Local Economic Shocks and Human Capital Formation: Evidence from University Students in Italy

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Abstract

We examine how local economic shocks shape human capital formation by studying the effects of mass layoffs on university students in Italy. Using population-wide administrative data on university enrolment matched to geographically localised mass layoff events, we exploit staggered employment displacement across municipalities in a difference-in-differences design. Mass layoffs raise university dropout rates by 8%, but also induce substantial behavioural responses: online bachelor enrolment increases by 15%, engineering enrolment rises by 10%, and master's students accelerate degree completion by 1.1 months. These patterns indicate that students actively adapt to economic shocks by reallocating across modes of study, fields, and timing of graduation. Our findings highlight the role of flexible higher-education pathways in buffering adverse labour market shocks and underscore the importance of education and labour market policies that support students' ability to remain enroled during periods of local economic distress.

Keywords: Mass layoffs; Local labour market shocks, Human capital formation
JEL codes: I26; J24; J63

1 Introduction

Mass layoffs have long-lasting consequences for unemployment, production, income, and local labour markets. Spillover effects extend beyond directly affected workers, generating employment losses in other firms within the region (Gathmann et al., 2020) that can persist long after the initial event (Celli et al., 2023). In southern Mediterranean countries, displaced workers face particularly severe challenges, with substantially lower re-employment probabilities (Bertheau et al., 2023).

The adverse effects of mass layoffs extend beyond labour market outcomes to broader measures of household well-being, including earnings stability (Davis and von Wachter, 2011), health outcomes (Ahammer et al., 2025), and even electoral behaviour (Braakmann and Vermeulen, 2023). A central concern is whether mass layoffs reduce human capital accumulation through impacts on workers' families. Prior research has documented lower educational achievement and altered educational trajectories among children of displaced workers (Ost et al., 2018; Minaya et al., 2023), yet little is known about how university students—who face imminent labour market entry—adjust their educational investments in response to local economic shocks.

These concerns are particularly salient in the Italian context, where educational attainment plays a critical role in mitigating unemployment risk. Among individuals aged 25–34, unemployment rates decline sharply from 14.8% for those without upper secondary qualifications to 6.5% (OECD (2025))for those with tertiary education, underscoring the protective role of continued education during periods of labour market instability. Yet Italy also exhibits pronounced spatial inequalities in access to flexible higher education pathways. Although total university enrolment has expanded over the past decade, driven largely by rapid growth in online programmes, this expansion has been geographically uneven, with southern regions experiencing declining enrollment in traditional universities even as online options proliferated. This institutional variation, combined with the regional concentration of mass layoff events, provides a unique opportunity to examine how students adapt their educational choices when local labour markets deteriorate and whether access to flexible study modes shapes these responses.

This paper contributes to the literature by examining how mass layoffs affect university students' human capital choices in Italy. Using high quality administrative data from the Italian National Student Registry (Anagrafe Nazionale Studenti, ANS) covering cohorts from 2010 to 2020, we analyse the universe of Italian university students during this period. The ANS data capture students' municipality of residence, gender, age, university and year of enrolment, degree programme, and subsequent outcomes including dropout and degree changes for both bachelor's and master's programs.

We match students' municipalities of residence with mass layoff events from Eurofound's European Restructuring Monitor (ERM), which tracks announcements of large-scale employment losses through systematic monitoring of national and local newspapers. Employing a staggered difference-in-differences design with not-yet-treated comparison units, we analyse several outcomes: dropout rates, enrolment patterns, geographic mobility (studying in other regions or provinces), and STEM and engineering degree uptake as well as student characteristics such as age and gender.

We find that mass layoffs increase university dropout by 8%, while also prompting substantial behavioural responses. Online bachelor enrolment rises by 15%, engineering enrolment increases by 10%, and master's students graduate about 1.1 months earlier. Overall, the evidence points to students adapting to economic shocks through adjustments in study mode, field choice, and time to completion. Our findings suggest that flexible higher-education pathways play an important role in buffering the educational consequences of local labour market shocks. While mass layoffs increase university dropout, students also adjust by shifting towards online programmes, employment-oriented fields, and faster degree completion. These patterns point to potential gains from policies that expand flexible study options, provide targeted support to students in affected areas, and better coordinate labour market and education policies during periods of local economic distress.

The remainder of the paper is organised as follows. Section 2 describes the data. Section 3 outlines the identification strategy and empirical framework. Section 4 presents the main results. Section 5 discusses ongoing work and extensions that are currently under development. Section 6 concludes.

2 Data

2.1 Data students

The ANS is an administrative dataset collected and managed by the Italian Ministry of Education (MIM), based on information reported by universities to track students' educational careers over time. Our sample covers the period from 2010 to 2020.

We first remove observations lacking information on key enrolment attributes, such as the location of the university, the institution attended, the degree programme, or the student's enrolment status. We then exclude individuals older than 64 years. After applying these restrictions, the ANS dataset includes 3,162,780 students (55% women and 45% men), yielding a balanced panel of 7,914 municipalities over time. For each municipality and year, we construct population-based rates of student outcomes by counting the number of individuals experiencing a given event—such as enrolment, dropout, geographic mobility, or enrolment in a STEM field—and dividing these counts by annual ISTAT population estimates for individuals aged 17 to 64. This age range corresponds to typical working ages and the period during which higher education participation is most common. Expressing outcomes relative to the working-age population allows comparisons across municipalities with different population sizes and demographic structures. In addition, we estimate municipality–year averages of students' final graduation grades, years required to complete the degree, age at enrolment, and accumulated university credits.

One limitation of the data is that we cannot observe students who work and study simultaneously. While we can identify whether a student drops out, for the most recent cohorts in the registry (2020–2021) we are unable to observe whether they return to education at a later stage. In addition, the data do not provide information on students' post-exit labour market outcomes, such as where they work or the type of job they take up. A complete list of variables and their descriptive statistics is reported in Appendix Tables 3, 4, and 5.

2.2 Mass Layoff Data

We identify mass layoff events using the European Restructuring Monitor (ERM), which systematically tracks large-scale employment restructuring events across Europe through monitoring of national and local press sources. For inclusion in the ERM database, an event must affect at least 100 jobs or 10 percent of the workforce in establishments with more than 250 employees.

We focus on layoff events occurring between 2010 and 2020, excluding business expansions and reshoring (which represent job gains rather than losses). We classify events as layoffs if they involve bankruptcy, closure, internal restructuring, merger/acquisition, offshoring/delocalisation, outsourcing, or relocation. This yields 567 layoff events affecting 323 Italian municipalities over the study period.

