SAPIENZA
UNIVERSITÀ DI ROMA

ISSN 2385-2755
DiSSE Working papers
[online]

WORKING PAPERS SERIES
DIPARTIMENTO DI SCIENZE SOCIALI ED ECONOMICHE

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N. 06/2022

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CF80209930587 – P.IVA 02133771002

The long-term effects of mass layoffs: do local economies (ever) recover?

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Abstract: This paper investigates the long-term reaction of local labor markets (LLMs) to a mass layoff in a manufacturing plant. We adopt a non-parametric generalization of the difference-in-differences estimator expressly developed for time-series cross-sectional data and a new comprehensive dataset to gauge the long-run sectoral effects of this negative employment shock in Italy. We find that, on average, a mass layoff abruptly decreases industry employment by 22% and that this negative impact is persistent even eight years later. The shock has a negative and statistically significant effect only on the same industry of the affected LLM, while the rest of the local economy is, at most, mildly affected. These findings do not depend on the initial level of development and call for the policymakers' intervention to design efficient employment policies aimed at reducing the social costs of a mass layoff at least for less dynamic economies.

JEL Codes: H53; J60; C14

Keywords: mass layoff; local labor market; spillover effects; causal inference

1. Introduction

"If Whirlpool closes down, Naples turns off." With this slogan, the mayor of Naples Luigi De Magistris organized several initiatives to convince the American multinational manufacturer not to leave Naples. However, despite this desperate attempt, Whirlpool's plant in Naples closed down on October 31, 2020, and in the following months the collective dismissal procedure for about 350 employees started. This is only one example of how disruptive mass layoffs can be, especially in countries with struggling economies and low labor mobility, such as Italy. This scenario may have serious economic and social consequences for the area concerned, justifying the great attention paid by policymakers to

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contrasting these events. Instruments to support firms and workers in the area are often implemented, and dialogue tables (‘*Tavoli di crisi*’) between representatives of firms, workers, and politicians, at central and local level, are proposed.

But is this attention really needed? If the closure of a plant was just a stage in a process of local optimal resources allocation and firms’ selection, which alternates the death of some companies with the birth or arrival of others, the concerns would be unfounded. If, on the other hand, the effects on the economy of the area persist in the long-run, with the creation of negative externalities, generating further losses of jobs, production and income, the need for public intervention would be more urgent. The limited empirical evidence available is mixed. Jofre-Monseny et al. (2018) find that when a large manufacturing plant closes down, for each job directly lost in the plant closure, only between 0.6 and 0.7 jobs are actually lost in the local affected industry; conversely Gathmann et al. (2020, pag. 428) suggest that a mass layoff in the manufacturing sector might “*not only harm workers in that plant but create a domino effect on the region as a whole, thereby multiplying job losses*”. In addition, the long-term effects of a mass layoff have been basically unexplored, due to the shortage of coherent data over a long time span and challenging identification issues.

We add to this nascent literature by investigating the regional long-term impact of a large manufacturing plant closure/downsizing on the employment of the same industry in which the mass layoff materializes. In addition, we investigate whether the mass layoff had an impact on the rest of the manufacturing sector, on the non-tradable sector and on other relevant outcome variables such as wages and total factor productivity (TFP). Our dataset is based on administrative time-series cross-sectional (TSCS) data on all 610 Italian LLMs covering the period from 2004 to 2019, thus including the Great Recession. In order to have ‘enough’ time periods before and after the mass layoff to investigate the long-term impact, we consider for treatment mass layoffs which occurred between 2008 and 2011 in the main analysis, investigating the effects up to 8 years after the mass layoff. To tackle the complex identification problem of separating the effects of the mass layoff from other factors that may interplay with the affected area or sector, we have adopted the non-parametric generalization of the difference-in-differences (DiD) estimator for TSCS data proposed by Imai et al. (2021). We match each LLM experiencing a mass layoff to LLMs that have a very similar history in terms of industrial, economic, territorial and demographic pre-treatment characteristics. We also investigate the heterogeneity of the effect to check whether the impact depends on the stage of economic development.

Our contribution to the literature is threefold. First, our study contributes to the literature on the effects of mass layoffs on local economies. Differently from the aforementioned studies, our analysis focuses on the long-term effects of a mass layoff on the affected LLM, which are estimated simultaneously and in a coherent way with the short-term ones, on the same sample of treated and untreated LLMs and using the same econometric model. Moreover, unlike previous literature, our estimates refer to a recent period, thus incorporating any structural changes related to the Great Recession. Second, our work presents an overall evaluation of the effects of a mass layoff on different dimensions of analysis. The long-term impact mainly depends on how the LLM reacts with respect to the net balance for employed and unemployed, replacement of production factors, and the ability to attract new businesses. Therefore, our analysis considers the impact of a mass layoff on aspects other than employment, such as TFP, wages, per capita income, and the number of local units in the affected industry. Third, the paper contributes to the analysis of the consequences of a shock in the LLM with respect to the local economic context (Pinch and Mason, 1991; Bailey et al., 2012; Hane-Weijman et al., 2018). The extent of the effects may vary in the presence of strong or weak labor markets, as mobility and absorption capacity can differ. In this case, an average measure of the effects may be of little use with respect to the variability of the labor market. To address this issue, we investigate the potentially heterogeneous impact of a mass layoff by the ex-ante economic development of the affected LLM.

We find that, on average, a mass layoff abruptly decreases industry employment by 22% and that this negative impact is persistent even eight years after the mass layoff. The effect on the other outcome variables is less pronounced and statistically not significant. More specifically, mass layoffs have a negligible impact on the rest of the manufacturing sector and on the non-tradable sector, with a multiplier close to 0. Differently, the TFP grows slightly in the first few years, whereas the number of local units in the affected industry and blue-collar wages decrease. At the same time, per capita income, and white-collar wages are basically not affected. Thus, a shock in the tradable sector has a negative and persistent effect only on the same industry of the LLM, demonstrating how Italian LLMs are not flexible to shocks with low dynamic adjustments. Our conclusion is that, in this kind of economy, the policymakers' intervention seems particularly important in order to design efficient employment policies, especially at a time of economic crisis.

The paper is structured as follows. Section 2 sets out our conceptual framework and presents the previous literature. Section 3 describes the construction of the data set and the empirical methodology. Section 4 provides the empirical estimates, in terms of employment and other variables, the analysis by sector, the evaluation of the heterogeneity of the impacts, and several robustness checks. Finally, Section 5 discusses the implications of our results and draws some policy suggestions.

2 Conceptual framework and previous literature

A central issue in recent crises is the link between layoffs and re-employment and the extent to which regions can absorb the redundant workforce (Hansen et al., 2021). However, there is no consensus among economists and policymakers on the direction or the extent of the impact.

From a theoretical point of view, when a labor market is characterized by perfect mobility across and between regions of capital and labor (Barro and Sala-i-Martin, 1995), any shock that moves the labor market from its equilibrium state automatically activates compensating adjustments that bring it back to equilibrium. A redundant workforce will be reabsorbed and spatial disparities will be reduced as the economy moves towards an optimal spatial equilibrium in the long-run (Martin and Sunley, 1998).

