94	3.21	2.61	2.73	2.96
Average						
Market income	26703	25195	24960	26590	25705	24568
Earnings	26696	25208	24968	26632	25717	24574
Benefits	1836	2067	1572	2270	2352	2246
Changed						
Field of education	0.17	0.17	0.16	0.14	0.16	0.20
Level of education	0.15	0.15	0.15	0.11	0.12	0.17
Observations	2493430	40663	12195	6101	7375	14992
Unique individuals	396841	39011	11527	5990	7181	14313

Note: Table 1 presents the summary statistics of unconditional averages measured at the base year for university and vocational school graduates. Columns 1 and 2 present the unconditional averages for the non-displaced and displaced, respectively. The displaced sample is further divided into four groups based on labor market conditions at graduation. Summary statistics for these four groups are presented in columns 3 to 6. All income-related variables are CPI-adjusted to 2019 euros and winsorized at the 1% level in the population. Average incomes refer to yearly averages since graduation.

Table 2: Effect of displacement by initial labor market conditions at graduation

	Employed	Log Market Income	Unemployment months	Outside of Labor force	Received Benefits (€)	Firm Changes	Employed in a firm with high productivity	wages	size
					Panel (a) University graduates				
Initial shock									
β_1	-0.058***	-0.060***	0.373***	0.015***	479.4***	0.436***	-0.029***	-0.075***	-0.013
$\delta_{1,2}$	-0.006	0.023	-0.031	0.006	-208.0	-0.003	-0.026	-0.009	0.016
$\delta_{1,3}$	-0.042***	-0.036*	0.149**	0.017***	-199.9	-0.025	-0.039**	-0.026*	-0.006
$\delta_{1,4}$	-0.020**	-0.021	0.093**	0.006	-12.6	-0.020	-0.042***	-0.035***	-0.007
Long-term									
β_7	-0.024***	-0.031***	0.176***	0.006	247.4*	0.005	0.041**	-0.017	-0.012
$\delta_{7,2}$	0.000	0.019	-0.001	0.000	-353.4	0.010	0.009	0.027	-0.064**
$\delta_{7,3}$	0.012	-0.071**	-0.049	0.005	-188.8	-0.018	-0.031	-0.006	-0.041**
$\delta_{7,4}$	0.005	-0.041**	-0.069	0.007	-41.9	-0.005	-0.034*	-0.024	-0.014
Observations	10,282,088	10,281,887	10,282,088	10,282,088	10,282,088	10,282,088	10,282,088	10,282,088	10,282,088
					Panel (b) Vocational school graduates				
Initial shock									
β_1	-0.161***	-0.170***	0.764***	0.048***	959.8***	0.414***	-0.032***	-0.064***	-0.094***
$\delta_{1,2}$	0.021**	0.047***	-0.160***	0.003	-234.8***	0.017	0.009	0.032***	0.044***
$\delta_{1,3}$	0.002	0.021	-0.016	0.003	21.2	0.013	0.004	-0.004	0.030***
$\delta_{1,4}$	0.015*	0.016	-0.056	-0.004	-81.6	0.020**	-0.005	0.006	0.019**
Long-term									
β_7	-0.044***	-0.072***	0.314***	0.017***	404.9***	-0.011**	0.082***	0.012*	-0.063***
$\delta_{7,2}$	0.012	0.028	-0.129*	-0.002	-290.9**	-0.018*	0.005	0.027*	0.014
$\delta_{7,3}$	0.009	0.025**	-0.065	-0.004	-163.7	-0.004	0.007	0.010	0.028**
$\delta_{7,4}$	0.019***	0.013	-0.105**	-0.008**	-144.6	-0.005	0.004	0.018**	0.022**
Observations	30,505,010	30,504,642	30,505,010	30,505,010	30,505,010	30,505,010	30,505,010	30,505,010	30,505,010

Note: This table presents estimates from Equation 2, where β_k captures the effect of displacement for the luckiest quartile and $\delta_{k,l}$ captures the additional effect from displacement for the individuals graduating when regional unemployment was in the l^{th} quartile ($l = 2, 3, 4$). The initial effect refers initial shock, which is measured at the peak of shock $k = 1$ ($k = 2$ for annual personal market income). The long-term effects display the coefficients at 7^{th} year after the displacement. Panel (a) and (b) present the results for the university and vocational school graduates, respectively. Standard errors are clustered at the level of graduation year and region, and statistical significance is denoted in stars: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Heterogeneity analysis of effects on Employment by early career characteristics

	Main	Δ Education Level		Δ Education Field		Early career mobility	
	specification	Changed	No change	Changed	No change	Above median	Below Median
				Panel (a) University graduates			
Initial shock							
β_1	-0.058***	-0.059***	-0.058***	-0.059***	-0.058***	-0.059***	-0.058***
$\delta_{1,2}$	-0.006	-0.027	-0.005	0.003	-0.007	0.011	-0.024*
$\delta_{1,3}$	-0.042***	-0.008	-0.044***	-0.014	-0.044***	-0.035***	-0.049***
$\delta_{1,4}$	-0.020**	-0.022	-0.019**	-0.042**	-0.018**	-0.007	-0.034***
Long-term							
β_7	-0.024***	-0.024***	-0.024***	-0.024***	-0.024***	-0.024***	-0.024***
$\delta_{7,2}$	0.000	0.013	-0.001	0.031	-0.004	-0.008	0.007
$\delta_{7,3}$	0.012	0.004	0.012*	0.005	0.013	0.005	0.020*
$\delta_{7,4}$	0.005	-0.016	0.006	0.029*	0.002	0.011	-0.003
Observations	10,282,088	3,287,589	9,737,749	3,281,358	9,743,980	6,316,934	6,708,404
				Panel (b) Vocational school graduates			
Initial shock							
β_1	-0.161***	-0.162***	-0.161***	-0.162***	-0.161***	-0.162***	-0.162***
$\delta_{1,2}$	0.021**	0.073***	0.015	0.019	0.022**	0.026**	0.016
$\delta_{1,3}$	0.002	0.051***	-0.005	0.016	0.000	0.017*	-0.015
$\delta_{1,4}$	0.015*	0.061***	0.005	0.020*	0.014	0.031***	0.003
Long-term							
β_7	-0.044***	-0.044***	-0.044***	-0.044***	-0.044***	-0.044***	-0.044***
$\delta_{7,2}$	0.012	0.018	0.011	0.021	0.010	0.020**	0.002
$\delta_{7,3}$	0.009	0.014	0.008	0.000	0.012	0.012	0.005
$\delta_{7,4}$	0.019***	0.026***	0.017***	0.025***	0.017***	0.022***	0.016**
Observations	30,505,010	12,765,885	27,391,520	13,204,447	26,952,958	19,134,770	21,022,636

Notes: This table presents the results of the heterogeneity analysis, where we examine the differential recovery from a plant closure for individuals with different early career characteristics from luckiness quartiles $l \in 2, 3, 4$ to all individuals from the luckiest quartile ($l = 1$). Column 1 presents the results using a main sample for comparison. where $\delta_{k,l}$ captures the differential recovery from a plant closure by . Columns 2 and 3 present this differential effect for those individuals who have and have not attained a higher degree, respectively. Columns 4 and 5 similarly for changes in the field of education. Finally, Columns 6 and 7 present the differential effect by frequency of firm changes during the first 5 years from graduation. Panel (a) and (b) present the results for university and vocational school graduates, respectively. The initial effect refers to shock, which is measured at the peak of shock $k = 1$. The long-term effects display the coefficients at 7^{th} year after the displacement. Standard errors are clustered at the level of graduation year and region, and statistical significance is denoted in stars: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Heterogeneity analysis of effects on Log Market Income by early career characteristics

	Main specification	Δ Education Level Changed	Δ Education Level No change	Δ Education Field Changed	Δ Education Field No change	Early career mobility Above median	Early career mobility Below Median
				Panel (a) University graduates			
Initial shock							
β_2	-0.060***	-0.059***	-0.060***	-0.059***	-0.060***	-0.060***	-0.060***
$\delta_{2,2}$	0.023	0.045	0.022	-0.003	0.026	0.020	0.025
$\delta_{2,3}$	-0.036*	0.013	-0.038*	-0.094*	-0.029	-0.035	-0.037
$\delta_{2,4}$	-0.021	-0.024	-0.021	-0.035	-0.019	-0.015	-0.029
Long-term							
β_7	-0.031***	-0.031**	-0.031***	-0.031**	-0.031***	-0.031**	-0.031**
$\delta_{7,2}$	0.019	0.083	0.014	0.033	0.018	-0.004	0.042*
$\delta_{7,3}$	-0.071**	-0.117	-0.068**	-0.070	-0.068*	-0.059*	-0.085
$\delta_{7,4}$	-0.041**	-0.070	-0.039**	0.010	-0.043**	-0.037*	-0.047*
Observations	10,281,887	3,287,507	9,737,556	3,281,280	9,743,783	6,316,805	6,708,258
				Panel (b) Vocational school graduates			
Initial shock							
β_2	-0.170***	-0.171***	-0.170***	-0.171***	-0.170***	-0.170***	-0.170***
$\delta_{2,2}$	0.047***	0.070***	0.043***	0.058***	0.046***	0.055***	0.037**
$\delta_{2,3}$	0.021	0.046***	0.017	0.023	0.022	0.029**	0.012
$\delta_{2,4}$	0.016	0.021	0.014	0.014	0.016	0.026**	0.007
Long-term							
β_7	-0.072***	-0.072***	-0.072***	-0.072***	-0.072***	-0.072***	-0.072***
$\delta_{7,2}$	0.028	0.051*	0.022	0.004	0.036**	0.039**	0.014
$\delta_{7,3}$	0.025**	0.046***	0.021*	0.027*	0.026**	0.025*	0.025**
$\delta_{7,4}$	0.013	0.022*	0.010	0.012	0.013	0.016	0.010
Observations	30,504,642	12,765,719	27,391,190	13,204,278	26,952,632	19,134,564	21,022,344

Notes: This table presents the results of the heterogeneity analysis, where we examine the differential recovery from a plant closure for individuals with different early career characteristics from luckiness quartiles $l \in 2, 3, 4$ to all individuals from the luckiest quartile ($l = 1$). Column 1 presents the results using a main sample for comparison. where $\delta_{k,l}$ captures the differential recovery from a plant closure by . Columns 2 and 3 present this differential effect for those individuals who have and have not attained a higher degree, respectively. Columns 4 and 5 similarly for changes in the field of education. Finally, Columns 6 and 7 present the differential effect by frequency of firm changes during the first 5 years from graduation. Panel (a) and (b) present the results for university and vocational school graduates, respectively. The initial effect refers to shock, which is measured at the peak of shock $k = 2$. The long-term effects display the coefficients at 7^{th} year after the displacement. Standard errors are clustered at the level of graduation year and region, and statistical significance is denoted in stars: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix A Defining key variables

Year of graduation is defined by the calendar year of the first completed tertiary- or secondary-level education. For tertiary education, we consider ISCED-level 7 (Master's or equivalent level) as Bachelor's degrees are relatively uncommon in Finland. For secondary-level education, we focus on vocational school graduates (ISCED-levels 32 or 33). We exclude high school graduation as it is a common path towards a tertiary level education. Information of the completed degrees is retrieved from the register data on completed degrees collected by Statistics Finland. See Appendix C for more information on the Finnish education system.

Level of education: Register data on Completed Degrees includes information on the level of education. This information is classified using the ISCED-level classification. In the analysis examining the effects by further education (See Section 4.4.1), we define the higher degree attainment if an individual has completed an additional degree of a higher ISCED-level.

Field of education: Register data on Completed Degrees includes information on field of education. We use 2-digit level information on the field of education. In the analysis examining the effects by further education (See Section 4.4.1), individual is defined to have attained education in a different field if an individual has completed an additional degree, higher or lower, in a different 2-digit field.

Primary activity is based on Statistics Finland's register data on the primary activity of an individual. This is divided into eight classes employed, unemployed, 0-14 years old, student, retired, military or civil service, unemployment retired, outside of labor force for other reasons. We use this data to compute regional unemployment rates.

Regional unemployment rate. We compute annual regional unemployment rates from register-data for each of the 19 regions taking into account the changes in regions occurred in Finland over time. From 1987 to 2013, the regional unemployment rate has a mean of 13.4% and within region standard deviation of 4.8%. In the analysis, our measure of luckiness is based on 4 distinctive groups based on the severity of the local labor market conditions at year and region of graduation. The first quartile includes those who graduated during the seven years with the lowest regional unemployment rates, followed by six years in the second quartile, seven years in the third quartile, and seven years in the fourth quartile.