Following the location information reported in ERM announcements, we match layoff events to Italian municipalities. When multiple locations are affected by a single event, we distribute the reported job losses proportionally across affected municipalities. For temporal assignment, we use the effective employment impact date when available, and the announcement date when the effective date is missing. When a municipality experiences multiple layoff events, we assign treatment based on the first event to ensure clean pre-treatment periods for identification.

The 567 events resulted in 46,765 total job losses across the 323 treated municipalities, with an average of 145 affected jobs per municipality. Internal restructuring represents the largest category (55% of events), followed by closures (21%) and bankruptcies (12%). The manufacturing sector accounts for the majority of job losses, followed by retail trade and transportation. Treatment timing is staggered throughout the 2010-2020 period, with peak activity in 2016 (see Figure 2).

Figure 1 illustrates the temporal distribution of mass layoff events across treated municipalities in our sample. The staggered pattern shows substantial variation in treatment timing, with mass layoffs occurring throughout the entire 2010-2020 period. Municipalities are ordered vertically by their treatment year, revealing a gradual accumulation of treated units over time. Notably, the number of newly treated municipalities increases in later years, with substantial layoff activity concentrated between 2012 and 2016. This staggered rollout of treatment provides the identifying variation for our difference-in-differences estimation strategy.

One limitation of the ERM data is that it relies on media coverage to identify restructuring events. As a result, mass layoffs that received limited or no press attention may not be captured in the database. Consequently, our measure of mass layoff exposure is likely to represent a lower bound of the true incidence of large-scale employment losses.

3 Identification Strategy

Our identification strategy exploits the staggered timing of mass layoff events across Italian municipalities between 2010 and 2020. As documented in Section 2.2, municipalities experienced mass layoffs in different years, generating variation in exposure both across municipalities within a given year and within municipalities over time.

We estimate the effect of mass layoffs on students' educational choices using a difference-in-differences design that compares outcomes in treated municipalities to those in municipalities that have not yet experienced a layoff in the same period. Municipalities that are never treated during the sample period also contribute to identification.

Recent methodological advances in difference-in-differences estimation have highlighted important limitations of traditional two-way fixed effects (TWFE) specifications when treatment timing varies across units and treatment effects are heterogeneous. Goodman-Bacon (2021) demonstrates that in settings with staggered treatment adoption, the TWFE estimator is a weighted average of all possible 2×2 difference-in-differences comparisons, including problematic comparisons that use earlier-treated units as controls for later-treated units. When treatment effects evolve over time, these "forbidden comparisons" can produce negatively weighted terms that bias the overall estimate.

To circumvent this problem, we use Callaway and Sant'Anna (2021) alternative estimation approach that addresses these concerns by constructing treatment effect estimates through explicit comparisons of each treatment cohort to not-yet-treated units. We adopt this estimator for several reasons. First, our setting features substantial variation in treatment timing, with mass layoffs occurring throughout 2010-2020 across 323 municipalities. Second, treatment effects are likely heterogeneous across cohorts, as the economic context and policy environment evolved over this period. Third, the Callaway-Sant'Anna estimator allows us to examine dynamic treatment effects through event study specifications while avoiding the negative weighting problems inherent in TWFE estimators.

Model For each treatment cohort g (defined as municipalities experiencing their first mass layoff in year g) and time period $t \geq g$, we estimate the group-time average treatment effect on the treated:

$$\text{ATT}(g,t) = E[Y_{it}(g) - Y_{it}(0) | G_i = g] \tag{1}$$

where $Y_{it}(g)$ denotes the potential outcome for municipality i at time t if first treated at time g, $Y_{it}(0)$ is the potential outcome under no treatment, and G_i indicates the year municipality i is first treated, with $G_i = \infty$ for never-treated units.

We implement the doubly robust inverse probability weighting (DR-IPW) estimator, which combines outcome regression and propensity score weighting to achieve robustness to misspecification of either model.

Our baseline specification does not include covariates, relying instead on the conditional parallel trends assumption that, absent treatment, municipalities treated at time g would have experienced the same outcome trajectory as not-yet-treated municipalities.

To summarize treatment effects across cohorts, we aggregate group-time ATTs using a simple weighted average:

$$\widehat{\text{ATT}} = \sum_{g \in \mathcal{G}} \sum_{t \geq g} w_{g,t} \cdot \widehat{\text{ATT}}(g,t) \tag{2}$$

where $\mathcal{G}$ denotes the set of treatment cohorts and $w_{g,t} = P(G_i = g, T_i = t | G_i \in \mathcal{G}, T_i \geq G_i)$ weights each group-time estimate by its share in the treated sample.

To examine dynamic treatment effects and test the parallel trends assumption, we estimate event study specifications that aggregate ATTs by event time relative to treatment:

$$\widehat{\text{ATT}}_e = \sum_{g \in \mathcal{G}} w_g \cdot \widehat{\text{ATT}}(g, g+e) \tag{3}$$

where $e \in \{-4, ..., 6\}$ indexes event time (years before or after first treatment), and $w_g = P(G_i = g | G_i \in \mathcal{G})$ weights by cohort size. Pre-treatment estimates ($e < 0$) provide a visual test of parallel trends, while post-treatment estimates ($e \geq 0$) reveal how effects evolve over time since the initial mass layoff.

4 Results

Tables 1 and 2 present our main findings from the Callaway-Sant'Anna (CS) difference-in-differences estimation. We report the simple average of post-treatment effects over the six years following a mass layoff. The choice of a six-year window reflects both data availability (2010–2020) and evidence from the literature showing that the employment effects of mass layoffs are highly persistent, with impacts remaining sizeable several years after the event and peaking around the sixth year ((Celli et al., 2023)). Focusing on this horizon allows us to capture medium-run dynamics while maximising the post-treatment window in a staggered adoption setting. Only outcomes satisfying the parallel trends assumption (joint pre-treatment test $p > 0.10$) are reported although the complete list of outcomes that were explored can be found in the Appendix (Tables 3 and 4). Event-study plots can be found in the Appendix 7.3.

Enrolment and Dropout Effects Mass layoffs increase university dropout rates in affected municipalities. The average treatment effect (ATT) for overall dropout rate is 1.435 per 10,000 working-age residents (p <0.05), representing a 0.14 percentage point increase. This translates to approximately 5.3 additional dropout events per year in an average treated municipality. When interpreted relative to the control group mean of 17.48 per 10,000, this represents an 8.2% increase in dropout rates.