Nevertheless, neo-classical assumptions are hard to make in practice, even at the local level. Factor mobility is less than perfect (Armstrong and Taylor, 2000), wages may not be fully flexible, and access to and availability of capital is markedly uneven geographically (Mason and Harrison, 1999). Moreover, although relatively underdeveloped regions could offer low-wage labor, this is likely to be offset by agglomeration economies which encourage capital and labor flows from lagging to developed regions (Martin and Sunley, 1998). A negative shock, then, may trigger a divergence process in the regions affected, causing a hysteretic downward shift in a regional economy's growth path. As shown in Martin (2012), this could happen when a negative shock destroys a significant proportion of a region's productive capacity and jobs. In this case, even if output and employment growth resume after the shock, there would be a permanent loss in productivity compared with the pre-shock position. Thus, closures involve a wide variety of factors and processes across a range of levels that ''interact in complex ways depending upon the specific situation'', with a heterogeneous long-term impact on local economy (Walker 1992, pag. 56). Given the lack of theoretical consensus on the long-term consequences of a mass layoff on an LLM, the identification of such effects appears to be basically an empirical question.

The previous empirical literature has confirmed that the local effects of a mass layoff are clearly heterogeneous, depending on many factors, which contribute to the formation of sizable production externalities and spillovers (Greenstone et al., 2010): input-output linkages, labor market interactions and the quality of job matches, agglomeration and knowledge spillovers, and consumption demand (Bisztray, 2016; Gathmann et al., 2020). The effects of local economic shocks are also heterogeneous across regions: they might depend on the labor market composition (Pinch and Mason, 1991), the urban-rural divide (Grimes and Young, 2011), and the thickness of the LLMs (Neffke et al., 2018). Overall, the empirical literature provides evidence that negative economic shocks weigh more heavily on peripheral and rural areas and on mono-industrial regions with a lower range of institutions (Amin and Thrift, 1995), suggesting that the effect of job displacement also depends on the local economy's industrial mix.

Despite these difficulties in isolating the effects, the reaction of the LLM to a mass layoff, in the short- and long-run, is a key element to understanding its consequences, which may occur directly, such as the loss of jobs and the decline of the affected industrial sector, or indirectly, such as the reorganization of production chain relationships, the erosion of shared knowledge or the decline in consumer demand. However, only a few studies evaluate the effects of mass layoffs on local economies[1] and they almost exclusively concern the short-term impact of plant closures/downsizing.[2] Jofre-Monseny et al. (2018) estimate

[1] Here we are referring to the overall analysis of the effects, and not that relating to specific cases of plant closures, for which the literature is much broader.

[2] The only exception is Gathmann et al. (2020), who carry out a brief analysis of the long-term effects of mass layoffs which mostly occurred after the fall of the Berlin Wall. They find that the negative employment effects are amplified over time.

the net industry employment effects of large manufacturing plant closures in Spain before the onset of the Great Recession. They find that when a large plant closes down due to relocation abroad, for each job directly lost in the plant closure, only between 0.6 and 0.7 jobs are actually lost in the local affected industry. Gathmann et al. (2020) use administrative data on firms and workers in Germany from 1975 to 2008 to quantify the spillover effects of mass layoffs. They find sizable and persistent negative spillover effects in terms of employment on the regional economy. However, their estimates suggest a relatively small negative impact for the workers affected. Holm et al. (2017) analyze what happens to redundant skills and workers when large companies close down and whether their skills are destroyed or reallocated. They find that getting a job in a skill-related industry or moving to a spinoff firm leads to skill reallocation. Thus, the result depends on regional idiosyncrasies such as industry structure and urbanization. Bisztray (2016) estimates the impact of foreign-owned large plant closures on local firms in Hungary. She finds that when a large, foreign-owned plant closes down, the firms located nearby are negatively affected by such an event. These studies can be considered part of a broader literature that evaluates the (positive or negative) local multiplier effect of manufacturing employment. Moretti (2010) finds that each additional job in manufacturing in a given American city creates 1.6 jobs in the tertiary sector in the same city[3], with a multiplier that varies across industries. Similar local multiplier estimates are found by Moretti and Thulin (2013) for Sweden, Faggio and Overman (2014) for the United Kingdom, Van Dijk (2017) for the US and Cerqua and Pellegrini (2020) for Italy.

Lastly, we consider the studies concerned with the long-term effects of sizable layoffs on wages or the participation rate even if they are not directly focused on the impact of mass layoffs on local economies. Displaced workers might experience earnings losses beyond a period of unemployment following their job losses for several reasons: i) workers possessing skills that were especially suited to their old positions are likely to be less productive, at least initially, in their subsequent jobs; ii) workers losing jobs that paid wage premiums are likely to earn less if their subsequent jobs pay standard wages; iii) displaced workers' long-term earnings will be lower if, in their previous jobs, they had accepted wages below their

[3] These effects are even larger for skilled jobs, generating 2.5 jobs in the tertiary sector every additional skilled job in the tradable sector.

level of productivity in return for higher earnings later in their careers (Jacobson et al., 1993). Von Wachter et al. (2009) studied the long-term cost of job displacements due to layoffs or plant closures using large administrative earnings data sets from several US states, estimating that displacements during the early 1980s led to large and persistent earnings losses that last over 20 years. They find large immediate losses in annual earnings of 30%. After 15 to 20 years, these losses are still about 20%. Jacobson et al. (1993) find that high-tenure workers incur large losses when they separate from distressed firms and there are larger losses among workers displaced from very large firms, when the workers are displaced in regions that have depressed rates of employment growth, whereas for manufacturing workers' earnings losses depend crucially on whether they obtain new jobs in the manufacturing sector. The results from Kodrzycki (2007) go in the same direction and find that, one decade later, permanently displaced workers were still earning between 11 and 17 percent less per year than recalled workers with comparable pre-layoff skills and experience. Foote et al. (2019), who examine the relationship between mass layoffs and the long-run size of the local labor force, show how out-migration accounts for more than half of the labor force reduction over the past two decades. They also find that labor force non-participation increased during the Great Recession accounting for most of the local labor force exits following a mass layoff and after 2007 it replaced out-migration as the predominant channel of labor force adjustment.

3. Data and methodology

3.1 Data

Our unit of analysis is the LLM. LLMs are sub-regional geographical areas where the bulk of the labor force lives and works, and where establishments can find the largest amount of the labor force necessary to occupy the jobs offered. LLMs are defined on a functional basis, the key criterion being the proportion of commuters who cross the LLM boundary on their way to work.[4] Italy counts 610 LLMs.

[4] The criteria used to determine Italian LLMs are similar to those used to define Metropolitan Statistical Areas in the US or Travel to Work Areas in the UK.

In this study, we define a mass layoff as a sudden reduction in size of a manufacturing plant by at least 100 employees in year *t*, accompanied by a reduction of at least 100 employees in the affected sector, guaranteeing with this second criterion that we are selecting a proper negative shock to the local economy. We have considered 6 different sources of data to select treated observations: i) the ASIA[5] dataset on local units; ii) the ASIA dataset on firms; iii) balance-sheet data from AIDA; iv) '*Tavoli di crisi*' official documents[6]; v) datasets on the payroll of subsidies; vi) national and local newspapers. Following the criteria above, for the main analysis we have selected the 24 treated LLMs (see Table 1) that experienced a mass layoff between 2008 and 2011.[7]

INSERT TABLE 1

We have data at the LLM-level on the number of employees for each manufacturing sector (2-digit NACE classification), the tertiary sector, and other economic and demographic variables from 2004 to 2019. The main dependent variable is the number of employees. In particular, for the main analysis we look at the change that occurred in the number of employees in the industry affected by the shock, using 2007 as base year. Then, we also check what happens to the number of employees in the rest of the manufacturing sector, to verify whether the other industries not directly affected by the shock also record some

[5] The Statistical Register of Active Enterprises (ASIA) archive is produced by the Italian National Institute of Statistics (ISTAT) and covers the universe of firms and employees of industry and services in each LLM. This is possible by integrating information coming from both administrative sources, managed by public agencies or private companies, and statistical sources owned by ISTAT.