Labor market status is defined based on individual's primary activity as recorded by Statistics Finland. The primary activity is originally recorded in eight categories of which the first two employed or unemployed are most crucial for us. The rest of the eight categories (children, student, retired, military or civil service, unemployment-retired and others outside of the workforce) are combined in our measure of 'Out of Labor force'.

Market income is measured as a sum of earnings and taxable capital income, where the former captures the income from wages (and employment related benefits) and the latter captures income from capital gains tax, dividends and income from self-employment.

Earnings measured by summed wages and including taxable benefits from employment.

Received transfers: The register data that we use also includes information on received tranfers by an individual on an annual basis. This includes unemployment benefits as well as various other benefits in the Finnish welfare system (e.g. housing allowance).

Firm Changes: Firm changes are based matched employer-employee data. This indicator receives value 1 if the person starts in a new firm, and 0 otherwise.

Quality of employment. We follow Oreopoulos et al (2012) and calculate the firm specific quality measures as averages over all years that the firm information is recorded in the data on firms' annual reports. Thus, a change in the firm quality measure for each individual can only result if individual changes the employer.

Employment in a high productivity firm: is defined as employment in a firm with above median productivity, where productivity is measured by firms' average value added per full-time equivalent (FTE) worker. This is based on the average annual value added per worker for each firm using all available years of data. We then compute the firm size weighted median from the universe of firms. The indicator receives value 1 if an individual is employed in a firm with above median productivity, and 0 otherwise.

Employment in high wage firm: We follow a similar procedure, as with high productivity firm, to compute an indicator for employment in high wage firm. The indicator receives value 1 if an individual is employed in a firm with above median wages, and 0 otherwise.

Employment in a large firm: Firm size is measured by the average annual full-time-equivalent (FTE) employees. We use the firms linked to the non-displaced and displaced individuals in our sample to define a median firm size. The indicator receives value 1 if an individual is employed in a firm with above median number of employees, and 0 otherwise.

Appendix B Finnish working age population (Ages 15-64) by region (NUTS3) in 2010

Finland is divided into 19 region at NUTS3-level (Nomenclature of Territorial Units for Statistics). These regions reflect relatively well the labor market regions in Finland. For example, the region with the highest population, Uusimaa, consists of 26 municipalities. Of which, the three largest cities of Uusimaa are Helsinki (Capital), Espoo and Vantaa, and it is not uncommon to commute between them. Figure B1 presents the Finnish NUTS3-level regions and the average working age (Ages 15-64) population between 2009 and 2010.

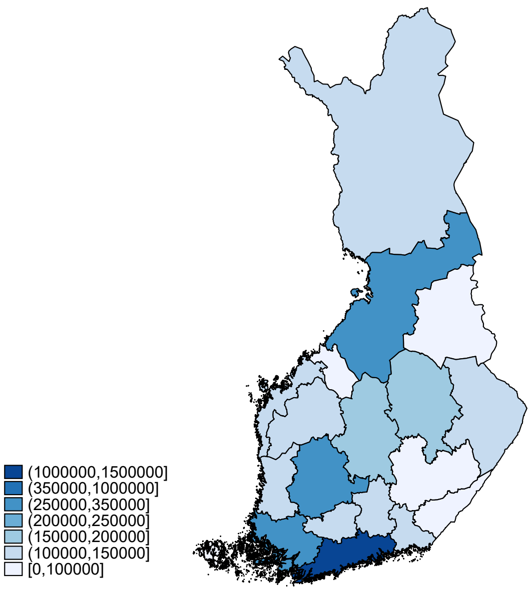


Fig. B1: Working age population (Ages 15-64) by NUTS3-region measured as the average between population at the end of the years 2009 and 2010. Data for regional working age population is retrieved from Statistics Finland. Spatial data from GeoServer.

Appendix C Finnish Education system

Figure C2 depicts the structure of the Finnish education system. Since the primary education reform in 1972-1977, it has been mandatory to complete nine years of primary education in a comprehensive school, typically starting around the age of 7. After comprehensive school, students have two main paths for secondary education: general upper secondary school (equivalent to high school) and vocational institutes. The former has traditionally been seen as the main route to tertiary education, while vocational institutes offer qualifications for specific occupations. While it is possible to pursue further studies after vocational school at the tertiary level, the majority of students conclude their formal education upon graduation from a vocational institute.

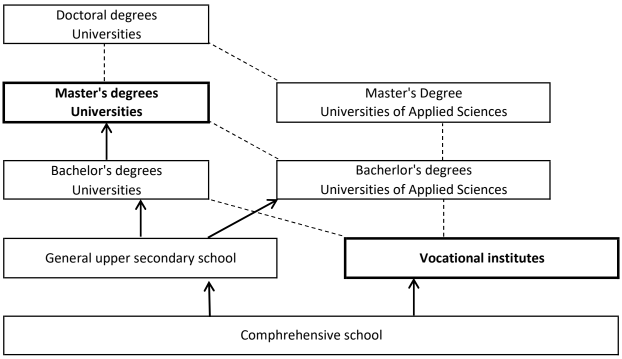


Fig. C2: Illustration of the Finnish education system. The arrows depict common paths from one level of education to the next. The dotted lines depict possibilities but are less common. Our study focuses on vocational school and university graduates (highlighted in bold) as these are the two main outcomes.

The path from general upper secondary school leads to tertiary education at either universities or universities of applied sciences. In the Finnish context, it is uncommon to terminate one's studies at the Bachelor's degree level in the traditional university path. Tertiary education often culminates in a university degree. Graduating with a Bachelor's degree is more common in the universities of applied sciences path, which includes fields such as engineering, nursing, and business administration. However, it is still possible to continue studies in either university path by applying to Master's programs or, after two years of working experience, applying to Master's programs in universities of applied sciences. Following the completion of a Master's degree, individuals can pursue a doctoral degree at universities.

Appendix D Non-positive outcomes

Log outcomes are computed as cell means, where a cell is based on graduation year c and region r, time relative to the event k around the base year b and separately for displaced and non-displaced (d).

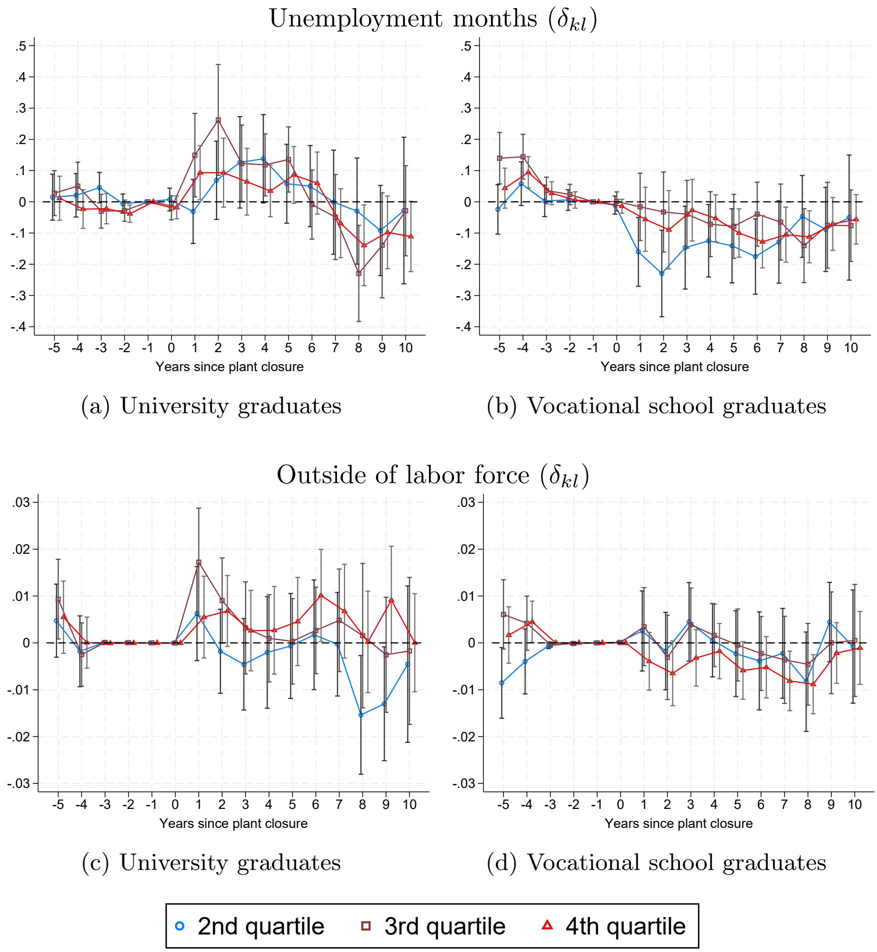
While similarly to Oreopoulos et al (2012) our outcomes are computed as cell means, our reason is slightly different. Our reason is to alleviate concerns of missing the non-positive earnings that would otherwise restrict the sample to essentially conditional on employed. An issue wherein employing cell means emerges as a pragmatic and straightforward resolution.[11]

The problem of non-positive earnings is emphasized due to our choice of earnings measure. We wish to capture the effect on the economic benefit of individual's economic activities, which we measure as a sum of wages and capital income, but excluding transfers. Including both wages and capital income allows to capture the income from a wide range of different employment, self-employment and other entrepreneurial activities. However, the choice of our income measure also has it's drawbacks. First, in case of longer unemployment spells it is not uncommon to have zero wage incomes, while total income (including transfers) and disposable income would be positive. Additionally, while we want to include capital income to capture the income from entrepreneurial activities, capital incomes can also be negative, even largely so. These caveats highlight the importance of taking the non-positive incomes into account.

[11] We have also considered other alternatives such as earnings relative to reference year and absolute values. We find these problematic, in cases of outliers and outcomes that can change from negative to positive.

Appendix E Effect of displacement by initial labor market conditions at graduation

Fig. E3: Labor market activity



(a) University graduates (b) Vocational school graduates

(c) University graduates (d) Vocational school graduates

Figure E3 presents the coefficients from estimating Equation 2. The outcome used in the estimation is indicated above each pair of panels. All panels display the triple difference-in-differences estimates δ_{kl}, which capture the differences in the recovery for the individuals graduating when regional unemployment was in the l^{th} quartile ($l = 2, 3, 4$). Panels (a) and (c) display the coefficients for University graduates, and panels (b) and (d) for vocational school graduates. Event-time $k = -1$ is omitted as a reference category ($k \in [-3, 0]$ for Outside of labor force). Standard errors are clustered at the level of graduation year and region.

Fig. E4: Labor market activity

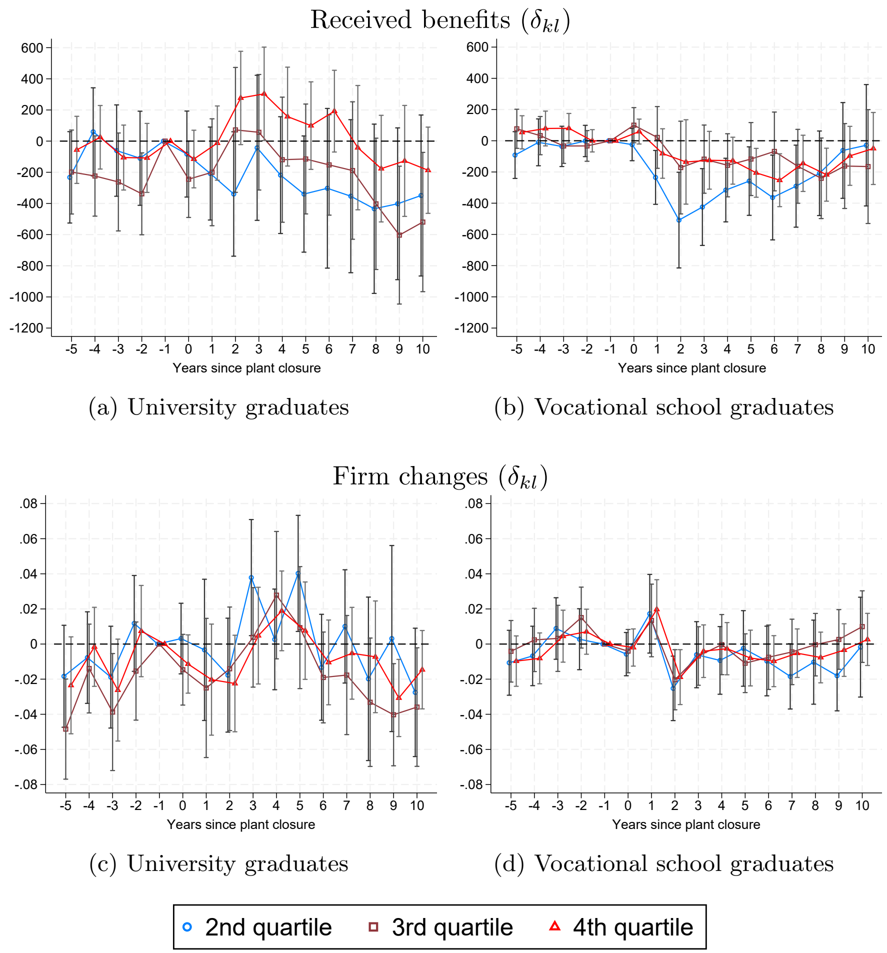
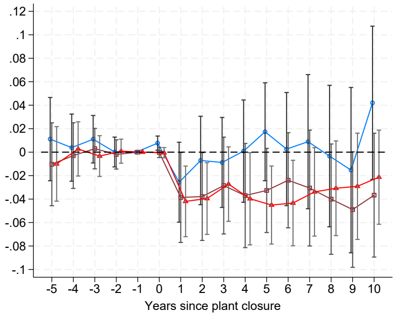