In terms of the dynamic effects, the increase on dropouts (Figure 3) is around the fourth year after the mass layoff, however, permanent dropouts start around the third year (Figure 4).

These results suggest that economic shocks in students' home municipalities affect their ability to continue higher education, due to reduced parental income support or if the student was currently working. The effect is concentrated among current students rather than prospective students, as the permanent dropout coefficient , while positive, is not statistically significant, suggesting some students who drop out may eventually return.

Table 1: Impact of Mass Layoffs on Educational Outcomes

	(1) Dropout Rate	(2) Permanent Dropout	(3) Online Education	(4) Online Bachelor	(5) Engineering Rate	(6) Changed University	(7) Degree Completed
ATT	1.435**	0.998	0.892**	0.931***	2.598***	0.813***	4.650***
	(0.645)	(0.658)	(0.417)	(0.321)	(0.595)	(0.253)	(0.990)
Control Mean	17.48	15.27	7.79	6.37	26.95	7.35	49.40

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports average treatment effects on the treated (ATT) from Callaway and Sant'Anna (2021) difference-in-differences estimation using the doubly robust inverse probability weighting (DR-IPW) method with not-yet-treated municipalities as the comparison group. Outcomes are measured as rates per 10,000 working-age residents (18-64 years). The estimation uses a balanced panel of 7,914 Italian municipalities observed annually from 2010-2020, of which 323 experienced at least one mass layoff (affecting 100+ jobs or 10% of workforce) during this period. Mass layoff data from the European Restructuring Monitor (ERM). Student data from the Italian National Student Registry (ANS). Standard errors clustered at the municipality level.

Shift Toward Online Education We found an increase in online education enrolment following mass layoff in the municipality of residence of the student. The ATT for online education rate is 0.892 per 10,000, while online bachelor enrolment increases by 0.931 per 10,000, representing a 14.6% increase relative to the control group mean of 6.37. This indicates a substantial shift toward online bachelor programs in treated municipalities, rather than online master's degree enrolment.

The event-study estimates are consistent with an increase in online education take-up around the time of mass layoffs. As shown in Figures 8 and 7, this pattern appears to be driven mainly by bachelor programmes and is concentrated in the year of the layoff.

Online (telematic) universities have fixed annual tuition fees ranging from approximately €1,500 to €5,900, regardless of family income. In contrast, traditional public universities employ income-based tuition, with fees ranging from €400 to €3,000 depending on the student's family ISEE. However, the total cost of university attendance extends beyond tuition fees. Traditional universities impose significant indirect costs when located far from students' residence, including transportation costs, living expenses (which vary depending on the city), and opportunity costs from commuting time that reduces available hours for part-time work. For students in municipalities experiencing mass layoffs, online education offers several advantages despite higher nominal tuition: elimination of transportation costs, ability to remain at home (avoiding relocation expenses), labour market flexibility to work while studying, and access to family support during economic hardship.

The online bachelor effect (0.931) is nearly two-thirds the magnitude of the overall dropout effect (1.435), suggesting that online education may absorb a substantial portion of students who might otherwise have dropped out.

Table 2: Impact of Mass Layoffs on Educational Transitions and Mobility

	(1) Switched Education Mode	(2) Study Away (Province)	(3) Years to Bachelor	(4) Years to Master
ATT	0.223	−0.494	−0.029	−0.092**
	(0.176)	(3.704)	(0.019)	(0.040)
Control Mean	3.64	161.60	2.10	4.16
Years	2010-2020	2010-2020	2010-2020	2010-2020

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports average treatment effects on the treated (ATT) from Callaway and Sant'Anna (2021) difference-in-differences estimation for educational transitions and degree timing. Switched Education Mode measures transitions between traditional and online education (per 10,000 residents). Study Away (Province) measures students whose residence province differs from university province (per 10,000 residents). Years to Bachelor and Years to Master measured in years from first enrolment. Standard errors clustered at the municipality level.

Field of Study Choices Mass layoffs substantially affect students' choice of field of study. The engineering enrolment rate increases by 2.598 per 10,000 (p ¡ 0.01) representing a 9.6% increase relative to the control mean (26.95). In absolute terms, this translates to approximately 9.6 additional engineering students per year in an average treated municipality. Figure 12 shows that the rate of enrolment to this kind of degree around the same year the mass layoff occurs. We do not observe any effects on overall STEM enrolment.

This pronounced shift toward engineering likely reflects defensive career choices in response to economic uncertainty. Students may perceive engineering fields as offering better job security, higher returns, and more stable career paths compared to other disciplines. This behavioural response suggests that economic shocks not only affect educational attainment but also reshape human capital accumulation by steering students toward fields perceived as more resilient to future economic downturns.

University Switching and Disruption Economic shocks disrupt students' educational trajectories beyond simple dropout decisions. The changed university rate increases by 0.813 per 10,000, an 11.1% increase relative to the control mean. Students may transfer to less expensive institutions, online universities, universities closer to home, or universities in regions with better job prospects. This finding highlights that mass layoffs create both exit effects (dropout) and reoptimisation effects (switching) in students' educational choices.

Degree Completion and Timing The degree completion rate increases by 4.650 per 10,000, a 9.4% increase relative to the control mean (49.40). In absolute terms, this translates to approximately 17.3 additional degree completions per year in an average treated municipality. Importantly, this positive completion effect (4.650) exceeds the dropout effect (1.435) by a factor of 3.2, indicating that economic shocks create both exit and acceleration effects, with acceleration dominating. This is also observed on the dynamic effects plot (Figure 6) were there is an immediate effect the year of the event. This result can be explained by several mechanisms. First, students near degree completion may accelerate their studies to enter the labour market quickly during economic uncertainty. Second, displaced workers or their children may return to complete interrupted degrees, viewing economic downturns as opportunities to invest in human capital when labour market opportunities are limited. Third, there may be compositional effects whereby economic shocks induce early-stage students to drop out while motivating near-graduates to finish.

Supporting this interpretation, we find that students in treated municipalities complete master's degrees 0.092 years (approximately 1.1 months) faster than control municipalities, representing a 2.2% reduction in time to master's degree relative to the control mean of 4.16 years. This decrease is already noticeable the same year the mass lay off happened (Figure 11). While the effect on bachelor's completion time is negative (-0.029 years), it is not statistically significant. The differential effects by degree level suggest that the acceleration is concentrated among graduate students who may face more immediate labour market pressures.