[6] In Italy, when a large plant has to face a financial and/or a patrimonial crisis, the Ministry of Economic Development (MISE) intervenes in the management of the negative productive and employment effects with the support of the Ministry of Labor, trade unions and local institutions. The action of the MISE and other public bodies is oriented towards safeguarding the productive assets of all companies and is focused on encouraging the continuation of activities and adopting all necessary measures to safeguard employment levels and protect workers. The MISE manages the dialogue tables ('*Tavoli di crisi*') until the transfer of the productive activity, or the achievement of an agreement that does not require any monitoring (e.g., the reorganization or stabilization of the activities, or the cessation of the activities). If the dialogue tables result in a reduction of business activity, in a transformation of the activity or in the cessation of the activity itself, the company can proceed with mass layoffs. The collective dismissal procedure must be initiated in collaboration with a trade union, which will attempt to avoid dismissal by means of another agreement or other alternative solutions to collective dismissal.

[7] We will consider as treated 56 LLMs in a subsequent analysis in which we consider as treated LLMs experiencing a mass layoff over a longer time-period (from 2008 to 2015).

changes in the output variable. We also run the analysis using as dependent variable the number of employees in the tertiary sector, the per capita income, the number of local units in the affected industry, the weekly earnings of native white-collar workers and blue-collar workers and the TFP.[8] These variables will all be used as control variables in our empirical analyses together with population and employment and unemployment rates. Table 2 presents summary statistics for all these variables. Lastly, we refine the sample used for the empirical analysis by excluding cases with large drops or large increases in the affected industry in the year before the treatment, cases in which the mass layoff is reabsorbed in the year after the negative shock and the four largest LLMs (Turin, Rome, Naples and Milan). Indeed, these LLMs are too vast to allow detection of any impact of a mass layoff. In addition, taking into account our definition of mass layoffs, we have dropped the LLM-industry observations for which the number of employees in 2007 was less than 100.

INSERT TABLE 2

3.2 Methodology

The key econometric challenge in analyzing the effects of a mass layoff is that LLMs experiencing such a shock may systematically differ from unaffected LLMs.

To identify proper counterfactuals for the affected LLM, we use a recent evaluation technique proposed by Imai et al. (2021), which consists of a non-parametric generalization of the DiD estimator expressly developed for TSCS data. In the proposed approach, we first select for each treated LLM a set of control LLMs that did not experience a mass layoff and belong to the same geographical area (North, Centre, or South Italy). We, then, refine this matched set, $M_{i,t}$, by using the Mahalanobis distance matching, which assigns a positive weight to the 5 control units within $M_{i,t}$ more similar to the treated unit in terms of pre-treatment trends of the outcome and control covariates. In particular, we use as pre-treatment covariates the lagged values of the number of employees in the industry, the

[8] Weekly earnings of native white-collar workers and blue-collar workers have been made available from the Italian social security administration (INPS) archive, which covers the universe of Italian employer-employee matches in the private sector, while TFP data come from the work of Locatelli et al. (2019) and Albanese et al. (2020).

number of employees in the manufacturing sector without the industry affected, the total number of employees, the per capita income, the employment rate, the unemployment rate, the population level, the share of graduates, TFP and the average size of manufacturing firms. Then, for each treated LLM, we estimate the counterfactual outcome using the weighted average of the control units in the refined matched set. Finally, we compute the DiD estimate of the ATT for each treated observation and then average it across all treated observations, adjusting for possible time trends.

An important step in this procedure is the choice of a non-negative integer F as the number of leads, which represents the outcome of interest measured at F time periods after the administration of treatment, where F=0 represents the contemporaneous effect. We selected F=8 implying the treatment effect on the outcome 8 years after the treatment is administered. We select another non-negative integer L as the number of lags to adjust for. The choice must take into account the bias-variance trade-off: while a greater value improves the credibility of the unconfoundedness assumption, it also reduces the efficiency of the resulting estimates by reducing the number of potential matches. We chose L=4.

Because the choice of L is arbitrary, we test the sensitivity of the empirical results to this choice in Section 4.1.2.

We define the average treatment effects among treated (ATT) as:

$$\delta(F,L) = E\left\{Y_{(i,t+F)}\left(X_{i,t}=1, X_{(i,t-1)}=0, \left(X_{(i,t-l)}\right)_{(l=2)}^{L}\right) - Y_{(i,t+F)}\left(X_{i,t}=0, X_{(i,t-1)}=0, \left(X_{(i,t-l)}\right)_{(l=2)}^{L}\right) \middle| X_{i,t}=1, X_{i,t-1}=0\right\}$$

Where the treated LLMs are those which experienced the mass layoff, i.e., $X_{(i,t-1)} = 0$ and $X_{it} = 1$. In this definition $Y_{(i,t+F)}\left(X_{i,t} = 1, X_{(i,t-1)} = 0, \left(X_{(i,t-l)}\right)_{(l=2)}^{L}\right)$ is the potential outcome under a treatment change, whereas $Y_{(i,t+F)}\left(X_{it} = 0, X_{(i,t-1)} = 0, \left(X_{(i,t-l)}\right)_{(l=2)}^{L}\right)$ represents the potential outcome without the shock, i.e. $X_{(i,t-1)} = 0$ and $X_{i,t} = 0$. In both cases, the rest of the treatment history, i.e., $\left(X_{(i,t-l)}\right)_{(l=2)}^{L} = \{X_{i,t}, \dots, X_{i,t-L}\}$, is set to the realized history. In our case, δ(8, 4) represents the average causal effect of a plant closure/downsizing on the outcome, eight years after the treatment, while assuming that the potential outcome depends on the treatment history up to four years earlier.

We then compute the DiD estimate of the ATT for each treated observation and then average it across all treated observations. Formally:

$$\hat{\delta}(F,L) = \frac{1}{\sum_{i=1}^{N}\sum_{t=L+1}^{T-F} D_{it}} \sum_{i=1}^{N}\sum_{t=L+1}^{T-F} D_{it}\left\{\left(Y_{i,t+F} - Y_{i,t-1}\right) - \sum_{i' \in M_{it}} \omega_{it}^{i'}\left(Y_{i',t+F} - Y_{i',t-1}\right)\right\}$$

The non-parametric generalization of the DiD estimator is based on three assumptions.

Assumption 1. Absence of the carryover effect.

This implies that the potential outcome for unit i at time $t + F$ does not depend on the previous treatment status of the same unit after L time periods, i.e., $\left(X_{i,t-l}\right)_{l=L+1}^{T-1}$. This implies that we allow for the possibility that past treatments affect future outcomes up to L years.

Assumption 2. Absence of an interference effect.

The potential outcome for unit i at time $t + F$ does not depend on the treatment status of other units, for example, $X_{i't'}$ with $i \neq i'$ and for any t'.

Assumption 3. Parallel trend assumption after conditioning on the treatment, outcome, and covariate histories.

$$E\left[Y_{i,t+F}\left(X_{it} = 0, X_{i,t-1} = 0, \left(X_{i,t-l}\right)_{l=2}^{L}\right) - Y_{i,t-1} \middle| X_{it} = 1, X_{i,t-1} = 0, \left(X_{i,t-l}, Y_{i,t-l}\right)_{l=2}^{L}, \left(Z_{i,t-l}\right)_{l=0}^{L}\right]$$
$$= E\left[Y_{i,t+F}\left(X_{it} = 0, X_{i,t-1} = 0, \left(X_{i,t-l}\right)_{l=2}^{L}\right) - Y_{i,t-1} \middle| X_{it} = 0, X_{i,t-1} = 0, \left(X_{i,t-l}, Y_{i,t-l}\right)_{l=2}^{L}, \left(Z_{i,t-l}\right)_{l=0}^{L}\right]$$

Where $Z_{i,t}$ is a vector of observed time-varying confounders for unit i at year t. Therefore, the conditioning set includes the treatment history, the lagged outcomes (except the immediate lag $Y_{i,t-1}$), and the covariate history. Choosing a relatively large value of L (in our case L=4) increases the credibility of a limited carryover effect and the parallel trend assumptions, while using data at the LLM level allows meeting the no-interference assumption.