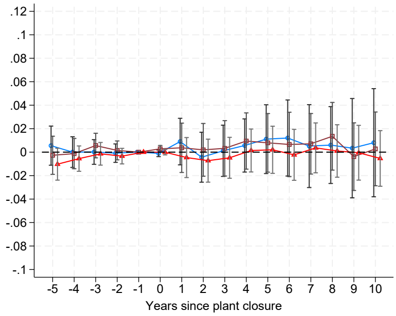
Figure E4 presents the coefficients from estimating Equation 2. The outcome used in the estimation is indicated above each pair of panels. All panels display the triple difference-in-differences estimates δ_{kl}, which capture the differences in the recovery for the individuals graduating when regional unemployment was in the l^{th} quartile ($l = 2, 3, 4$). Panels (a) and (c) display the coefficients for University graduates, and panels (b) and (d) for vocational school graduates. Event-time $k = -1$ is omitted as a reference category ($k \in [-3, 0]$ for Outside of labor force). Standard errors are clustered at the level of graduation year and region.

Fig. E5: Quality of employment

Employment in High Productivity Firm (δ_{kl})

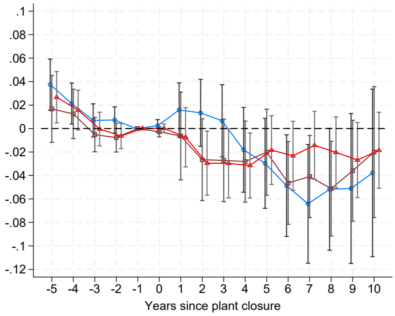


(a) University graduates

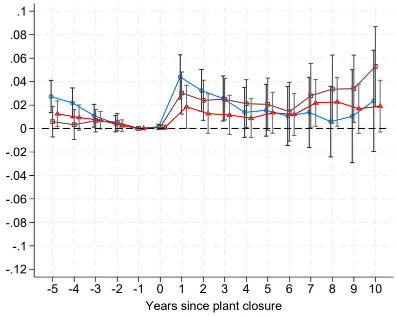


(b) Vocational school graduates

Employment in a large firm (δ_{kl})

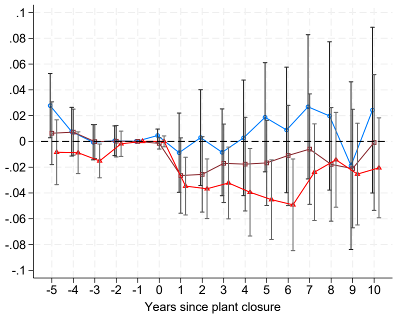


(c) University graduates

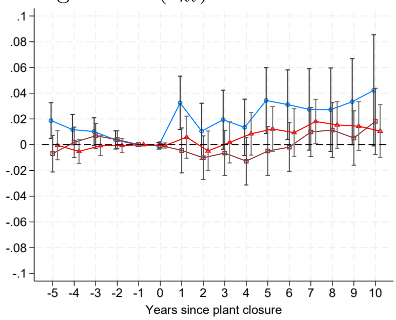


(d) Vocational school graduates

Employment in High Wage Firm (δ_{kl})



(e) University graduates



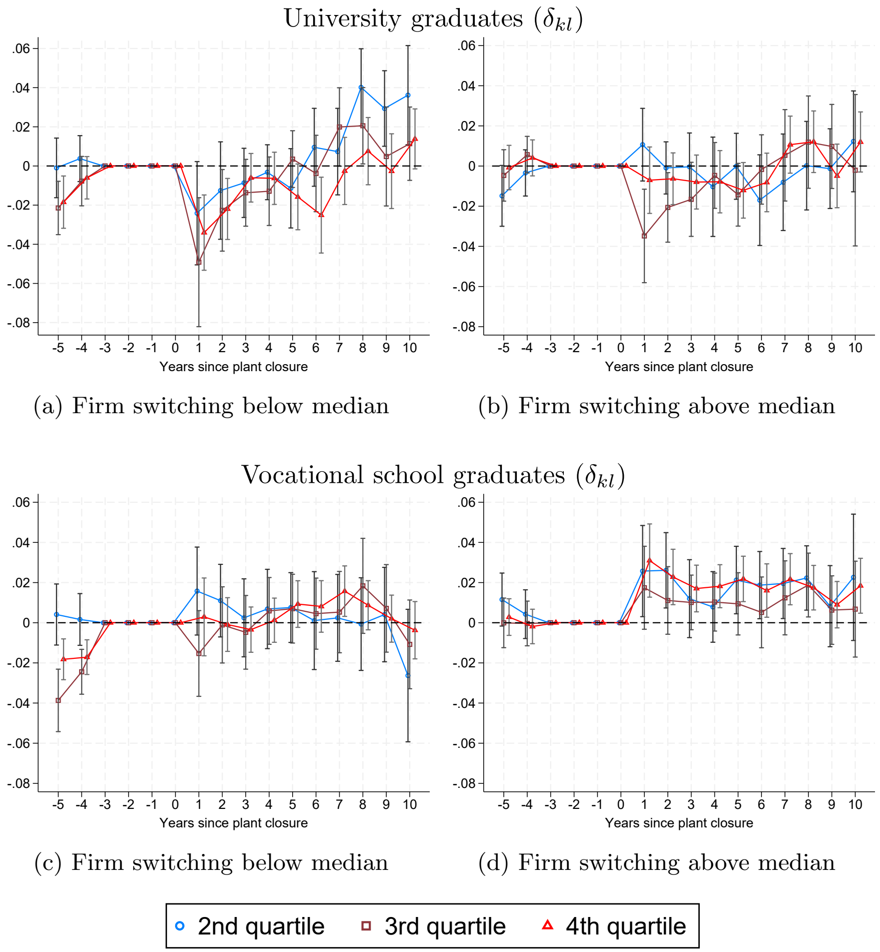
(f) Vocational school graduates

○ 2nd quartile □ 3rd quartile △ 4th quartile

Figure E5 presents the coefficients from estimating Equation 2. The outcome used in the estimation is indicated above each set of panels. All panels displey the triple difference-in-differences estimates δ_{kl}, which capture the differences in the recovery for the individuals graduating when regional unemployment was in the l^{th} quartile ($l = 2, 3, 4$). Panels (a) and (c) display the coefficients for University graduates, and panels (b) and (d) for vocational school graduates. Event-time $k = -1$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

Appendix F Heterogeneity analysis by early career characteristics

Fig. F6: Employment by early career firm switching



(a) Firm switching below median (b) Firm switching above median

(c) Firm switching below median (d) Firm switching above median

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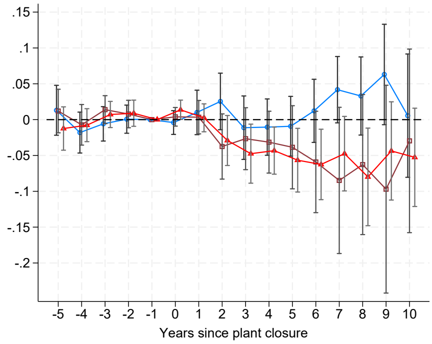
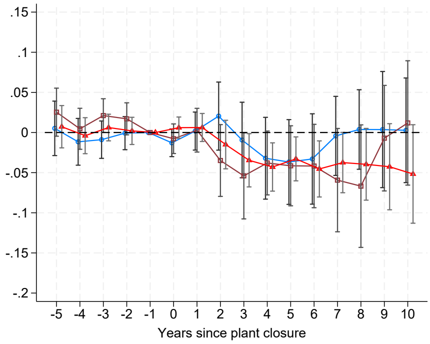
Figure F6 presents the coefficients from a heterogeneity analysis estimating Equation 2 using a sub-sample of unlucky graduates. We compare a sub-sample of unlucky individuals, who during the first five years since graduation have switched between firms above or below median, to everyone among the luckiest graduates. Panels (a) and (b) displays the coefficient δ_{kl} on employment by cumulative firm changes for university graduates. Panels (c) and (d) similarly for vocational school graduates. Event-time $k \in [-3, 0]$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

Fig. F7: Log Market Income by early career firm switching

University graduates (δ_{kl})

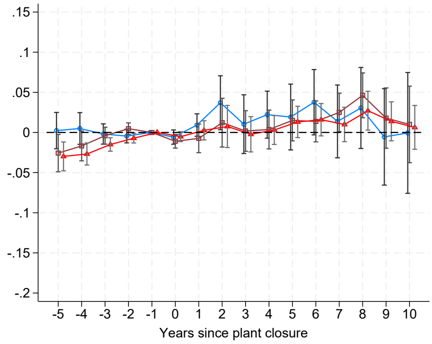


(a) Firm switching below median

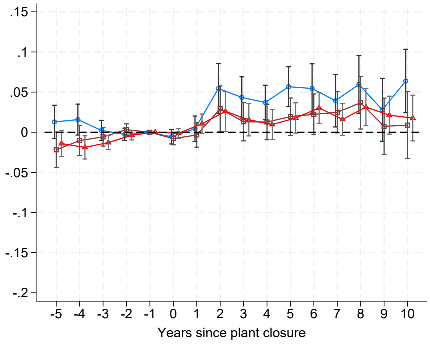


(b) Firm switching above median

Vocational school graduates (δ_{kl})



(c) Firm switching below median



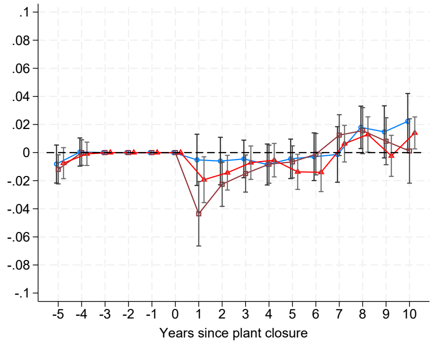
(d) Firm switching above median

○ 2nd quartile □ 3rd quartile △ 4th quartile

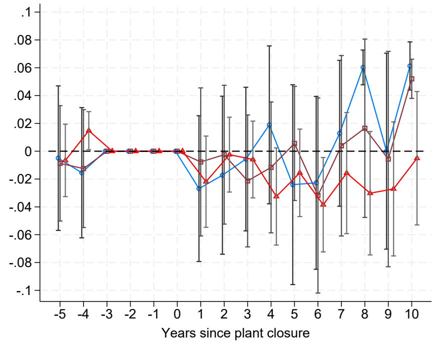
Figure F7 presents the coefficients from a heterogeneity analysis estimating Equation 2 using a sub-sample of unlucky graduates. We compare a sub-sample of unlucky individuals, who during the first five years since graduation have switched between firms above or below median, to everyone among the luckiest graduates. Panels (a) and (b) displays the coefficient δ_{kl} on log market income by cumulative firm changes for university graduates. Panels (c) and (d) similarly for vocational school graduates. Event-time $k = -1$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

Fig. F8: Employment by further education (Level)

University graduates (δ_{kl})