Null Results and Interpretation We find no significant effects on educational mode switching or geographic mobility, measured as studying away from home province. The large standard error on geographic mobility (3.704) suggests substantial heterogeneity across municipalities or measurement challenges. The lack of significant switching between online and traditional education modes, despite the increase in online enrolment, suggests that the online education response primarily reflects new enrolment decisions rather than existing students switching institutions.

5 Future Research Directions

While our analysis provides compelling evidence of mass layoffs' effects on educational outcomes at the municipality level, we are still working on promising extensions that could deepen our understanding of these mechanisms and their broader implications.

5.1 Housing Market Dynamics

One planned extension incorporates data from Italy's Real Estate Market Observatory (Osservatorio del Mercato Immobiliare, OMI), which reports semi-annual property valuations across Italy at both the municipal and sub-municipal level. These data provide price ranges per square metre for different property categories (residential, commercial, and industrial) and allow us to explore housing market dynamics as a potential channel through which mass layoffs influence educational choices.

By linking OMI valuations to our municipality-level analysis, we can examine whether local housing costs mediate or amplify the educational responses we document. This extension is particularly relevant for understanding the observed increase in online education: higher rental prices in study locations may be associated with higher dropout rates, a shift towards online university enrolment, or students' decisions to return to their home municipalities.

5.2 Gender Heterogeneity in Educational Responses

Despite substantial progress in closing the gender gap in educational attainment, significant disparities persist in field of study choices, particularly in STEM and engineering fields where women remain underrepresented. Our finding of a pronounced shift toward engineering following mass layoffs raises important questions about whether this response differs by gender.

If economic shocks disproportionately push male students toward engineering while having weaker effects on female students' field choices, mass layoffs could inadvertently widen existing gender gaps in STEM. Alternatively, economic necessity might reduce gender-stereotypical field choices if both male and female students converge on fields perceived as offering the highest returns and job security. Our administrative data from the ANS include individual-level gender information, allowing us to decompose our main effects by student gender and test whether mass layoffs exacerbate or attenuate gender disparities in educational trajectories.

5.3 Local labour Market Analysis

Our current municipality-level analysis may understate the true geographic scope of mass layoffs' effects. Workers often commute across municipal boundaries, and a mass layoff in one municipality likely affects educational decisions in neighbouring communities through direct employment linkages, information spillovers, and changes in commuting patterns.

We plan to aggregate our data to the local labour market (Sistema Locale del Lavoro, SLL) level, defined by ISTAT based on commuting flows to capture functional economic areas. This aggregation has three advantages. First, it better aligns the geographic unit of analysis with the relevant economic shocks, as workers and students operate within integrated local labour markets rather than within strict municipal boundaries. Second, it allows us to examine whether mass layoffs trigger changes in commuting and mobility patterns, as students may be more likely to study locally when employment opportunities contract regionally. Third, labour market-level analysis may reveal spillover effects on neighbouring municipalities, providing insight into the spatial extent of economic shocks' educational consequences.

By examining effects at the labour market level, we can distinguish between localized shocks (affecting only the immediate municipality) and broader regional disruptions (affecting entire commuting zones), with potentially different implications for educational policy responses.

6 Conclusion

This paper examines how local economic shocks shape human capital decisions by analysing the effects of mass layoffs on university students' educational choices in Italy. Using comprehensive administrative data from the Italian National Student Registry matched with detailed records of mass layoff events from 2010 to 2020, we implement a difference-in-differences design that exploits the staggered timing of employment displacement across 323 Italian municipalities.

Our findings reveal substantial and multifaceted responses to economic shocks. Mass layoffs increase university dropout rates by 8.2%, translating to approximately 5.3 additional dropouts per year in an average affected municipality. However, this negative effect on educational persistence is partially offset by students' adaptation strategies. We document a pronounced 14.6% increase in online bachelor enrolment, suggesting that distance learning provides a crucial buffer against economic hardship by allowing students to continue their education whilst remaining at home and maintaining labour market flexibility.

Beyond affecting whether students persist in higher education, mass layoffs substantially reshape what students study and where. Engineering enrolment increases by 9.6%—the largest effect we observe—indicating that economic uncertainty induces defensive career choices favouring fields perceived as offering greater job security. Students also respond by switching universities, with transfer rates rising by 11.1%. Furthermore, degree completion rates increase by 9.4%, suggesting that economic shocks create both exit effects among early-stage students and acceleration effects among those closer to graduation, with the latter dominating.

The pattern of effects we document highlights important complementarities between traditional and online universities within Italy's higher education system. Whilst traditional public universities offer income-based tuition that can be quite affordable for low-income families, they impose substantial indirect costs—including accommodation, transportation, and forgone earnings—when students must relocate or commute long distances. Online universities, despite charging higher fixed tuition fees, eliminate these indirect costs and provide the flexibility to work whilst studying. When economic shocks tighten household budget constraints, the total cost advantage shifts decisively towards online education, particularly for bachelor students from families experiencing income losses.

Our results have several implications for education policy and labour market regulation. First, the substantial increase in online enrolment following economic shocks highlights the importance of maintaining a diverse higher education ecosystem that includes both traditional and distance learning options.

Second, the pronounced shift towards engineering suggests that economic uncertainty significantly influences field of study choices, potentially creating mismatches between students' career decisions and actual labour market demand.

Third, the faster completion times we observe amongst master's students indicate that economic shocks accelerate transitions from education to the labour market. Whilst this may benefit some students by advancing their entry into employment, it could also reflect suboptimal rushing through advanced degrees or premature labour market entry. Universities and policymakers should consider whether additional support—such as extended financial aid or flexible completion timelines—might enable students to maintain educational quality whilst responding to economic pressures.

More broadly, European labour markets continue to evolve in response to technological change and the adoption of artificial intelligence, with displacement risks remaining concentrated in certain sectors. Given that the majority of the mass layoffs we study occur in manufacturing, our findings underscore the importance of policies that strengthen protection and adjustment mechanisms for affected workers and their families. In particular, labour market policies that combine income support with retraining opportunities may help mitigate the educational disruptions associated with large employment shocks, while reducing the need for students to make defensive or constrained human capital choices.