This set of assumptions is arguably milder than those used by the most common methodologies adopted to analyze TSCS data, such as the linear regression models with fixed effects, dynamic panel models, matching methods, and the DiD estimator (Imai et al., 2021). Furthermore, differently from the above-mentioned estimators, the non-parametric generalization of the DiD estimator is ideal for our evaluation study as it also works well in situations with a small number of treated units. Lastly, this approach explicitly tests for pre-treatment differences in all covariates and can be more flexible than the difference-in-differences estimator with multiple time periods proposed by Callaway and Sant'Anna (2021).

4. Empirical analysis

In this section, we estimate the effects of a large manufacturing plant closure/downsizing on local employment. We focus primarily on the employment changes that occurred up to eight years after the negative event in the industry affected by the shock and in the rest of economy and then we analyze the potential heterogeneity of these effects. We then test the sensitivity of our results using different robustness checks.

Before presenting the estimates, it is important to verify whether Assumption 3 is met in order to guarantee the robustness of the empirical analysis. To this end, the non-parametric generalization of the DiD estimator allows examination of the covariate balancing between treated and matched control observations. This enables the investigation of whether the treated and matched control observations are comparable with respect to observed confounders (Imai et al., 2021). The covariate balance plot is reported in Figure 1. The black line represents the balance of the lagged outcome (in absolute values as well as in changes), whereas grey lines show the balance of the other covariates. It clearly emerges that the level of imbalance remains stable across the 4 pre-treatment years and fully within the (-1, 1) range of the standard deviation. It is important to notice that we use the same control variables for all empirical analyses, meaning that the covariate balance plot presented in Figure 1 is the same for all the analyses presented below. In addition, as the level of imbalance for the lagged values of our primary dependent variable, that is, the change that occurred in the number of employees in the industry affected by the shock, stays relatively constant over the entire pre-treatment period, this demonstrates that the parallel trend assumption is satisfied.

INSERT FIGURE 1

4.1 Main estimates

We start by estimating the impact of a manufacturing plant closure/downsizing on the employment level of the affected industry and that of the rest of the local economy up to eight years after the shock. We then check the robustness of these estimates and investigate the impact on aspects other than employment, such as TFP, wages, per capita income, and the number of local units in the affected industry.

4.1.1 Analysis by sector

In this section, we run the analysis for the main outcomes of interest. The key variable is the share of jobs lost, which is defined as the layoff count divided by the number of employees in the sector under analysis in the LLM in 2007. We begin by analyzing what happens to the number of employees in the industry affected by the shock.

Figure 2 (Panel A) shows that the industry affected by the shock suffers severe and persistent negative consequences. With respect to the number of employees in the matched control LLMs, the employment level is about 22% smaller in the year of the mass layoff and almost 30% smaller in the 5th year after the shock. All the estimates are statistically significant at the 1% level. The negative impact is not reabsorbed over time, as it persists even 8 years after the mass layoff.

We also investigate what happens in the other manufacturing industries not directly affected by the mass layoff, using as outcome variable the share of jobs lost in the rest of the manufacturing sector. As shown in Figure 2 (Panel B), mass layoffs do not spillover on the other manufacturing industries. The effect is negligible and not statistically significant over the whole period. This means that the shock affecting one industry does not transmit to the other manufacturing industries of the same LLM but, at the same time, it demonstrates that the loss of workers in one industry is not reabsorbed by other manufacturing industries. We then run a further analysis to explore what happens to the tertiary sector once the shock materializes. As shown in Figure 2 (Panel C), the effect is generally negative but statistically not significant for the entire period under analysis. This means that, in our analysis, a mass layoff in a manufacturing industry has, at most, a mild negative impact on the tertiary sector.

INSERT FIGURE 2

4.1.2 Robustness checks

We test the sensitivity of our results to a broad set of robustness checks and summarize the results of interest in Table 3. First, we check the sensitivity of our estimates to the choice of the number of lags (L). In the main analysis we have set L=4, while in the first two rows of each panel of Table 3 we present the estimates obtained by setting L=3 and L=5. Then, we change the dimension of the matched set, using ten and three neighbors instead of five. We also test the sensitivity of the main analysis using different matching and weighting methods to refine the matched set of control units. In the first case, we use propensity score matching (PSM) (Rosenbaum and Rubin, 1983), while in the second case, we use the inverse propensity score weighting (IPW) method (Hirano et al., 2003). All these estimates are in line with those reported in the main analysis: the shock has a negative and statistically significant impact after 8 years for the industry affected by the shock in all the robustness checks, while in the rest of manufacturing and in the non-tradable sector the effect is in no case statistically significant. In addition, we test the sensitivity of our method by adopting an alternative estimator: the difference-in-differences estimator with multiple time periods and variation in treatment timing developed by Callaway and Sant'Anna (2021) on our data. As for the estimator developed by Imai et al. (2021), the key assumption is that the parallel trend assumption holds after conditioning on observed covariates. Small differences emerge when looking at the point estimates reported in Table 3 but, overall, they resemble our main estimates.

We then run a placebo test in which we used as "fake" treatment cases 13 firms that managed to avoid mass layoffs by striking a deal with the Italian government for new buyers or received public subsidies (see Table A1 in the Appendix). As shown in panel A of Table 3, the effect is statistically non-significant for the entire period after the "fake" treatment when considering the industry affected by the shock. Likewise, negligible effects also emerge when considering the rest of the manufacturing and the tertiary sector. These results allow us to strengthen the robustness of our main estimates: the point estimates of this falsification test are close to zero and show no discernible impact whatsoever. Furthermore, the placebo estimates highlight that government intervention is not only crucial for manufacturing firms on the verge of a mass layoff, but also for the affected industry in the local economy.

One of the main novelties of our research is given by the fact that we run a long-term analysis, using 8 years after the treatment. The cost of this advantage is that we have only 24 treated cases. To check the robustness of our estimates, we run also a short-term analysis using 4 years after the treatment. In this case our treated sample gets larger as it is formed by 56 treated cases (see Table A2 in the Appendix), i.e., large manufacturing firms which experienced a mass layoff between 2008 and 2015. Table A3 in the Appendix reports the short-term estimates, which are highly consistent with what we found for the long-term analysis.

INSERT TABLE 3

4.1.3 Mass layoff impact on other outcome variables

Finally, to have a more comprehensive picture of what happens in an LLM after a mass layoff, we run the analysis using alternative outcome variables: TFP, per capita income, the number of local units in the affected industry, the weekly earnings of native white-collar workers and blue-collar workers.[9] As shown in Table 4, all estimates are not statistically significant at the 5% level, however, it is possible to identify some trends. For example, the TFP seems to grow in the first few years after the shock and then to settle at near zero values. Differently, the number of local units in the affected industry and the earnings of native blue-collar workers slightly decrease in the long-run. The other variables, instead, do not seem to be affected by the shock. These findings lead to several considerations. The first is that a mass layoff is generally not driven by the need to increase productivity or reduce specific inefficiencies but by a decrease in the production capacity in the affected area. This can occur due to a corporate decision to abandon specific markets, even in anticipation of a drop in demand, or to move to areas with lower labor costs. On the other hand, as we do not observe a substantial increase, mass layoffs are likely not linked to technological restructuring. This consideration implies that the occurrence of a mass layoff is not directly linked to the human capital of laid-off workers, which can also be of high quality. However,

[9] Because TFP data ends in 2017, we fix the leads at 6 and 2 periods for the long-term and short-term analysis respectively, in order to have the same number of treated cases with respect to the rest of the analysis. Similarly, as data on wages are available for the period 2007-2018, we fix the lag at 1 and the leads at 7 and 3 periods for the long-term and short-term analysis respectively.

these considerations could justify policies to retain and relocate human capital, often implemented by policymakers.