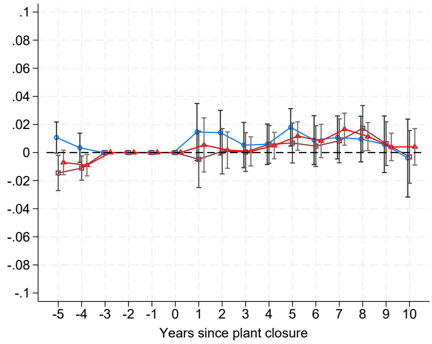


(a) No change in level of education

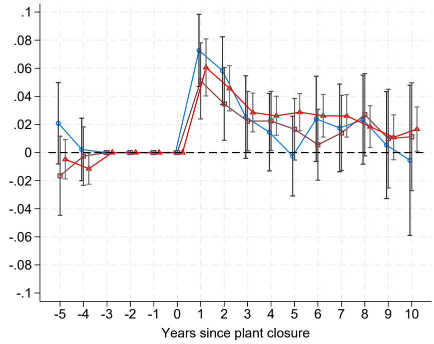


(b) Increase in the level of education

Vocational school graduates (δ_{kl})



(c) No change in level of education



(d) Increase in the level of education

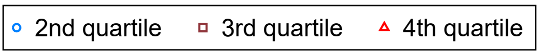
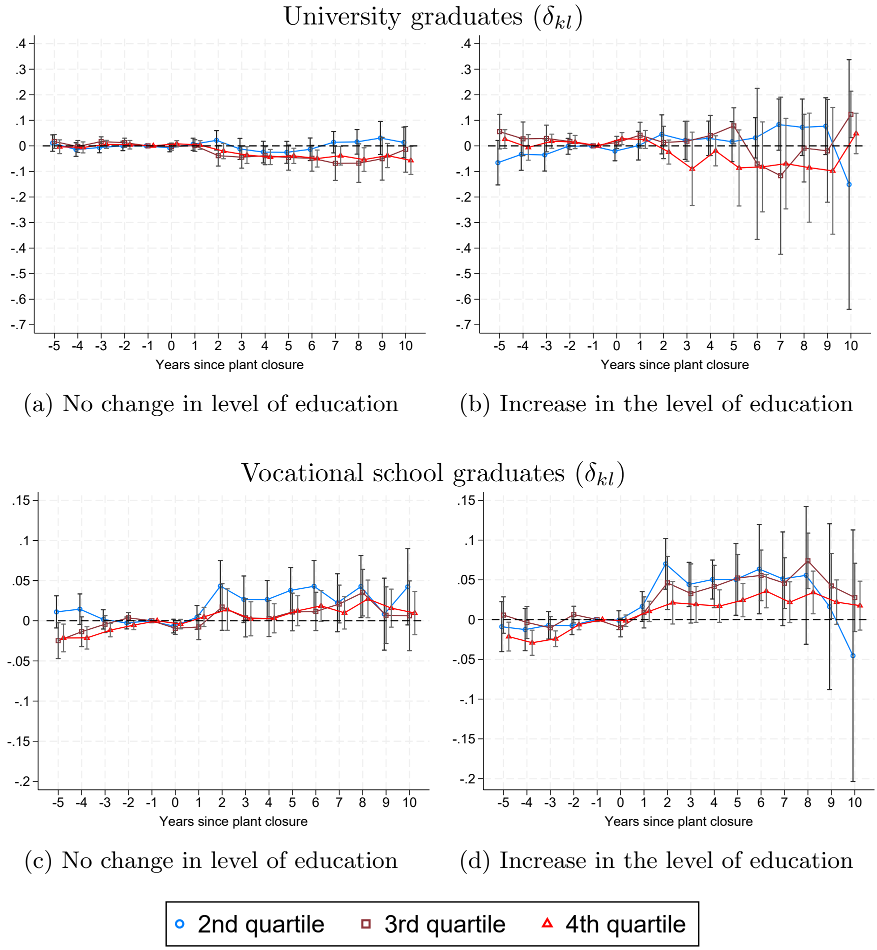


Figure F8 presents the coefficients from a heterogeneity analysis estimating Equation 2 using a sub-sample of unlucky graduates. We compare a sub-sample of unlucky individuals, who by base year have attained further education at a higher level, to everyone among the luckiest graduates. Panels (a) and (b) displays the coefficient δ_{kl} on employment by change in the level of education for university graduates. Panels (c) and (d) similarly for vocational school graduates. Event-time $k \in [-3, 0]$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

Fig. F9: Log Market Income by further education (Level)



(a) No change in level of education

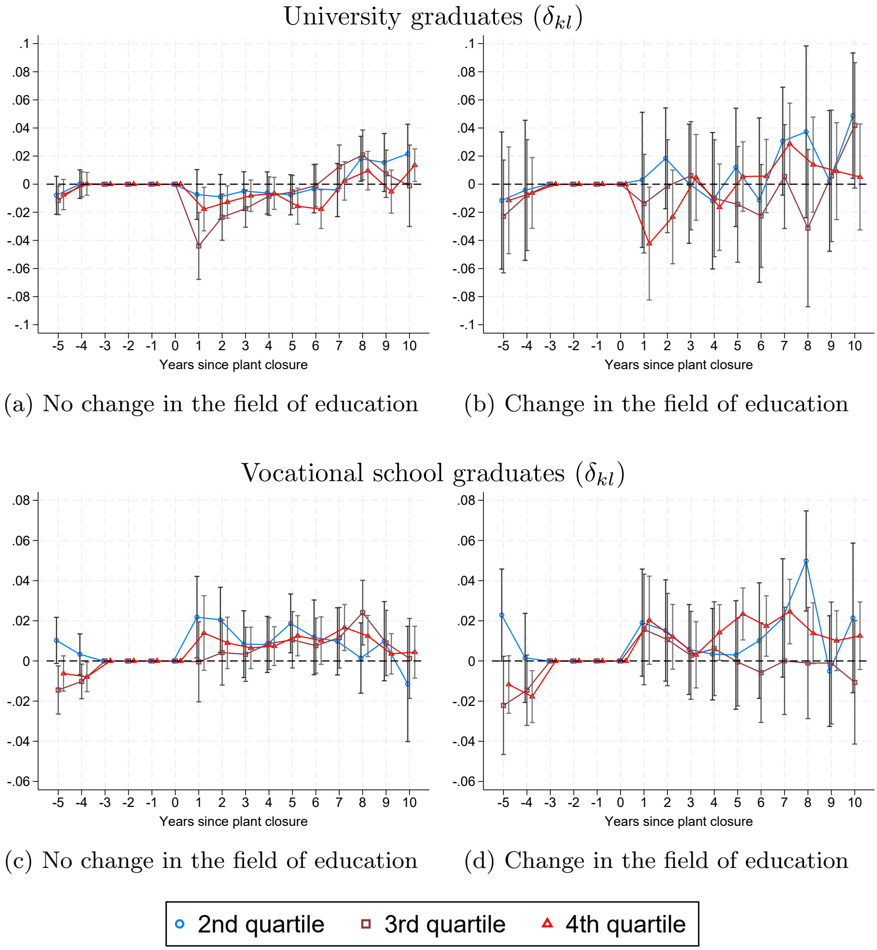
(b) Increase in the level of education

(c) No change in level of education

(d) Increase in the level of education

Figure F9 presents the coefficients from a heterogeneity analysis estimating Equation 2 using a sub-sample of unlucky graduates. We compare a sub-sample of unlucky individuals, who by base year have attained further education at a higher level, to everyone among the luckiest graduates. Panels (a) and (b) displays the coefficient δ_{kl} on log market income by change in the level of education for university graduates. Panels (c) and (d) similarly for vocational school graduates. Event-time $k = -1$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

Fig. F10: Employment by further education (Field)



(a) No change in the field of education (b) Change in the field of education

(c) No change in the field of education (d) Change in the field of education

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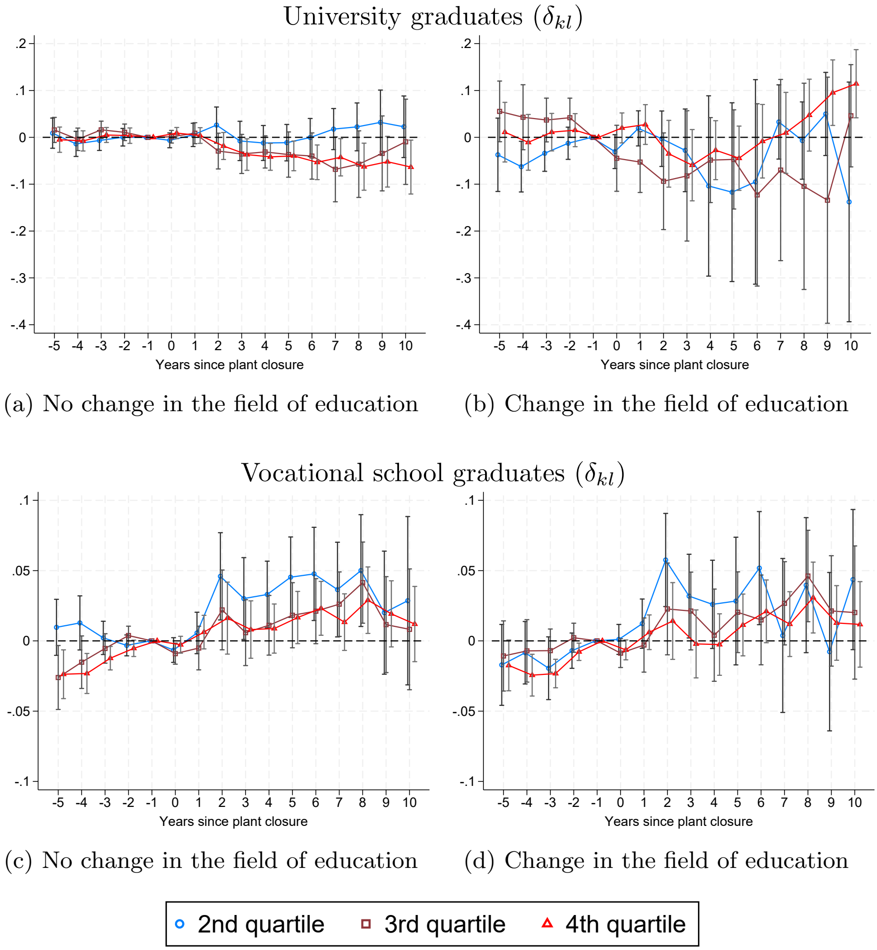
Figure F10 presents the coefficients from a heterogeneity analysis estimating Equation 2 using a sub-sample of unlucky graduates. We compare a sub-sample of unlucky individuals, who by base year have attained further education in a different field, to everyone among the luckiest graduates. Panels (a) and (b) displays the coefficient δ_{kl} on employment by change in the level of education for university graduates. Panels (c) and (d) similarly for vocational school graduates. Event-time $k \in [-3, 0]$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

Fig. F11: Log Market Income by further education (Field)



(a) No change in the field of education (b) Change in the field of education

(c) No change in the field of education (d) Change in the field of education

Figure F11 presents the coefficients from a heterogeneity analysis estimating Equation 2 using a sub-sample of unlucky graduates. We compare a sub-sample of unlucky individuals, who by base year have attained further education in a different field, to everyone among the luckiest graduates. Panels (a) and (b) displays the coefficient δ_{kl} on log market income by change in the field of education for university graduates. Panels (c) and (d) similarly for vocational school graduates. Event-time $k = -1$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