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7 Appendix

7.1 Variable definitions

Table 3: Variable Definitions and Measurement (I)

Variable	Definition
Panel A: enrolment and Dropout	
enrolled_rate	Number of students enrolled in university in a given year
dropout_rate	Number of students who definitively abandoned university
dropout_perm_rate	Students who dropped out and never returned
dropout_temp_rate	Students who dropped out but later re-enrolled
new_enrolment	First-time university enrolments
continuing	Students continuing their studies
Panel B: Online Education	
online_rate	Students enrolled in online/distance universities
switch_online_rate	Switch from traditional to online education
switch_from_online_rate	Switch from online to traditional education
online_bachelor_rate	Online bachelor enrolments
online_master_rate	Online master enrolments
trad_bach_online_ma_rate	Traditional bachelor to online master
switched_edu_mode_rate	Any transition between education modes
started_online_rate	New enrolments directly into online programs
Panel C: Geographic Mobility	
studying_away_comune_rate	Residence comune differs from university comune
studying_away_prov_rate	Residence province differs from university province
studying_away_region_rate	Residence region differs from university region
studying_home_comune_rate	Studying in residence comune
studying_home_prov_rate	Studying in residence province
studying_home_region_rate	Studying in residence region
Panel D: University and Program Changes	
changed_uni_rate	Changed to a different university

This table provides definitions and measurement units for all variables used in the analysis. Student data come from the Italian National Student Registry (ANS: Anagrafe Nazionale Studenti), covering all Italian university students from 2010–2020. Population data come from ISTAT. Rates are expressed per 10,000 working-age residents (18–64 years). STEM fields include science, technology, engineering, and mathematics as defined by the Italian Ministry of Education. Bachelor programs (*laurea triennale*) last three years; master programs (*laurea magistrale*) last two years.

Table 4: Variable Definitions and Measurement (II)

Variable	Definition
Panel E: Degree Type and Field of Study	
`bachelor_rate`	Enrolment in bachelor programs
`master_rate`	Enrolment in master programs
`stem_rate`	Enrolment in STEM fields
`engineering_rate`	Enrolment in engineering programs
`computer_science`	Enrolment in computer science
`natural_sciences`	Enrolment in natural sciences
Panel F: Degree Completion and Time to Degree	
`degree_completed_rate`	Degree completions in a given year
`bachelor_on_time`	Bachelor completed within 3 years
`bachelor_delayed`	Bachelor completed after 3 years
`master_on_time`	Master completed within 2 years
`master_delayed`	Master completed after 2 years
`ba_to_ma_rate`	Enrolment in master within 1 year of bachelor
`years_to_degree`	Years from first enrolment to degree
`years_to_bachelor`	Years to complete bachelor
`years_to_master`	Years to complete master
`years_bachelor_to_master`	Years between bachelor and master
Panel G: Student Characteristics and Performance	
`age_imma`	Age at first enrolment
`diff_year`	Years between high school and university
`voto_laurea`	Graduation grade (out of 110)
`cfu_sostenuti_anno`	Credits earned per year
`female`	Female students
`male`	Male students
`n_students`	Total students
Panel H: Treatment Variables	
`ever_treated`	Municipality ever exposed to mass layoff
`treat_year`	Year of first mass layoff
`treated`	Post-treatment indicator
`masslayoff`	Treatment-year indicator
`event_time`	Years relative to treatment
`total_layoffs`	Jobs lost in first layoff event
`n_layoff_events`	Number of layoff events
Panel I: Demographics	
`pop_total`	Population aged 18–64
`pop_female`	Female population aged 18–64
`pop_male`	Male population aged 18–64

This table provides definitions and measurement units for all variables used in the analysis. Student data come from the Italian National Student Registry (ANS: Anagrafe Nazionale Studenti), covering all Italian university students from 2010–2020. Population data come from ISTAT.

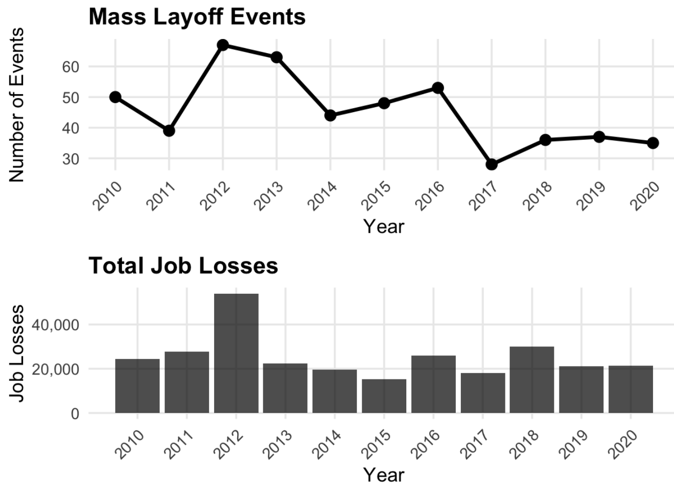
7.2 Descriptive statistics

Table 5: Summary Statistics: Treated vs Control Municipalities

	Treated				Control			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max
Panel A: Student Outcomes (counts)								
Total students	5,878	22,643	0.0000	439,905	469.66	1,063	0.0000	27,613
Panel B: Student Outcomes (rates per capita)								
enrolment rate	235.74	106.34	0.0000	702.02	212.81	120.39	0.0000	1,582
Dropout rate	19.65	15.46	0.0000	125.00	17.48	20.50	0.0000	476.19
Permanent dropout	17.13	14.18	0.0000	120.48	15.27	18.99	0.0000	344.83
Online education	8.51	11.00	0.0000	104.19	7.79	15.28	0.0000	555.56
STEM rate	71.38	44.35	0.0000	255.94	60.92	49.63	0.0000	595.24
Engineering rate	31.01	18.71	0.00	115.91	26.95	25.27	0.00	454.55
Changed university	8.60	7.52	0.00	125.00	7.35	11.00	0.00	270.27
Study away (region)	65.47	70.20	0.0000	533.45	73.98	83.30	0.0000	962.34
Online bachelor	7.11	8.70	0.00	68.61	6.37	12.61	0.00	454.55
Study away (province)	154.38	117.81	0.00	589.17	161.60	124.75	0.00	1392.41
Switched education mode	3.88	4.90	0.00	52.75	3.64	8.49	0.00	555.56
Degree completed	56.20	35.03	0.00	176.07	49.40	41.00	0.00	625.00
Panel C: Student Performance								
Age at enrolment	19.97	0.6332	18.00	30.00	19.91	1.30	18.00	63.00
Graduation grade	102.14	2.86	77.00	111.00	102.12	4.22	72.00	111.00
Years to degree	2.42	1.29	0.0000	7.00	2.58	1.38	0.0000	10.00
Years to bachelor	1.96	0.9610	0.0000	7.00	2.10	1.09	0.0000	10.00
Credits per year	46.93	6.91	18.75	163.11	47.09	21.59	0.0000	2,063
Degree completed	56.20	35.03	0.00	176.07	49.40	41.00	0.00	625.00
Years to master	3.60	1.98	0.00	8.00	4.16	1.80	0.00	10.00
Panel D: Demographics								
Population (18-64)	37,128	121,171	79	1,764,085	3,374	6,170	0.0000	120,158
Female population	18,914	62,309	32	907,671	1,686	3,124	0.0000	60,590
Male population	18,214	58,870	44	856,414	1,688	3,047	0.0000	59,694