INSERT TABLE 4

4.2 Impact heterogeneity

The timing and extent of mass layoff reabsorption can also depend on the unemployment rate of the affected LLM. To verify the potential presence of heterogeneity in the effect of a mass layoff in the tradable sector, we repeat the same analysis by splitting LLMs in three groups determined by the tertiles of the unemployment rate in 2007 (with cut-off values of 3.48% and 6.89%). This analysis allows us to analyze whether the effect changes with respect to the initial different economic situation of the treated LLMs. The estimates are reported in Table 5.

Looking at the affected industry, the three subsamples show a similar trend: in all instances, the initial negative impact is not reabsorbed over time. LLMs having a higher unemployment rate, experience a larger initial shock (-31.6%) but they then partially recover this loss (-25.4%) in the 8^{th} year after the mass layoff. Conversely, LLMs characterized by a lower unemployment rate, experience a smaller initial reduction in the workforce which gets worse over time. Overall, the heterogeneity analysis shows that LLMs affected by negative shocks do not recover and do not reabsorb the lost workforce in the affected industry. Differently from what suggested by some economic theories, this result does not depend on the initial level of economic development or the stage of the business cycle.

We also investigate how the effect materializes for the rest of the manufacturing sector. Although the effect is always non-statistically significant at the 5% level, LLMs characterized by low unemployment rate show positive coefficients in absolute terms for the whole period. On the contrary, for the observations in the second and third tertiles, the point estimate is negative, even if statistically non-significant for the entire period.

Finally, we analyze the impact for the services sector. In this case, the effect is negligible for each subsample implying that the effect does not depend on the initial level of unemployment rate.

INSERT TABLE 5

5. Conclusion

The negative shock on a large plant opens a scenario that deserves a comprehensive and accurate analysis: in addition to knowing how many workers leave the company undergoing downsizing or closure, it is crucial to grasp how LLMs react to negative employment shocks.

Shutdowns generate important questions of public policy as well as more theoretically informed analyses as researchers seek to understand how communities respond and look to unpack the implications for the functioning of contemporary labor markets (Beer et al., 2019). To this end, our study contributes to the literature on several fronts. We create a comprehensive database and use a methodology expressly developed for TSCS data to analyze Italian LLMs' economic resilience undergoing a deep economic contraction. Indeed, this is the first study on the local impact of mass layoffs covering the Great Recession. Furthermore, our study is the first devoted to examining the long-term effects of a mass layoff in the local economy.

The results show that a shock in the tradable sector has a negative and persistent effect on the local economy only on the industry experiencing the mass layoff, with a negative but statistically non-significant impact for the rest of the local economy. These estimates demonstrate how Italian LLMs are not flexible to shocks with low dynamic adjustments, and the external multiplier is close to 0. Although we do not find evidence of a domino effect as Gathmann et al. (2020), there are no signs that the local economy alone can overcome the shock in socially acceptable times. For this reason, the actions taken by national or local authorities to reduce these employment shocks appear justified. In less dynamic economies, the intervention of policymakers seems extremely important to design efficient employment policies able to mitigate the long-lasting negative effect on the local economy.

The arrival of the pandemic has likely amplified these negative effects. On the one hand, uncertainty in the markets and reduced consumer demand has resulted in lower investment and decreased labor demand, reducing the likelihood of finding other employment for dismissed workers. On the other hand, pandemic risks and administrative measures have reduced the possibility of mobility and thus of finding new jobs outside the local area. Therefore, the pandemic crisis might determine negative multipliers larger than those we have found in this study. Following these considerations, the economic crisis engendered by COVID-19 (see Cerqua and Letta, 2022) reinforces the calls for specific place-based policies aimed at contrasting the reduction of employment at the time of a severe economic crisis and supporting struggling firms as jobs might be lost forever rather than only temporarily.

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TABLES

Table 1. Treated cases for the long-term analysis

Firm	Sector	Closure/mass layoff	Year	Municipality	LLM	Job losses (local unit)	Job losses (industry)
Coca-Cola + Peroni	11	Closure	2009	Bari	Bari	109 +110	227
Olimpias S.P.A.	13	Closure	2011	Grumolo Delle Abbadesse	Vicenza	110	135
Playtex	14	Closure	2010	Pomezia	Pomezia	159	177
Golden Lady	14	Closure	2011	Gissi	Vasto	386	389
Golden Lady	14	Closure	2011	Faenza	Faenza	346	356
Ferrania	20	Mass layoff	2008	Cairo Montenotte	Cairo Montenotte	112	143
Montefibre	20	Closure	2008	Ottana	Macomer	139	154
Montefibre	20	Closure	2011	Venezia	Venezia	247	299
Pfizer	21	Closure	2009	Latina	Latina	152	126
Manuli rubber	22	Mass layoff	2008	Ascoli Piceno	Ascoli Piceno	129	206
Arcelor Mittal	24	Mass layoff	2010	Piombino	Piombino	205	145
Renopress	24	Closure	2011	Budrio	Bologna	93	119
SAT	25	Almost closure	2009	Aci Sant'Antonio	Catania	137	312
Jabil Circuit	26	Closure	2008	San Marco Evangelista	Caserta	500	434
Imit	26	Mass layoff	2010	Castelletto Sopra Ticino	Borgomanero	160	205
Electrolux	27	Mass layoff	2008	Porcia	Pordenone	502	374
Antonio Merloni	27	Mass layoff	2008	Nocera Umbra	Gualdo Tadino	501	447
Electrolux	27	Mass layoff	2009	Susegana	Conegliano	194	337
Electrolux	27	Closure	2010	Scandicci	Firenze	281	430
Nexans	27	Mass layoff	2011	Latina	Latina	110	98
Acc Compressors	28	Closure	2009	Rovigo	Rovigo	144	176
CNH - gruppo Fiat	28	Closure	2010	Imola	Imola	130	158
Berco	28	Mass layoff	2010	Copparo	Copparo	119	156
Eaton	28	Closure	2011	Massa	Massa	303	631

Notes: Coca-Cola and Peroni closed down in the LLM of Bari in the same year. As they belong to the same industry, namely 'manufacture of beverages', we count these closures as a single treated case.