Table G1: Identification and sample selection

	(1) Main Specification	(2) Region and field specific UR	(3) Graduated at mode age	(4) Until first displacement
University graduates				
		Panel (a) Employed		
β_1	-0.058***	-0.061***	-0.065***	-0.055***
$\delta_{1,2}$	-0.006	-0.027***	0.004	-0.008
$\delta_{1,3}$	-0.042***	-0.021**	0.002	-0.046***
$\delta_{1,4}$	-0.020**	-0.012*	0.001	-0.023***
β_7	-0.024***	-0.022***	-0.024**	-0.021***
$\delta_{7,2}$	0.000	-0.007	-0.026	-0.003
$\delta_{7,3}$	0.012	0.016*	0.024	0.008
$\delta_{7,4}$	0.005	0.001	0.025*	0.002
Obs.	10,282,088	10,280,140	2,145,284	9,967,584
		Panel (b) Log Market Income		
β_2	-0.060***	-0.106***	-0.055***	-0.059***
$\delta_{2,2}$	0.023	0.007	0.025	0.023
$\delta_{2,3}$	-0.036*	-0.003	-0.003	-0.037*
$\delta_{2,4}$	-0.021	0.013	-0.011	-0.021
β_7	-0.031***	-0.079***	-0.016	-0.028**
$\delta_{7,2}$	0.019	-0.008	0.001	0.015
$\delta_{7,3}$	-0.071**	0.001	-0.006	-0.077**
$\delta_{7,4}$	-0.041**	-0.031	-0.038	-0.043**
Obs.	10,281,887	10,278,851	2,145,260	9,967,393
Vocational school graduates				
		Panel (c) Employed		
β_1	-0.161***	-0.162***	-0.163***	-0.163***
$\delta_{1,2}$	0.021**	0.015**	0.026**	0.023**
$\delta_{1,3}$	0.002	0.009	0.007	0.003
$\delta_{1,4}$	0.015*	0.015**	0.023**	0.015
β_7	-0.044***	-0.043***	-0.039***	-0.044***
$\delta_{7,2}$	0.012	0.006	0.017*	0.012
$\delta_{7,3}$	0.009	0.010	0.014*	0.010
$\delta_{7,4}$	0.019***	0.018***	0.013**	0.019***
Obs.	30,505,010	30,501,736	18,626,492	29,458,948
		Panel (d) Log Market Income		
β_2	-0.170***	-0.210***	-0.169***	-0.172***
$\delta_{2,2}$	0.047***	0.014	0.045***	0.049***
$\delta_{2,3}$	0.021	0.026*	0.023	0.022
$\delta_{2,4}$	0.016	0.005	0.016	0.017
β_7	-0.072***	-0.128***	-0.062***	-0.072***
$\delta_{7,2}$	0.028	0.027	0.029	0.028
$\delta_{7,3}$	0.025**	0.033*	0.022*	0.025**
$\delta_{7,4}$	0.013	0.024	0.008	0.012
Obs.	30,504,642	30,497,288	18,626,328	29,458,580

Note: This table summarizes the results from the robustness check on identification and sample selection. Panels (a) and (b) present the results for University graduates on employment and incomes, respectively. Panels (c) and (d) for Vocational school graduates. Column 1 presents the results from our main specification (Equation 2) for comparison. Column 2 presents results, where labor market conditions at graduation are region and field specific. Column (3) presents results for a subset of individuals graduated at field and gender specific mode age. Lastly, Column (4) presents the results using a sample, where individual remains in the sample until first experiences plant closure. The table reports effects at event-time 1 (2) and 7 for employment (incomes). Figures reporting estimates for all time to event coefficients are presented in the Figures G12-G17. Standard errors are clustered at the level of graduation year and region, and statistical significance is denoted in stars: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix G Robustness checks

G.1 Identification and sample selection

G.1.1 Education field-specific regional unemployment at graduation

Most earlier studies have identified labor market conditions at graduation using regional variation in unemployment rates. van den Berge (2018) introduced a different approach by linking individuals to the unemployment rates specific to their field of study at the time of graduation. As a robustness check, we calculated the region×field of study-specific unemployment rates and divided the graduation years in each region-field cell into four luckiness groups. This approach also helps to alleviate the concentration of the unluckiest graduation years into the same calendar years.

We augment Equation 2 with graduation-field-specific fixed effects and cluster the standard errors at the level of graduation year, field, and region. We report the results from this analysis in Figures G12 and G13 and in Column (2) of Table G1.[12]

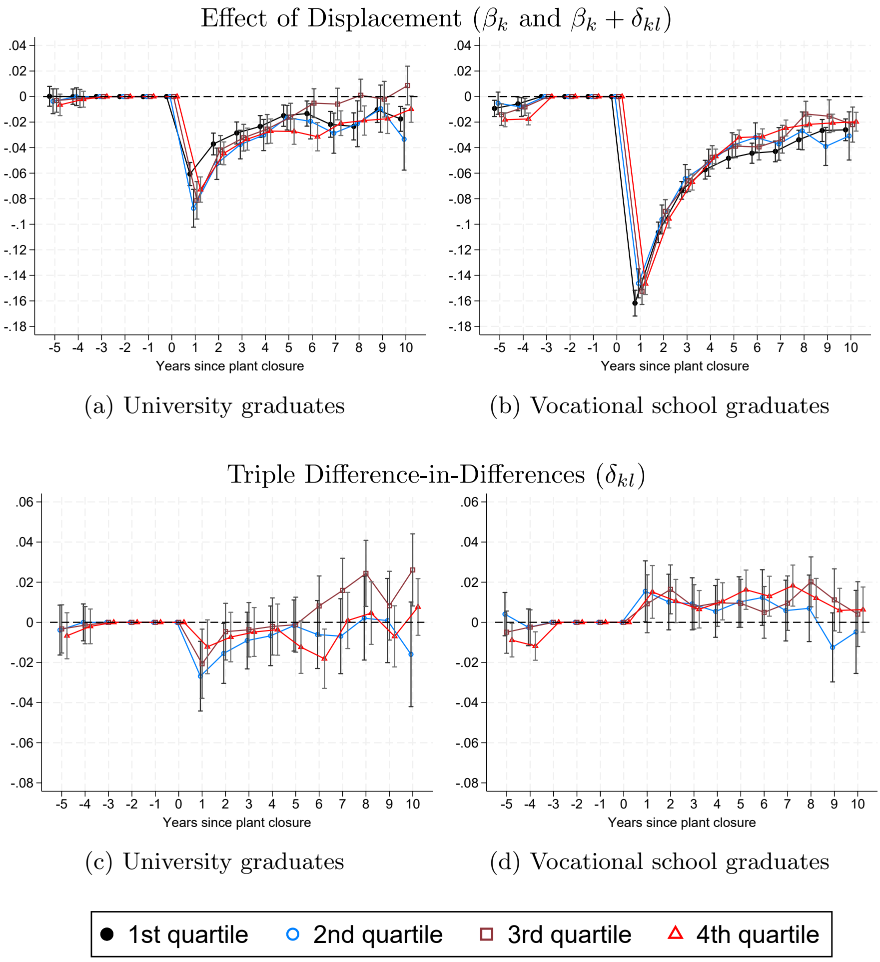
For university graduates, the results indicate that the unlucky graduates experience larger losses in employment in the short-term but not in the long-term. In terms of income, the unluckiest university graduates start facing larger losses than the luckiest group from year b+3 onwards and this difference persists for the remainder of the sample period, although it is not statistically significant at the 5% level in this specification.

For vocational school graduates, our findings are consistent with our main results, showing that the negative impact on employment and income is not

[12] In this analysis, we lose some observations because some graduates do not have information about their field of study. Additionally, we lose further observations when analyzing the effects on income, as some region-field-specific cells include only individuals with zero market earnings.

larger for the unlucky graduates. In fact, there are indications that unluckiness may enhance resilience to plant closures. However, it is important to note that we must reject the assumption of parallel pre-trends for vocational school graduates.

Fig. G12: Employment



(a) University graduates

(b) Vocational school graduates

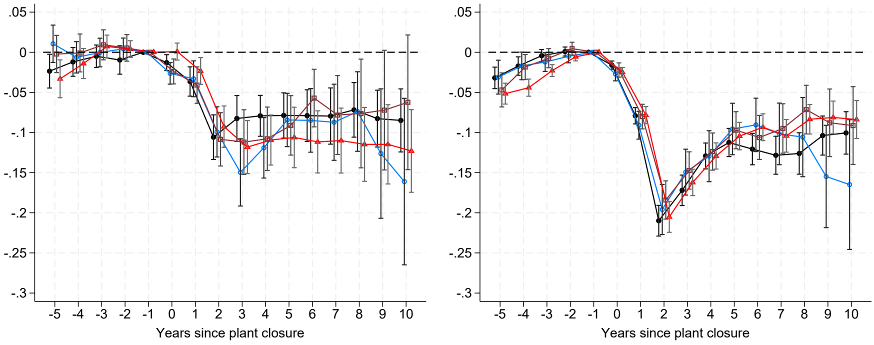
(c) University graduates

(d) Vocational school graduates

Figure G12 presents the coefficients from estimating an augmented version of Equation 2 with graduation-field-specific fixed effects, and where identification of the labor market conditions are region and field specific. The outcome used in the estimation is indicated in the caption. Panels (a) and (b) displays the coefficients β_k and $\beta_k + \delta_{kl}$ for university and vocational school graduates, respectively. Panels (c) and (d) display the triple difference-in-differences estimates δ_{kl}, which capture the differences in the recovery for the individuals graduating when region and field specific unemployment was in the l^{th} quartile ($l = 2, 3, 4$). Event-time $k \in [-3, 0]$ is omitted as a reference category. Standard errors are clustered at the level of graduation year, field, and region.

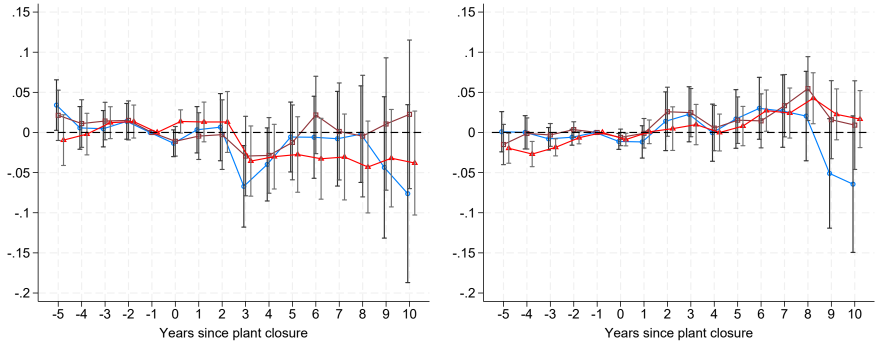
Fig. G13: Log Market Income

Effect of Displacement (β_k and $\beta_k + \delta_{kl}$)



(a) University graduates (b) Vocational school graduates

Triple Difference-in-Differences (δ_{kl})



(c) University graduates (d) Vocational school graduates

Figure G13 presents the coefficients from estimating an augmented version of Equation 2 with graduation-field-specific fixed effects, and where identification of the labor market conditions are region and field specific. The outcome used in the estimation is indicated in the caption. Panels (a) and (b) displays the coefficients β_k and $\beta_k + \delta_{kl}$ for university and vocational school graduates, respectively. Panels (c) and (d) display the triple difference-in-differences estimates δ_{kl}, which capture the differences in the recovery for the individuals graduating when region and field specific unemployment was in the l^{th} quartile ($l = 2, 3, 4$). Event-time $k = -1$ is omitted as a reference category. Standard errors are clustered at the level of graduation year, field, and region.

G.1.2 Endogeneity in graduation timing

Whether an individual is classified as a lucky or unlucky graduate in our model depends on the regional unemployment rate at the time of graduation. However, previous studies have highlighted the possibility of endogenous sorting into graduation years among the highly educated individuals (e.g., Kahn, 2010; Oreopoulos et al, 2012; Liu et al, 2016; van den Berge, 2018). Namely, adverse labor market conditions may lead individuals to delay graduation. We address this issue in two ways. First, we take an approach similar to Liu et al (2016) and examine how the regional unemployment rate at expected graduation year impacts the probability of delaying the graduation. Second, we estimate Equation 2 for the sub-sample of individuals who graduated in their expected graduation year.

To determine the expected graduation year, we use individual's age since our data lacks enrollment date information for individuals enrolled before 1999. In contrast to Kahn (2010) and Liu et al (2016) who calculate the modal graduation age using the entire sample, we consider education-field and gender-specific differences. Specifically, we utilise the six-digit education codes of Statistics Finland. We have chosen to use field and gender-specific modes of graduation ages to retain a sufficient number of observations.[13] In addition, our approach accounts for field-specific differences in graduation times and acknowledges that in Finland, mandatory military or civilian service often leads men to graduate one year later than women.

In an analysis similar to Liu et al (2016), we determine a variable $Delay_{icr}$ that gets value one if an individual has not graduated by their predicted graduation year. Next we take a cross-section of individuals from the year following

[13] However, our method still leaves out many graduates from the more exotic six-digit fields. If, for example, the modal of the graduation age in a field is 44, then graduates from that field who are born after 1979 will not be included in the sample. Thus, the estimation puts more weight on the more common fields and on cohorts who have had the time to graduate before the end of the data.

the predicted graduation year and estimate

$$Delay_{icr} = \gamma + \sum_{l=2}^{4} (\beta_l L_{cr}) + \phi_c + \theta_r + \nu_{icr}, \tag{G1}$$

where c now refers to the *predicted* year of graduation and r to the region where individual lives at the *predicted* year of graduation. The outcomes of estimating Equation G1 are presented in columns 1 and 3 of Table G2, corresponding to university and vocational school graduates, respectively. These results indicate that the more unlucky graduates (quartiles 2, 3 and 4) do not differ from the luckiest graduates (quartile 1) in terms of delaying the graduation. Furthermore, we can observe from the constant terms of the regressions that individuals graduating from the vocational school track basically always graduate at the predicted age while for the university graduates the variation in timing is much higher, with about half of individuals graduating later than the modal age would suggest.