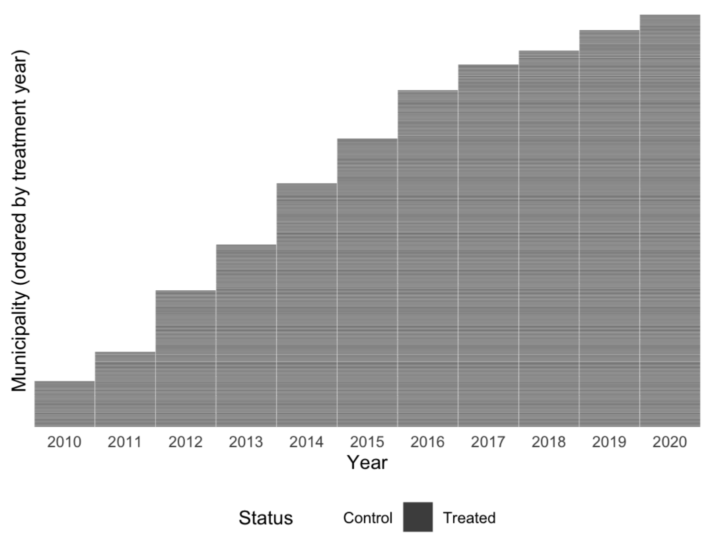
Notes: Summary statistics for all municipality-year observations, 2010-2020. Treated municipalities experienced at least one mass layoff during this period (N=323). Control municipalities never experienced a mass layoff (N=7,591). Rates per 10000 inhabitants of working-age population (18-64 years). Student data from Italian National Student Registry (ANS).

Figure 2: Mass layoffs and job loss



Notes: This figure displays the number of mass layoff events and the number of job losses across treated municipalities from 2010 to 2020 according to ERM dataset.

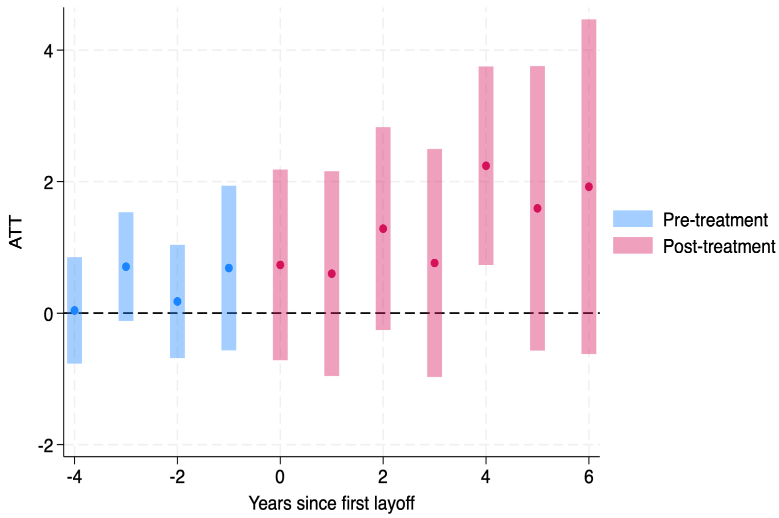
Figure 1: Treatment Pattern of Mass Layoffs Across Municipalities, 2010-2020



*Notes:*This figure displays the temporal distribution of mass layoff events across treated municipalities. Each horizontal line represents a municipality, ordered by the year of treatment (earliest at bottom, latest at top). White cells indicate pre-treatment periods, while dark grey cells indicate post-treatment periods. The staggered nature of treatment adoption is evident, with municipalities experiencing mass layoffs across all years from 2010 to 2020.

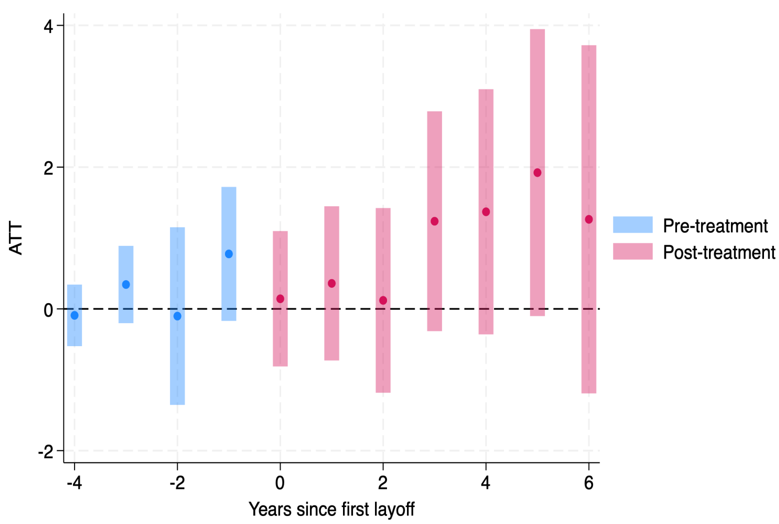
7.3 Event studies

Figure 3: Effects of mass layoffs on the dropout rate



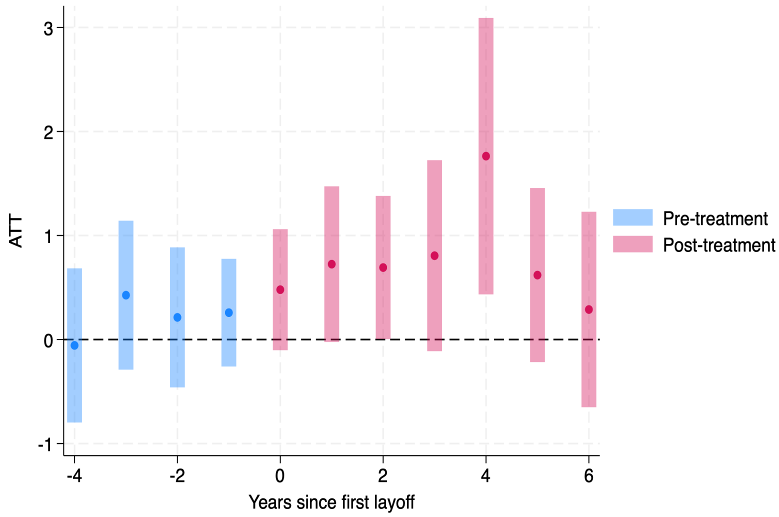
Notes: This figure plots the event-study coefficients and 95% confidence intervals, showing the dropout rate relative to the cohort first exposed to the mass layoff in each municipality. Estimates are obtained using the Callaway and Sant'Anna (2021) estimator.