Table 2. Descriptive statistics

Variable	Mean	Standard deviation	Min	Max
Population	117,615.80	289,091.20	3,138	3,960,537
Number of employees - Manufacturing	7,901.46	18,650.54	124	348,557
Number of local units - Manufacturing	931.42	2,094.37	21	47,497
Number of employees - Services	25,694.71	85,390.44	447	1,490,902
Number of local units - Services	8,482.55	23,701.59	216	406,161
Per capita income (€)	16,980	3,436	8,082	29,107
TFP	4.62	0.72	1.68	11.08
Employment rate (%)	43.45	7.80	23.97	62.29
Unemployment rate (%)	9.86	5.55	1.43	39.08
Blue-collar workers weekly wage (€)	391.28	44.44	256.05	548.13
White-collar workers weekly wage (€)	513.87	58.23	317.62	715.67

Table 3. Robustness checks

	Panel A - Industry								
	Years after treatment								
	t	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8
Main Estimates	**-0.194*** (0.034)**	**-0.177*** (0.035)**	**-0.223*** (0.040)**	**-0.201*** (0.062)**	**-0.214*** (0.055)**	**-0.265*** (0.059)**	**-0.245*** (0.065)**	**-0.224*** (0.072)**	**-0.221*** (0.072)**
L=3	-0.190*** (0.032)	-0.174*** (0.032)	-0.221*** (0.039)	-0.192*** (0.063)	-0.202*** (0.055)	-0.252*** (0.059)	-0.235*** (0.063)	-0.214*** (0.069)	-0.219*** (0.069)
L=5	-0.193*** (0.0416)	-0.169*** (0.038)	-0.215*** (0.051)	-0.208*** (0.058)	-0.171*** (0.065)	-0.217*** (0.063)	-0.205*** (0.063)	-0.188*** (0.067)	-0.195*** (0.068)
Mahalanobis with 10 neighbors	-0.199*** (0.032)	-0.189*** (0.030)	-0.237*** (0.037)	-0.220*** (0.055)	-0.233*** (0.047)	-0.275*** (0.052)	-0.267*** (0.055)	-0.245*** (0.060)	-0.243*** (0.061)
Mahalanobis with 3 neighbors	-0.195*** (0.036)	-0.184*** (0.035)	-0.235*** (0.041)	-0.200*** (0.067)	-0.226*** (0.058)	-0.261*** (0.062)	-0.251*** (0.068)	-0.232*** (0.074)	-0.236*** (0.074)
PSM with 5 neighbors	-0.194*** (0.038)	-0.180*** (0.039)	-0.201*** (0.046)	-0.192*** (0.065)	-0.204*** (0.061)	-0.226*** (0.070)	-0.259*** (0.069)	-0.242*** (0.076)	-0.207*** (0.081)
IPW	-0.181*** (0.033)	-0.179*** (0.035)	-0.214*** (0.041)	-0.201*** (0.060)	-0.223*** (0.052)	-0.247*** (0.061)	-0.263*** (0.063)	-0.230*** (0.069)	-0.221*** (0.071)
Callaway and Sant'Anna estimator	-0.237*** (0.034)	-0.249*** (0.034)	-0.247 (0.032)	-0.217*** (0.038)	-0.222*** (0.037)	-0.208*** (0.041)	-0.234*** (0.044)	-0.212*** (0.058)	-0.197*** (0.086)
Placebo test	-0.055 (0.042)	0.031 (0.061)	0.039 (0.063)	-0.009 (0.093)	-0.033 (0.120)	0.071 (0.131)	0.038 (0.148)	0.130 (0.172)	0.053 (0.130)
	Panel B – Rest of manufacturing								
Main Estimates	**-0.007 (0.016)**	**-0.011 (0.026)**	**-0.021 (0.034)**	**-0.005 (0.036)**	**0.006 (0.043)**	**-0.008 (0.047)**	**-0.009 (0.051)**	**-0.026 (0.051)**	**-0.026 (0.050)**
L=3	-0.005 (0.016)	-0.011 (0.026)	-0.021 (0.033)	-0.004 (0.034)	0.008 (0.042)	-0.005 (0.045)	-0.005 (0.049)	-0.022 (0.050)	-0.023 (0.047)
L=5	0.007 (0.015)	0.005 (0.023)	-0.007 (0.033)	0.002 (0.040)	0.003 (0.045)	-0.001 (0.048)	0.001 (0.047)	-0.012 (0.046)	-0.011 (0.044)
Mahalanobis with 10 neighbors	-0.008 (0.016)	-0.012 (0.026)	-0.021 (0.033)	-0.005 (0.034)	0.003 (0.039)	-0.012 (0.043)	-0.013 (0.047)	-0.030 (0.047)	-0.029 (0.046)
Mahalanobis with 3 neighbors	-0.009 (0.016)	-0.016 (0.026)	-0.023 (0.034)	-0.010 (0.035)	0.005 (0.043)	-0.009 (0.047)	-0.009 (0.051)	-0.027 (0.052)	-0.026 (0.050)
PSM with 5 neighbors	-0.010 (0.016)	-0.012 (0.027)	-0.023 (0.034)	-0.009 (0.035)	-0.002 (0.041)	-0.008 (0.047)	-0.004 (0.052)	-0.016 (0.053)	-0.012 (0.052)
IPW	-0.012 (0.015)	-0.021 (0.025)	-0.029 (0.032)	-0.011 (0.034)	-0.002 (0.040)	-0.013 (0.045)	-0.013 (0.049)	-0.028 (0.050)	-0.020 (0.050)
Callaway and Sant'Anna estimator	-0.004 (0.006)	-0.004 (0.008)	-0.006 (0.010)	0.001 (0.009)	0.005 (0.015)	-0.004 (0.017)	-0.014 (0.023)	-0.051 (0.032)	-0.057 (0.039)
Placebo test	-0.016 (0.014)	-0.004 (0.029)	-0.011 (0.035)	-0.016 (0.046)	-0.028 (0.054)	-0.024 (0.060)	-0.028 (0.062)	-0.022 (0.065)	-0.028 (0.064)

	Panel C - Tertiary								
Main Estimates	**-0.001 (0.007)**	**-0.014* (0.008)**	**-0.017 (0.011)**	**-0.010 (0.015)**	**-0.010 (0.016)**	**-0.005 (0.018)**	**-0.008 (0.019)**	**-0.009 (0.017)**	**-0.003 (0.022)**
L=3	-0.001 (0.007)	-0.013 (0.008)	-0.015 (0.011)	-0.009 (0.016)	-0.009 (0.017)	-0.005 (0.019)	-0.007 (0.020)	-0.009 (0.016)	-0.001 (0.021)
L=5	0.001 (0.009)	-0.005 (0.010)	-0.007 (0.015)	-0.006 (0.019)	-0.004 (0.022)	0.002 (0.023)	0.007 (0.020)	0.000 (0.015)	0.001 (0.023)
Mahalanobis with 10 neighbors	-0.005 (0.007)	-0.018** (0.008)	-0.021** (0.010)	-0.014 (0.015)	-0.010 (0.016)	-0.006 (0.018)	-0.006 (0.020)	-0.006 (0.016)	0.004 (0.020)
Mahalanobis with 3 neighbors	-0.001 (0.008)	-0.012 (0.009)	-0.013 (0.013)	-0.004 (0.018)	-0.003 (0.019)	-0.001 (0.021)	-0.005 (0.021)	-0.006 (0.018)	-0.001 (0.023)
PSM with 5 neighbors	-0.008 (0.007)	-0.015* (0.009)	-0.020** (0.010)	-0.014 (0.014)	-0.014 (0.015)	-0.013 (0.017)	-0.013 (0.018)	-0.011 (0.016)	0.001 (0.021)
IPW	-0.004 (0.006)	-0.013 (0.008)	-0.018* (0.010)	-0.012 (0.014)	-0.011 (0.015)	-0.008 (0.017)	-0.012 (0.018)	-0.009 (0.016)	-0.004 (0.021)
Callaway and Sant'Anna estimator	-0.005* (0.003)	-0.007** (0.003)	-0.012*** (0.004)	-0.007 (0.005)	-0.010* (0.006)	-0.011 (0.007)	-0.013 (0.010)	-0.016 (0.012)	-0.024 (0.017)
Placebo test	-0.008 (0.007)	0.001 (0.012)	-0.001 (0.018)	0.001 (0.021)	-0.007 (0.027)	-0.014 (0.028)	-0.016 (0.027)	-0.012 (0.021)	-0.015 (0.017)