We have also examined how the continuous measure of regional unemployment rate at the predicted graduation year is associated with delaying the graduation. For this purpose, we substituted the luckiness quartile dummies in Equation G1 with the regional unemployment rate at the predicted year of graduation. These results are reported in columns 2 and 4 in Table G2. These results show patterns similar to columns 1 and 3. For university graduates we can not reject the null hypothesis of no delay at the 5% level but we can reject it at the 10% level. The point estimate indicates that a one-percentage-point rise in the regional unemployment rate would increase the likelihood of delaying graduation by 0.37 percentage points.

These estimates are relatively small compared to the average probability of delaying graduation. However, we still want to check whether our main results are robust to using only those individuals who graduated at the modal graduation year based on their six-digit education field and gender.[14] The results for this narrower sample are presented in Figures G14 and G15 and in Column (3) of Table G1.

Our findings indicate that university graduates who completed their studies in the modal graduation year do not experience increased employment losses if they are from unlucky cohorts. However, consistent with our main analysis, the unluckiest graduates still face more negative income effects.

For vocational school graduates, we lose relatively fewer observations due to less variation in graduation ages at the secondary level. The results for vocational graduates mirror our main findings. There is no evidence that unlucky vocational school graduates suffer more from displacement compared to their luckier counterparts. In fact, the unlucky may experience less negative impacts on both employment and income.

[14] We acknowledge that this way we might still end up with a different group of graduates during good and bad times. However, the selection is different than in our main analysis.

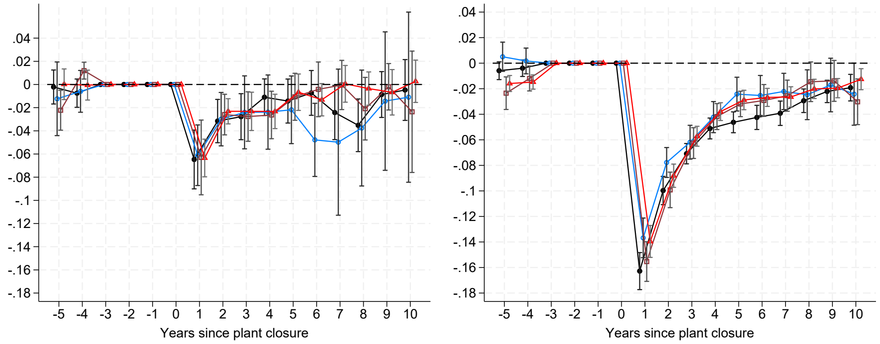
Table G2: The effect of regional unemployment rate at expected graduation year on the probability of delaying the graduation

	University graduates		Vocational school graduates	
	(1)	(2)	(3)	(4)
	Delay	Delay	Delay	Delay
2nd luckiness quartile	0.007		0.000	
	(0.012)		(0.000)	
3rd luckiness quartile	0.011		0.000	
	(0.013)		(0.000)	
4th luckiness quartile	-0.006		-0.000	
	(0.021)		(0.001)	
Regional unemployment rate		0.367*		-0.004
at predicted year of graduation		(0.197)		(0.006)
Constant	0.529***	0.489***	0.000	0.001
	(0.011)	(0.023)	(0.000)	(0.001)
Observations	139389	139389	255251	255251

Note: Table G2 presents results from Equation G1. Columns 1 and 2 presents results from two alternative models to study the effects of regional unemployment rate at expected graduation year on the probability of delaying the graduation for university graduates. Columns 3 and 4 presents the results for the vocational school gradates. Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

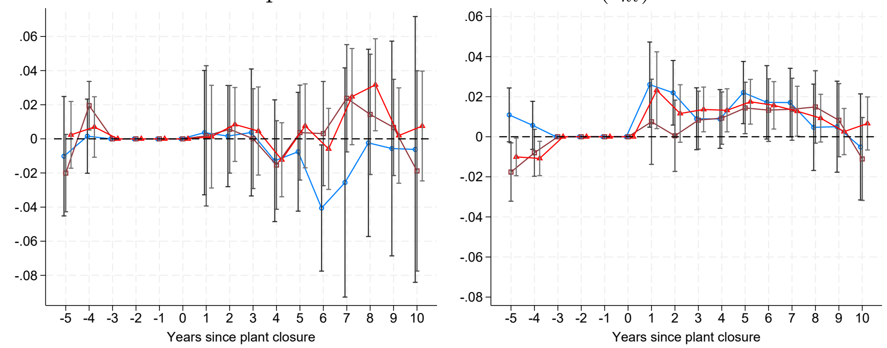
Fig. G14: Employment

Effect of Displacement (β_k and $\beta_k + \delta_{kl}$)



(a) University graduates (b) Vocational school graduates

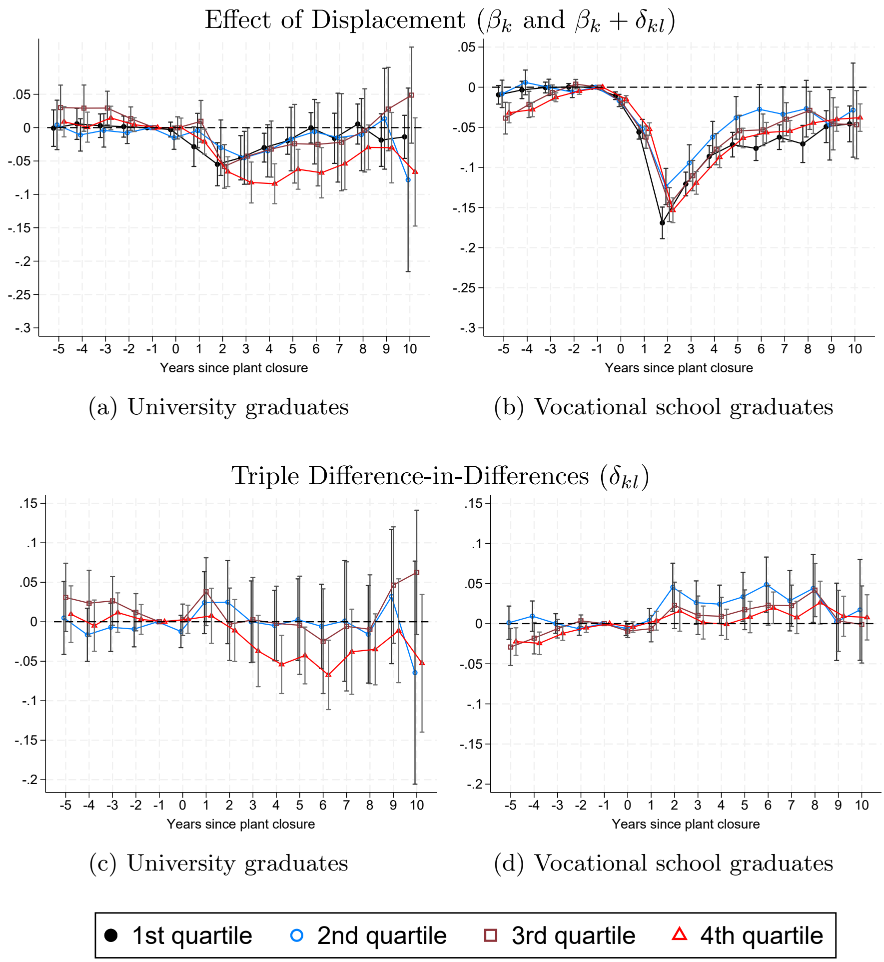
Triple Difference-in-Differences (δ_{kl})



(c) University graduates (d) Vocational school graduates

Figure G14 presents the coefficients from estimating Equation 2 using a sample of individuals who have not delayed their graduation. The outcome used in the estimation is indicated in the caption. Panels (a) and (b) displays the coefficients β_k and $\beta_k + \delta_{kl}$ for university and vocational school graduates, respectively. Panels (c) and (d) display the triple difference-in-ifferences estimates δ_{kl}, which capture the differences in the recovery for the individuals graduating when regional unemployment was in the l^{th} quartile ($l = 2, 3, 4$). Event-time $k \in [-3, 0]$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

Fig. G15: Log Market Income



(a) University graduates

(b) Vocational school graduates

(c) University graduates

(d) Vocational school graduates

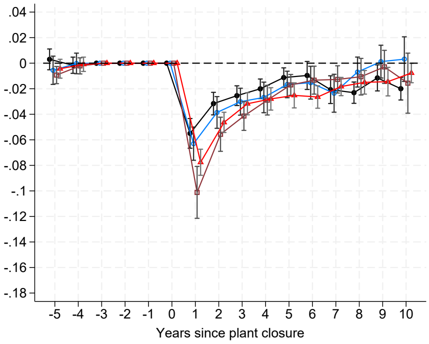
Figure G15 presents the coefficients from estimating Equation 2 using a sample of individuals who have not delayed their graduation. The outcome used in the estimation is indicated in the caption. Panels (a) and (b) displays the coefficients β_k and $\beta_k + \delta_{kl}$ for university and vocational school graduates, respectively. Panels (c) and (d) display the triple difference-in-ifferences estimates δ_{kl}, which capture the differences in the recovery for the individuals graduating when regional unemployment was in the l^{th} quartile ($l = 2, 3, 4$). Event-time $k \in [-3, 0]$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

G.1.3 Until first displacement

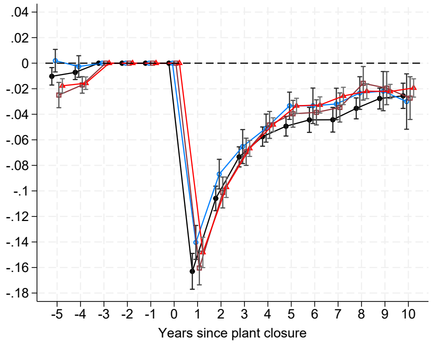
To ensure that our results are not skewed by individuals undergoing multiple plant closures, we have limited our sample to those who, in the base year, have either not yet encountered a plant closure or are facing their first displacement. Results from estimating Equation 2 for this sub-sample are reported in Figures G16 and G17 and in Column (4) of Table G1. Implementing this restriction results in a loss of only about 3 percent of observations in both samples, suggesting that our other restrictions are often binding. Specifically, individuals must have been employed three years prior to the base year, worked in the same firm for two years, and not experienced a plant closure in the three years preceding the base year. The robustness of our results to this sample restriction is evident when comparing the outcomes reported in Columns (1) and (4) of Table G1.

Fig. G16: Employment

Effect of Displacement (β_k and $\beta_k + \delta_{kl}$)

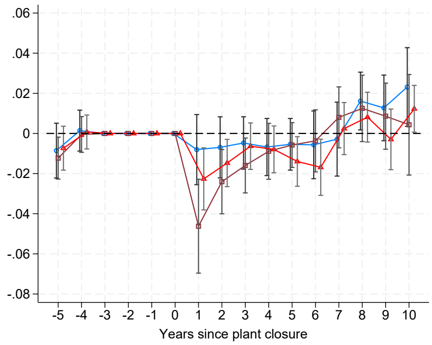


(a) University graduates

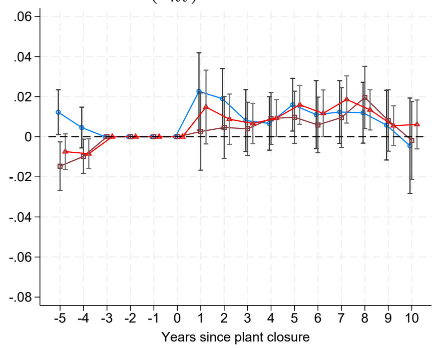


(b) Vocational school graduates

Triple Difference-in-Differences (δ_{kl})