Figure 4: Effects of mass layoffs on the permanent dropout rate



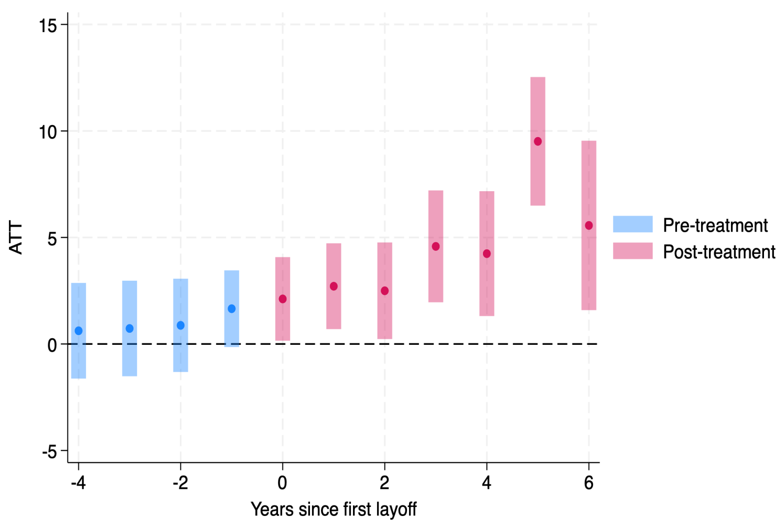
Notes: This figure plots the event-study coefficients and 95% confidence intervals, showing the permanent dropout rate relative to the cohort first exposed to the mass layoff in each municipality. Estimates are obtained using the Callaway and Sant'Anna (2021) estimator.

Figure 5: Effects of mass layoffs on the rate of students that changed to a different university



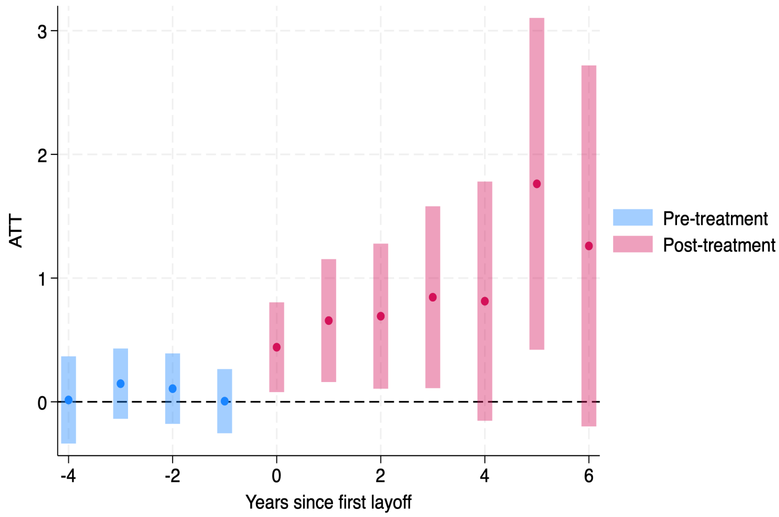
Notes: This figure plots the event-study coefficients and 95% confidence intervals, showing the rate of students that changed to a different university relative to the cohort first exposed to the mass layoff in each municipality. Estimates are obtained using the Callaway and Sant'Anna (2021) estimator.

Figure 6: Effects of mass layoffs on the rate of degree completion



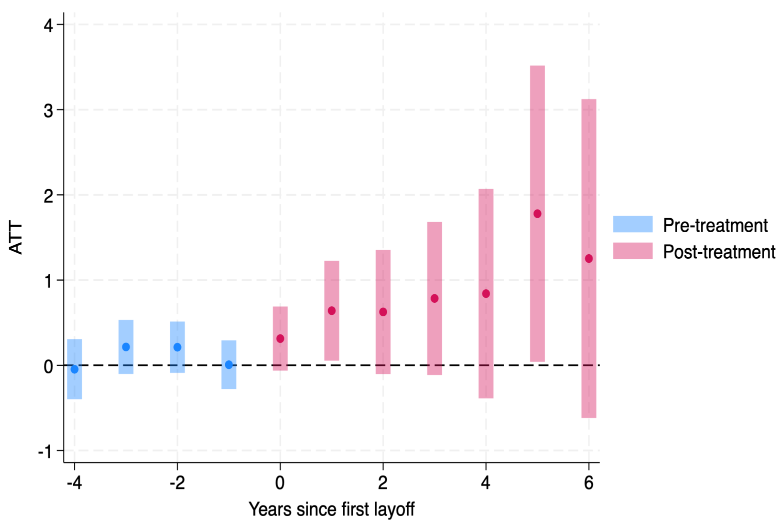
Notes: This figure plots the event-study coefficients and 95% confidence intervals, showing the rate of degree completion relative to the cohort first exposed to the mass layoff in each municipality. Estimates are obtained using the Callaway and Sant'Anna (2021) estimator.