Notes: ***p<0.01, **p<0.05, -p<0.1

Table 4. Mass layoff impact on other outcome variables

	Years after treatment								
	t	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8
TFP	0.031 (0.069)	0.141 (0.090)	0.088 (0.082)	0.079 (0.096)	0.028 (0.089)	0.018 (0.078)	0.041 (0.081)	-	-
Per capita income (€)	-5.80 (72.9)	31.65 (120.5)	2.49 (183.5)	26.01 (255.4)	15.11 (326.3)	-9.08 (406.5)	-47.36 (444.0)	-82.18 (540.2)	-119.72 (601.4)
Number of local units	0.43 (2.25)	-2.55 (2.12)	-2.96 (2.59)	-3.58 (3.86)	-2.87 (4.30)	-4.02 (5.83)	-3.20 (6.59)	-2.84 (6.87)	-2.11 (6.45)
Blue-collar workers wages (€)	-0.63 (2.72)	-0.22 (3.60)	-0.96 (5.70)	-1.13 (7.07)	-2.58 (9.07)	-4.15 (10.85)	-4.82 (11.44)	-3.71 (12.28)	-
White-collar workers wages (€)	0.56 (4.16)	1.89 (5.39)	0.65 (7.63)	-0.54 (9.38)	-0.11 (10.69)	-1.66 (12.13)	-1.75 (12.96)	-2.56 (14.19)	-

Notes: ***p<0.01, **p<0.05, -p<0.1

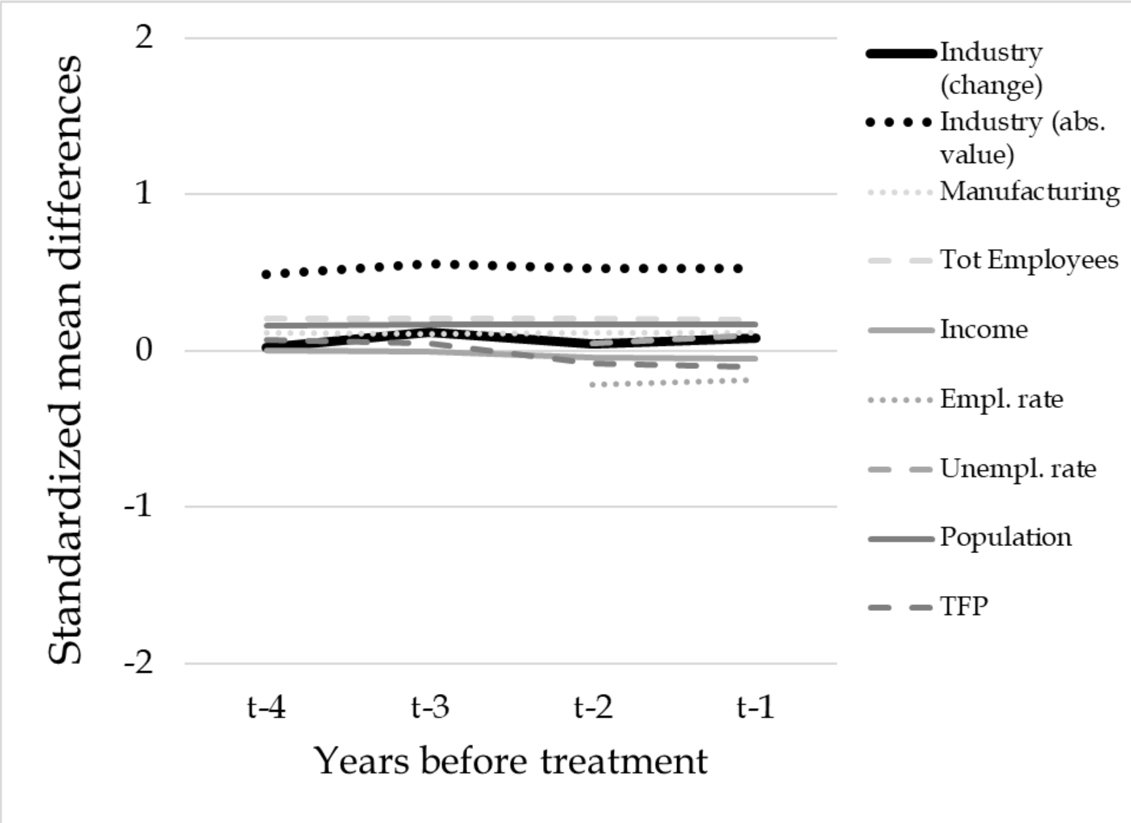
Table 5. Effect heterogeneity by sector

	t+0	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8
Panel A - Industry									
	Years after treatment								
1rst tertile	-0.132***	-0.099	-0.197**	-0.117	-0.176	-0.219*	-0.240*	-0.195	-0.205
	(0.038)	(0.063)	(0.079)	(0.126)	(0.120)	(0.120)	(0.139)	(0.154)	(0.149)
2nd tertile	-0.135**	-0.117**	-0.125*	-0.201*	-0.194*	-0.269**	-0.221*	-0.215	-0.212
	(0.059)	(0.056)	(0.066)	(0.122)	(0.114)	(0.132)	(0.132)	(0.132)	(0.138)
3rd tertile	-0.317***	-0.315***	-0.348***	-0.283*	-0.270*	-0.306**	-0.273	-0.262	-0.245
	(0.075)	(0.071)	(0.091)	(0.148)	(0.151)	(0.150)	(0.176)	(0.187)	(0.185)
Panel B – Rest of manufacturing									
1rst tertile	0.026	0.040	0.044	0.054	0.057	0.039	0.040	0.018	0.023
	(0.026)	(0.049)	(0.062)	(0.073)	(0.085)	(0.087)	(0.087)	(0.081)	(0.074)
2nd tertile	-0.014	-0.026	-0.030	-0.046	-0.022	-0.039	-0.037	-0.059	-0.060
	(0.024)	(0.045)	(0.060)	(0.077)	(0.090)	(0.096)	(0.099)	(0.104)	(0.100)
3rd tertile	-0.034	-0.047	-0.078	-0.024	-0.018	-0.026	-0.030	-0.037	-0.041
	(0.044)	(0.073)	(0.097)	(0.097)	(0.126)	(0.145)	(0.159)	(0.158)	(0.146)
Panel C – Tertiary sector									
1rst tertile	0.010	-0.014	-0.017	-0.010	-0.007	-0.005	-0.015	-0.005	0.029
	(0.016)	(0.015)	(0.019)	(0.028)	(0.031)	(0.033)	(0.033)	(0.024)	(0.038)
2nd tertile	-0.006	-0.009	-0.019	-0.005	-0.019	-0.012	-0.012	-0.028	-0.012
	(0.013)	(0.023)	(0.027)	(0.036)	(0.038)	(0.044)	(0.049)	(0.039)	(0.040)
3rd tertile	-0.008	-0.020	-0.014	-0.016	-0.003	0.001	0.003	0.005	-0.027
	(0.015)	(0.017)	(0.033)	(0.048)	(0.055)	(0.062)	(0.055)	(0.041)	(0.041)