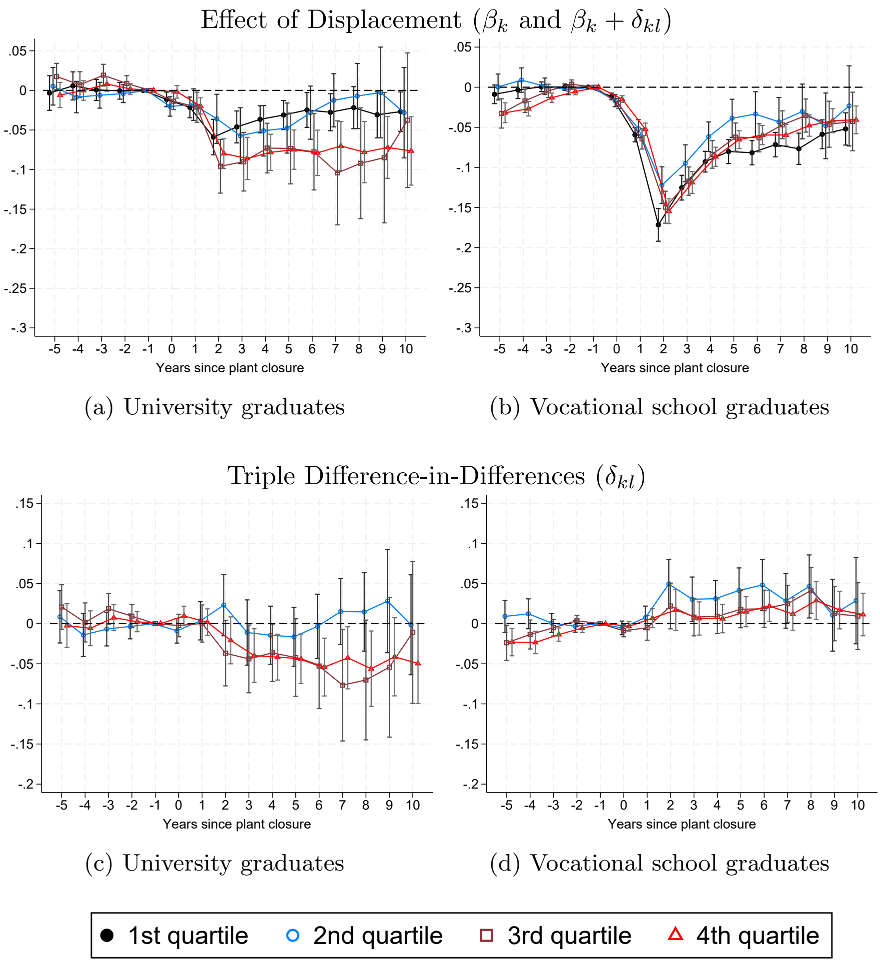
(c) University graduates



(d) Vocational school graduates

Figure G16 presents the coefficients from estimating Equation 2 using a sample, where individual, in the base year, have either not yet encountered a plant closure or are facing their first displacement. The outcome used in the estimation is indicated in the caption. Panels (a) and (b) displays the coefficients β_k and $\beta_k + \delta_{kl}$ for university and vocational school graduates, respectively. Panels (c) and (d) display the triple difference-in-ifferences estimates δ_{kl}, which capture the differences in the recovery for the individuals graduating when regional unemployment was in the l^{th} quartile ($l = 2, 3, 4$). Event-time $k \in [-3, 0]$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

Fig. G17: Log Market Income



(a) University graduates
(b) Vocational school graduates
(c) University graduates
(d) Vocational school graduates

Figure G17 presents the coefficients from estimating Equation 2 using a sample, where individual, in the base year, have either not yet encountered a plant closure or are facing their first displacement. The outcome used in the estimation is indicated in the caption. Panels (a) and (b) displays the coefficients β_k and $\beta_k + \delta_{kl}$ for university and vocational school graduates, respectively. Panels (c) and (d) display the triple difference-in-ifferences estimates δ_{kl}, which capture the differences in the recovery for the individuals graduating when regional unemployment was in the l^{th} quartile ($l = 2, 3, 4$). Event-time $k \in [-3, 0]$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

G.2 Robustness: Model specification

Table G3: Summary of Model specification robustness checks

	Main Specification	Firm FE	Education Field FE	Labor Earnings
Fixed effects				
Baseyear × event-time (γ_{bk})	Yes	Yes	Yes	Yes
Potential experience, (μ_e)	Yes	Yes	Yes	Yes
Graduation year (ϕ_c)	Yes	Yes	Yes	Yes
Graduation region (θ_r)	Yes	Yes	Yes	Yes
Displacement firm (α_j)	-	Yes	-	-
Field of studies (α_f)	-	-	Yes	-
University graduates				
	Panel (a) Employed			
β_1	-0.058***	-0.059***	-0.058***	
$\delta_{1,2}$	-0.006	-0.007	-0.006	
$\delta_{1,3}$	-0.042***	-0.041***	-0.042***	
$\delta_{1,4}$	-0.020**	-0.020**	-0.020**	
β_7	-0.024***	-0.023***	-0.024***	
$\delta_{7,2}$	0.000	0.003	-0.001	
$\delta_{7,3}$	0.012	0.010	0.012	
$\delta_{7,4}$	0.005	0.005	0.005	
Obs.	10,282,088	8,306,523	10,282,088	
	Panel (b) Log Market Income			Log Earnings
β_2	-0.060***	-0.067***	-0.060***	-0.050***
$\delta_{2,2}$	0.023	0.022	0.023	0.021
$\delta_{2,3}$	-0.036*	-0.032	-0.036*	-0.026
$\delta_{2,4}$	-0.021	-0.018	-0.021	-0.019
β_7	-0.031***	-0.035***	-0.031***	-0.030**
$\delta_{7,2}$	0.019	0.023	0.019	0.030
$\delta_{7,3}$	-0.071**	-0.060*	-0.071**	-0.038
$\delta_{7,4}$	-0.041**	-0.041**	-0.040**	-0.023
Obs.	10,281,887	8,306,344	10,281,887	10,281,711
Vocational school graduates				
	Panel (c) Employed			
β_1	-0.161***	-0.161***	-0.161***	
$\delta_{1,2}$	0.021**	0.022**	0.021**	
$\delta_{1,3}$	0.002	0.001	0.002	
$\delta_{1,4}$	0.015*	0.012	0.015*	
β_7	-0.044***	-0.043***	-0.044***	
$\delta_{7,2}$	0.012	0.013	0.012	
$\delta_{7,3}$	0.009	0.009	0.009	
$\delta_{7,4}$	0.019***	0.017***	0.019***	
Obs.	30,505,010	29,062,702	30,505,010	
	Panel (d) Log Market Income			Log Earnings
β_2	-0.170***	-0.171***	-0.170***	-0.155***
$\delta_{2,2}$	0.047***	0.046***	0.047***	0.043***
$\delta_{2,3}$	0.021	0.020	0.021	0.018
$\delta_{2,4}$	0.016	0.014	0.016	0.014
β_7	-0.072***	-0.073***	-0.072***	-0.060***
$\delta_{7,2}$	0.028	0.027*	0.028	0.042***
$\delta_{7,3}$	0.025**	0.025**	0.025**	0.024**
$\delta_{7,4}$	0.013	0.014	0.013	0.014
Obs.	30,504,642	29,062,340	30,504,642	30,504,594

Note: This table summarizes the results from the robustness check on model specification. Panels (a) and (b) present the results for University graduates on employment and incomes, respectively. Column 1 presents the results from our main specification (Equation 2) for comparison. Column 2 and 3 presents the results including displacement firm and education field fixed effects, respectively. Lastly, Column (4) presents the results from our main specification on alternative income measure, earnings. The table reports effects at event-time 1 (2) and 7 for employment (incomes). Figures reporting estimates for all time to event coefficients are presented in Figures G18-G22. Standard errors are clustered at the level of graduation year and region, and statistical significance is denoted in stars: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

G.2.1 Role of displacement firm and field of education

The recovery trajectories following plant closures may be influenced by pre-displacement characteristics not accounted for in our main analysis. In this robustness check, we examine two potential factors that could affect the recovery paths of lucky and unlucky individuals: unobserved firm characteristics and the individual's field of education.

Let us first focus on the potential differences in unobserved firm characteristics. In this setting, unlucky graduates who lose jobs at less prestigious firms might struggle to secure positions with comparable pay compared to lucky counterparts facing displacement. On the other hand, losing firm-specific wage premiums could exacerbate the negative income effect of displacement for individuals who were employed by more prestigious firms (Fackler et al, 2021).

In the case of education fields, cyclical variations in the labor market may influence the selection into specific fields of study. If those who graduate during unfavorable economic times are more likely to come from certain education fields–either by changing their field of study for their first degree or by completing a second degree in a particular field–this could affect our results regarding the differing reactions to plant closures between unlucky and lucky graduates.

We investigate these possibilities by including fixed effects for the employer firm at base year and for the education field at base year in Columns (2)[15] and (3), respectively.

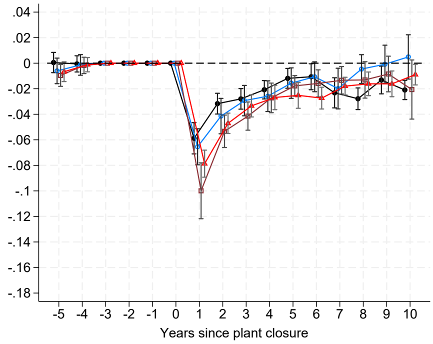
The inclusion of firm- or education field fixed effects does not seem to impact our main results. Both the short and long-term impacts of displacement for all luckiness groups are of similar magnitude in Columns (1), (2) and (3) of Table G3. We still observe that the effect of displacement is more negative

[15] The sample size for the analysis with firm fixed effects is slightly smaller than in our main analysis because we lack information on the firm of some individuals at the base year, although we do have data on the plant of each individual at base year.

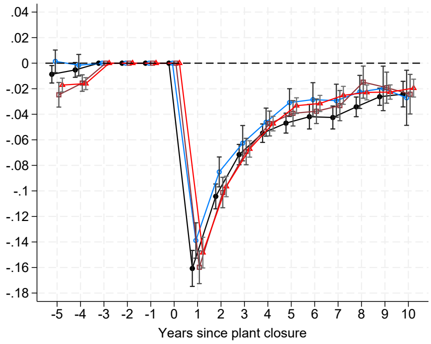
for unlucky university graduates compared to their lucky counterparts, while it is less negative for unlucky vocational school graduates. This suggests that unobserved differences in employer quality or individuals education field at the base year do not drive our results.

Fig. G18: Employment with firm fixed effects

Effect of Displacement (β_k and $\beta_k + \delta_{kl}$)

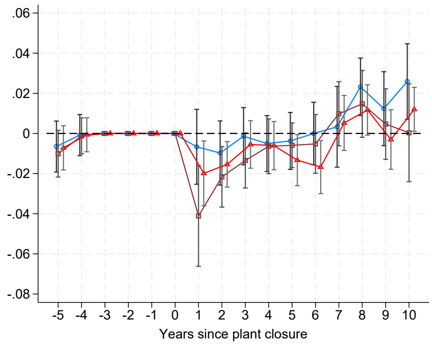


(a) University graduates

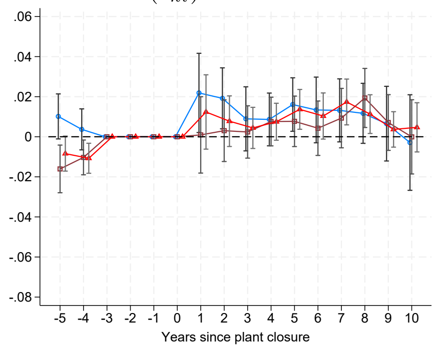


(b) Vocational school graduates

Triple Difference-in-Differences (δ_{kl})