Figure 7: Effects of mass layoffs on the rate of students studying an online bachelor degree



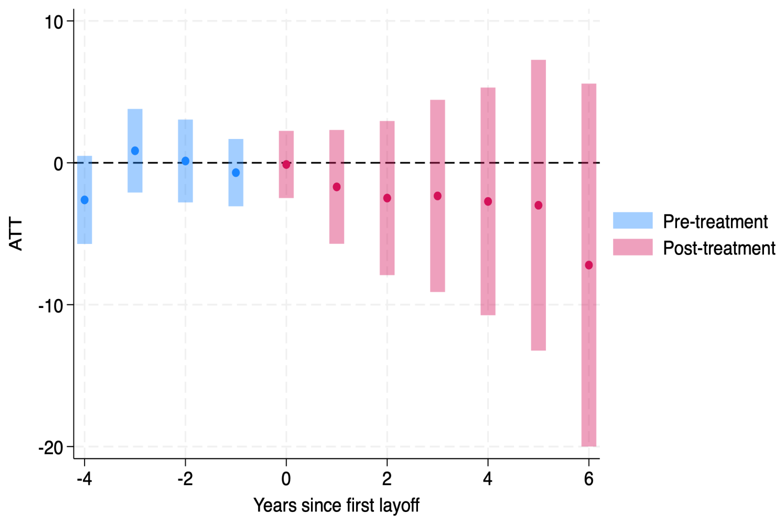
Notes: This figure plots the event-study coefficients and 95% confidence intervals, showing the rate of students studying an online bachelor degree relative to the cohort first exposed to the mass layoff in each municipality. Estimates are obtained using the Callaway and Sant'Anna (2021) estimator.

Figure 8: Effects of mass layoffs on the rate of students in online universities



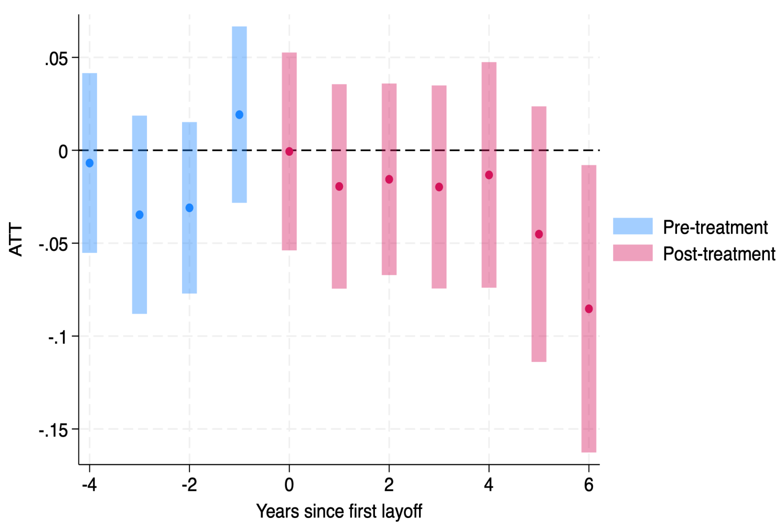
Notes: This figure plots the event-study coefficients and 95% confidence intervals, showing the rate of students in online universities relative to the cohort first exposed to the mass layoff in each municipality. Estimates are obtained using the Callaway and Sant'Anna (2021) estimator.

Figure 9: Effects of mass layoffs on the rate of students studying in another province



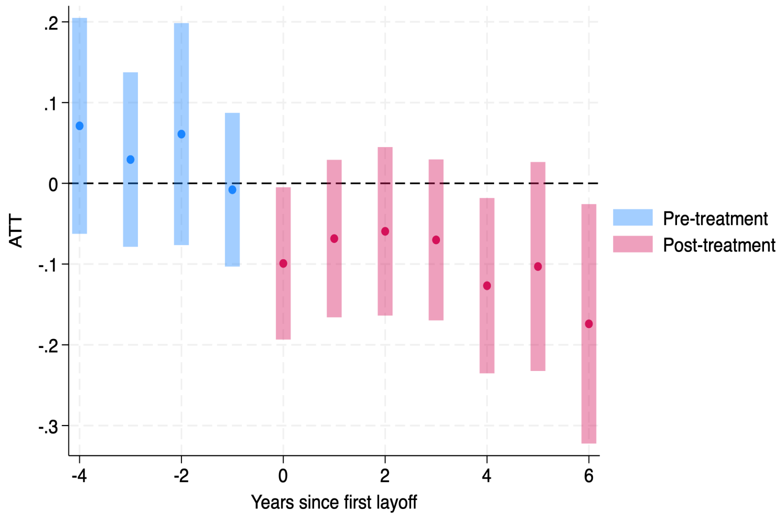
Notes: This figure plots the event-study coefficients and 95% confidence intervals, showing the rate of students studying in another province relative to the cohort first exposed to the mass layoff in each municipality. Estimates are obtained using the Callaway and Sant'Anna (2021) estimator.

Figure 10: Effects of mass layoffs on the years to complete a bachelor degree



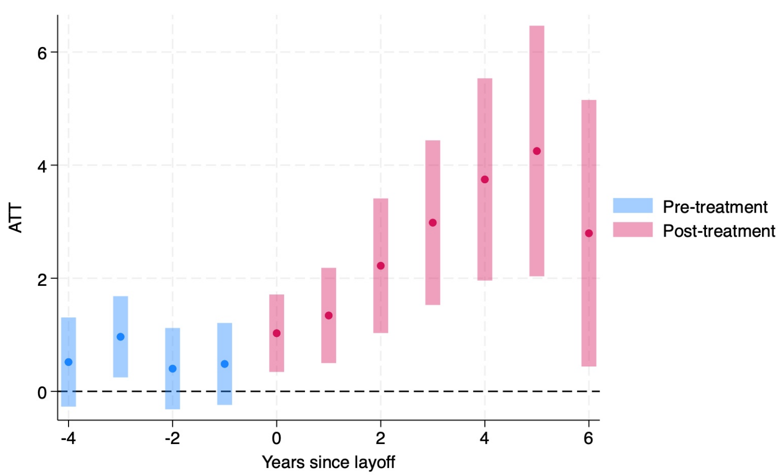
Notes: This figure plots the event-study coefficients and 95% confidence intervals, showing the on the years to complete a bachelor degree relative to the cohort first exposed to the mass layoff in each municipality. Estimates are obtained using the Callaway and Sant'Anna (2021) estimator.

Figure 11: Effects of mass layoffs on the years to complete a master's degree



Notes: This figure plots the event-study coefficients and 95% confidence intervals, showing the years to complete a master's degree relative to the cohort first exposed to the mass layoff in each municipality. Estimates are obtained using the Callaway and Sant'Anna (2021) estimator.

Figure 12: Effects of mass layoffs on the rate of enrolment in engineering programs



Notes: This figure plots the event-study coefficients and 95% confidence intervals, showing the Enrolment in engineering programs relative to the cohort first exposed to the mass layoff in each municipality. Estimates are obtained using the Callaway and Sant'Anna (2021) estimator.