(c) University graduates

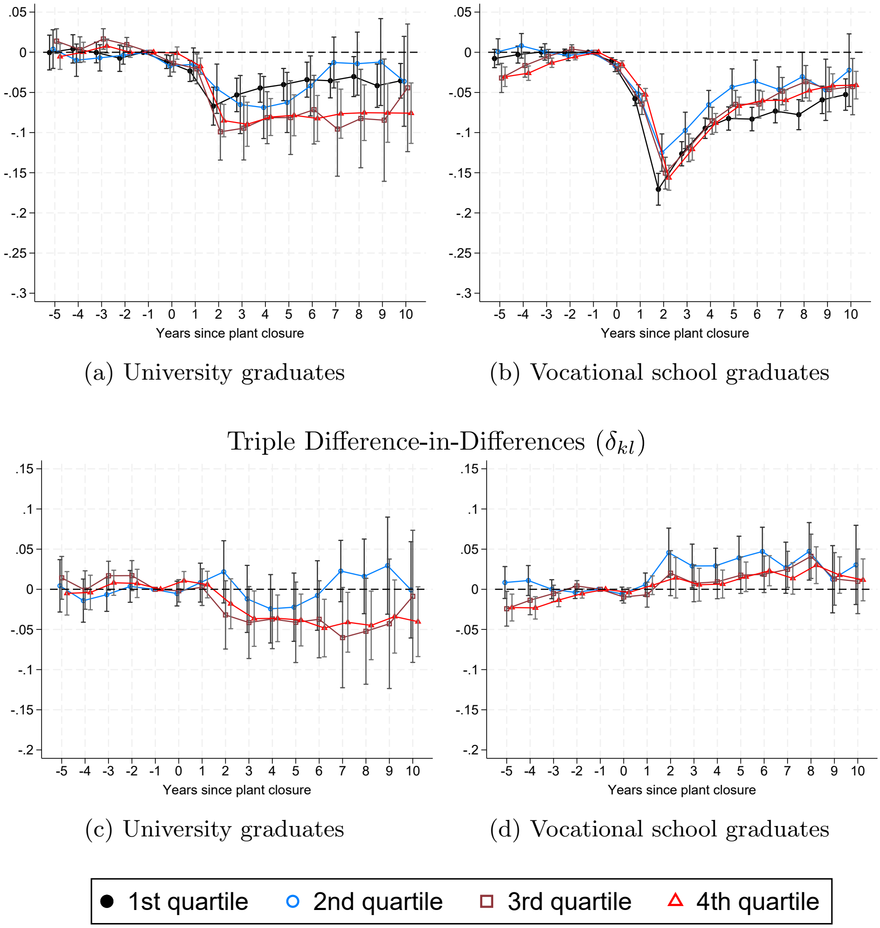


(d) Vocational school graduates

Figure G18 presents the coefficients from estimating an augmented version of Equation 2, where we also include fixed effects for the displacement firm. The outcome used in the estimation is indicated in the caption. Panels (a) and (b) displays the coefficients β_k and $\beta_k + \delta_{kl}$ for university and vocational school graduates, respectively. Panels (c) and (d) display the triple difference-in-ifferences estimates δ_{kl}, which capture the differences in the recovery for the individuals graduating when regional unemployment was in the l^{th} quartile ($l = 2, 3, 4$). Event-time $k \in [-3, 0]$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

Fig. G19: Log Market Income with firm fixed effects

Effect of Displacement (β_k and $\beta_k + \delta_{kl}$)



(a) University graduates

(b) Vocational school graduates

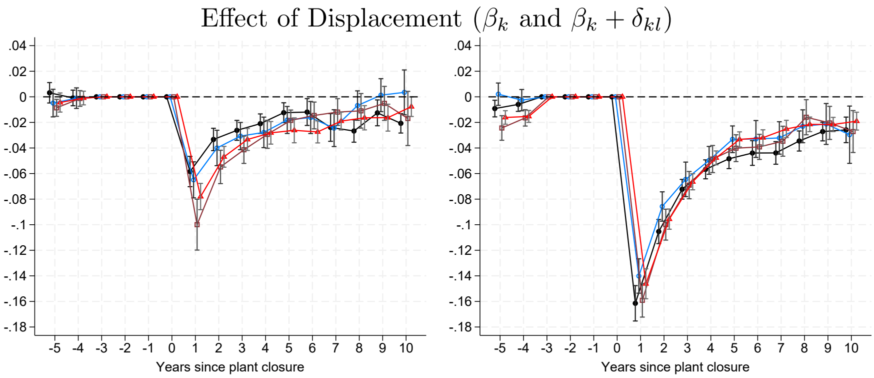
Triple Difference-in-Differences (δ_{kl})

(c) University graduates

(d) Vocational school graduates

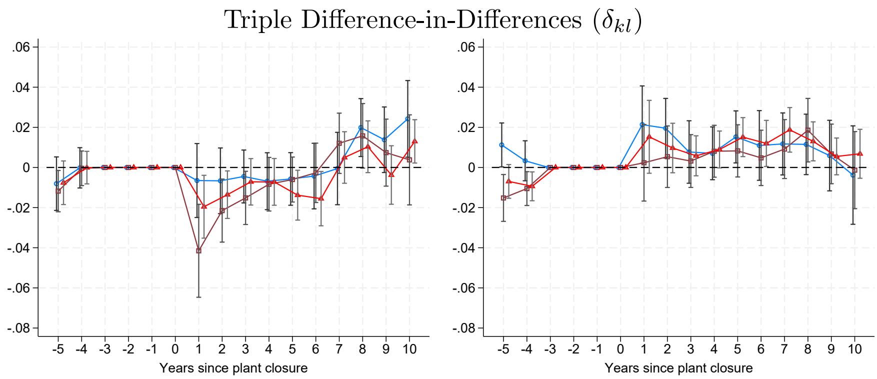
Figure G19 presents the coefficients from estimating an augmented version of Equation 2, where we also include fixed effects for the displacement firm. The outcome used in the estimation is indicated in the caption. Panels (a) and (b) displays the coefficients β_k and $\beta_k + \delta_{kl}$ for university and vocational school graduates, respectively. Panels (c) and (d) display the triple difference-in-ifferences estimates δ_{kl}, which capture the differences in the recovery for the individuals graduating when regional unemployment was in the l^{th} quartile ($l = 2, 3, 4$). Event-time $k \in [-3, 0]$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

Fig. G20: Employment with education field fixed effects



(a) University graduates

(b) Vocational school graduates



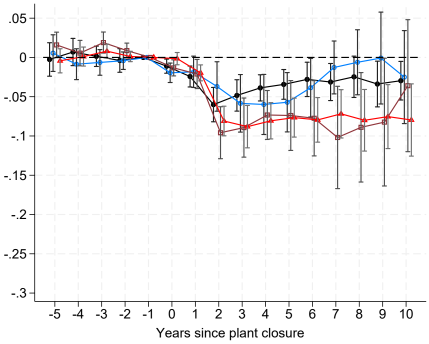
(c) University graduates

(d) Vocational school graduates

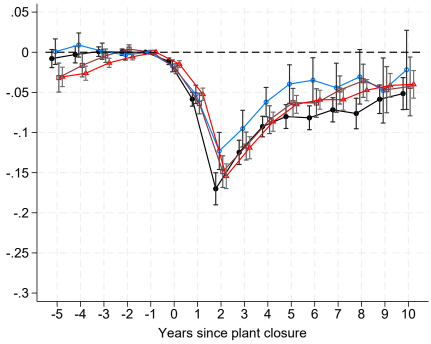
Figure G20 presents the coefficients from estimating an augmented version of Equation 2, where we also include fixed effects for field of graduation. The outcome used in the estimation is indicated in the caption. Panels (a) and (b) displays the coefficients β_k and $\beta_k + \delta_{kl}$ for university and vocational school graduates, respectively. Panels (c) and (d) display the triple difference-in-ifferences estimates δ_{kl}, which capture the differences in the recovery for the individuals graduating when regional unemployment was in the l^{th} quartile ($l = 2, 3, 4$). Event-time $k \in [-3, 0]$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

Fig. G21: Log Market Income with education field fixed effects

Effect of Displacement (β_k and $\beta_k + \delta_{kl}$)

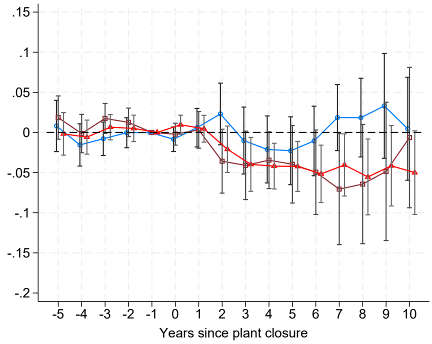


(a) University graduates

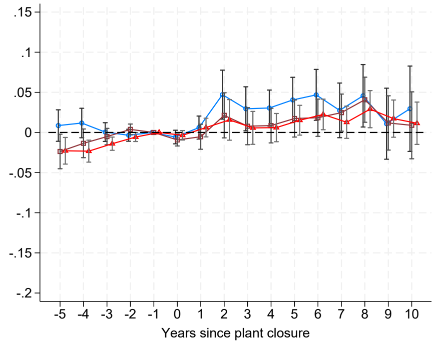


(b) Vocational school graduates

Triple Difference-in-Differences (δ_{kl})



(c) University graduates



(d) Vocational school graduates

● 1st quartile ○ 2nd quartile □ 3rd quartile △ 4th quartile

Figure G21 presents the coefficients from estimating an augmented version of Equation 2, where we also include fixed effects for field of graduation. The outcome used in the estimation is indicated in the caption. Panels (a) and (b) displays the coefficients β_k and $\beta_k + \delta_{kl}$ for university and vocational school graduates, respectively. Panels (c) and (d) display the triple difference-in-ifferences estimates δ_{kl}, which capture the differences in the recovery for the individuals graduating when regional unemployment was in the l^{th} quartile ($l = 2, 3, 4$). Event-time $k \in [-3, 0]$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.

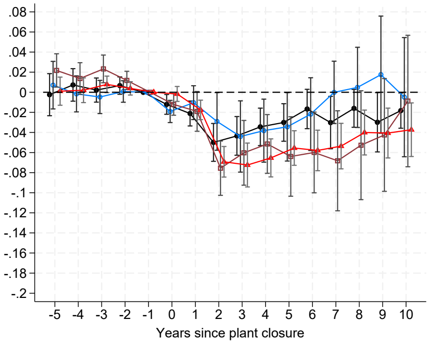
G.2.2 Role of Capital Incomes

Our main analysis on differential effects of displacement on incomes focuses on the effect of market incomes, which is defined as a sum of labor and capital incomes, but excludes transfers. We use this income definition to capture different types of wages and self-employment income. We specifically include capital incomes to take into account the income from self-employment, which can to some extent be registered as capital incomes. The use of market income can present problems if the groups differ in their traditional capital incomes, such as sales profits and dividends. As a robustness check, we have use a more narrow definition of income, which includes taxable labor income and entrepreneurial incomes, a part of the more broad taxable capital incomes. This allows us to restrict much of the capital incomes, while keeping at least some income from the entrepreneurial activities.

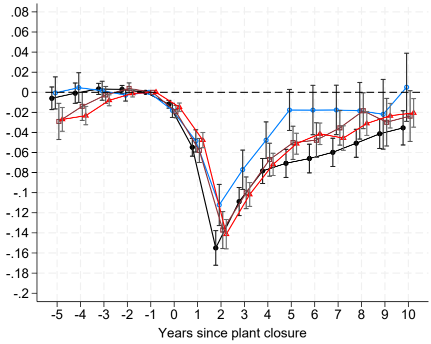
The results for this alternative income measures are presented in Figure G22 and in column (4) of Table G3. Although a negative effect persists for the unluckiest university graduates, it diminishes and becomes statistically insignificant by the seventh year following the displacement, remaining so thereafter. This suggests that part of the negative impact on market income is mediated through less favorable development in capital income. For vocational school graduates, the results for labor earnings generally align with our main findings on market income, though the impact sizes are slightly smaller for labor earnings.

Fig. G22: Log Earnings

Effect of Displacement (β_k and $\beta_k + \delta_{kl}$)

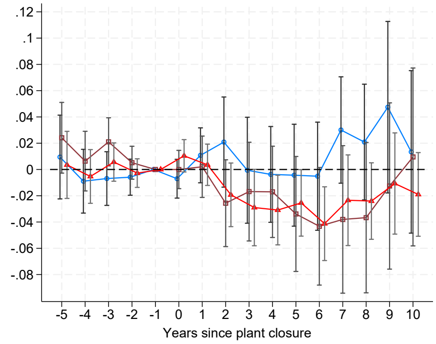


(a) University graduates

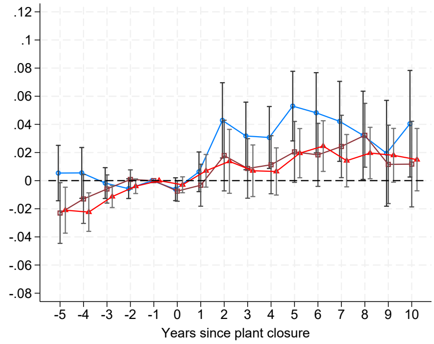


(b) Vocational school graduates

Triple Difference-in-Differences (δ_{kl})



(c) University graduates



(d) Vocational school graduates

Figure G22 presents the coefficients from estimating Equation 2 on Log Earnings. Panels (a) and (b) displays the coefficients β_k and $\beta_k + \delta_{kl}$ for university and vocational school graduates, respectively. Panels (c) and (d) display the triple difference-in-differences estimates δ_{kl}, which capture the differences in the recovery for the individuals graduating when regional unemployment was in the l^{th} quartile ($l = 2, 3, 4$). Event-time $k = -1$ is omitted as a reference category. Standard errors are clustered at the level of graduation year and region.