Notes: ***p<0.01, **p<0.05, -p<0.1

FIGURES

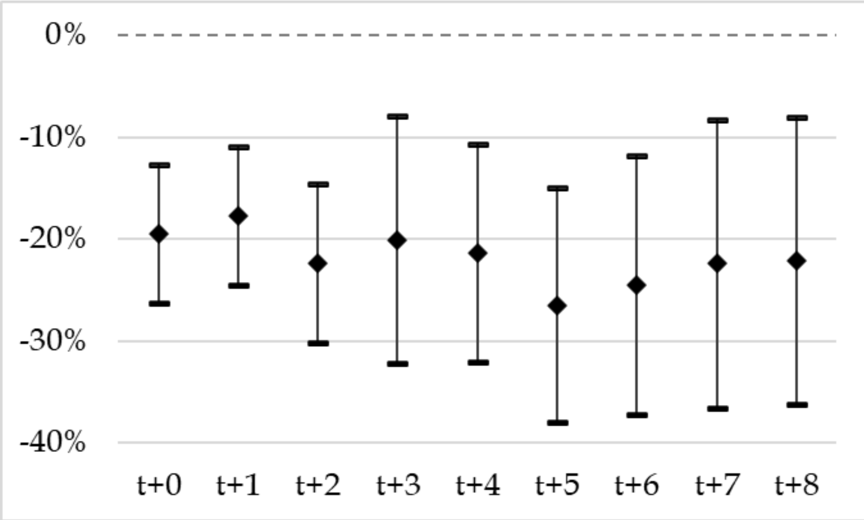
Figure 1. Covariate balancing



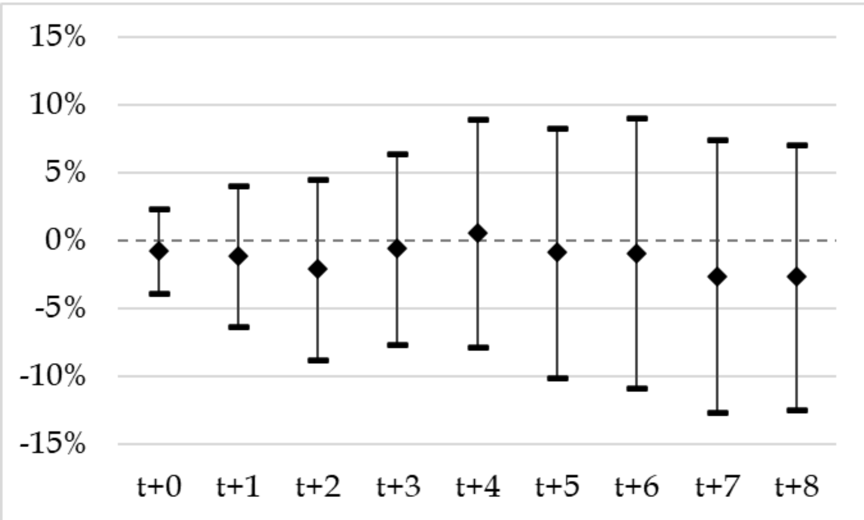
Notes: We also control for the weekly earnings of native white-collar and blue-collar workers. These variables do not show up in the Figure because they are available only from 2007. This means that we can control for only one pre-treatment year. However, the 1-year pre-treatment standardized mean difference in weekly earnings between treated and control LLMs is close to 0.

Figure 2. Long-term analysis by sector

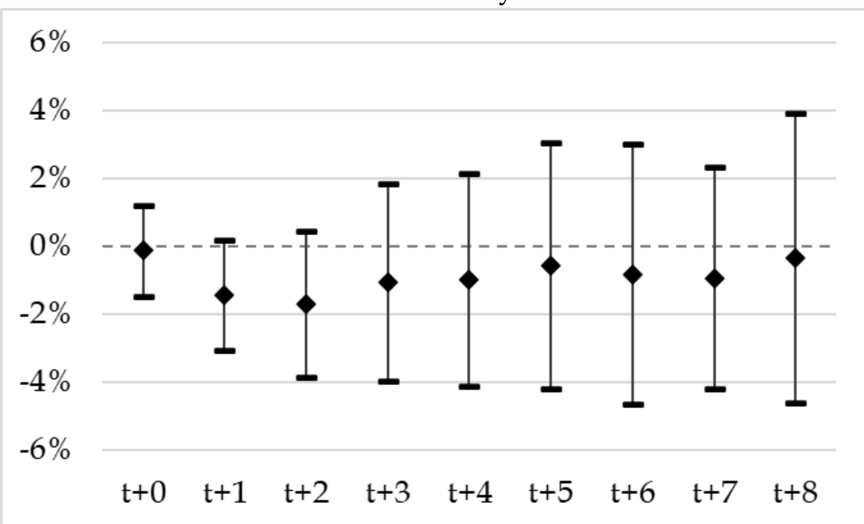
Panel A - Industry



Panel B – Rest of Manufacturing



Panel C – Tertiary sector



Appendix

Table A1. Treated cases for the placebo test

Firm	Sector	Year	Municipality	LLM
Newcocot	13	2010	Perosa Argentina	Pinerolo
Liri	22	2010	Pont Canavese	Rivarolo Canavese
ITT	29	2009	Barge	Saluzzo
Industrie tessili Adler	13	2010	Virle Piemonte	Savigliano
Grimeca	22	2010	Ceregnano	Rovigo
Fincantieri	30	2009	Trieste	Trieste
Sp.el S. Giorgio	24	2010	La Spezia	La Spezia
Tecnogas	28	2009	Gualtieri	Guastalla
AM Clynders	25	2010	Matelica	Matelica
Pleytex	13	2010	Pomezia	Pomezia
Campari	10	2008	Sulmona	Sulmona
ATR	22	2010	Colonnella	Martinsicuro
Fincantieri	30	2010	Castellammare di Stabia	Castellammare di Stabia

Table A2. Additional treated cases for the short-term analysis

Firm	Sector	Closure/mass layoff	Year	Municipality	LLM	Job losses (local unit)	Job losses (industry)
Nestlé	10	Mass layoff	2012	Perugia	Perugia	180	258
Manifattura di valle brembana	13	Closure	2015	Zogno	Zogno	314	315
Sixty	14	Closure	2015	Chieti	Chieti	213	297
Trombini	16	Closure	2015	Codigoro	Comacchio	119	135
Burgo	17	Closure	2014	Mantova	Mantova	171	175
Raffineria ies/mol	19	Closure	2014	Mantova	Mantova	377	375
Sgl carbon	20	Closure	2014	Narni	Terni	111	81
Evotape	22	Closure	2013	Santi cosma e damiano	Formia	123	122
Marangoni tyres	22	Closure	2015	Anagni	Frosinone	373	353
Richard ginori	23	Mass layoff	2013	Sesto fiorentino	Firenze	183	176
Ideal standard	23	Closure	2014	Zoppola	Pordenone	400	835
Ideal standard	23	Mass layoff	2015	Trichiana	Belluno	222	230
Kme	24	Closure	2013	Firenze	Firenze	147	185
Entrematic ditec	25	Closure	2014	Quarto d'altino	Venezia	100	61
Marcegaglia buildtech	25	Closure	2014	Taranto	Taranto	106	437
Ritel s.p.a.	26	Closure	2014	Cittaducale	Rieti	127	107
Whirlpool	27	Mass layoff	2012	Biandronno	Varese	152	508
Askoll p&c	27	Closure	2014	Castell'alfero	Asti	133	155
Whirlpool	27	Mass layoff	2014	Trento	Trento	228	227
Prysmian	27	Closure	2015	Ascoli piceno	Ascoli Piceno	117	117
Fiat	29	Mass layoff	2013	Termini imerese	Termini imerese	653	961
Compagnia italiana rimorchi	29	Closure	2013	Tocco da casauria	Chieti	175	177
Ufi filters	29	Mass layoff	2014	Nogarole rocca	Villafranca di verona	196	195
Compagnia italiana rimorchi	29	Mass layoff	2015	Bussolengo	Verona	143	194
De tomaso	29	Closure	2015	Collesalvetti/livorno	Livorno	146	204
Fincantieri	30	Mass layoff	2012	Sestri levante	Sestri levante	103	100
Keller	30	Closure	2013	Palermo	Palermo	193	314

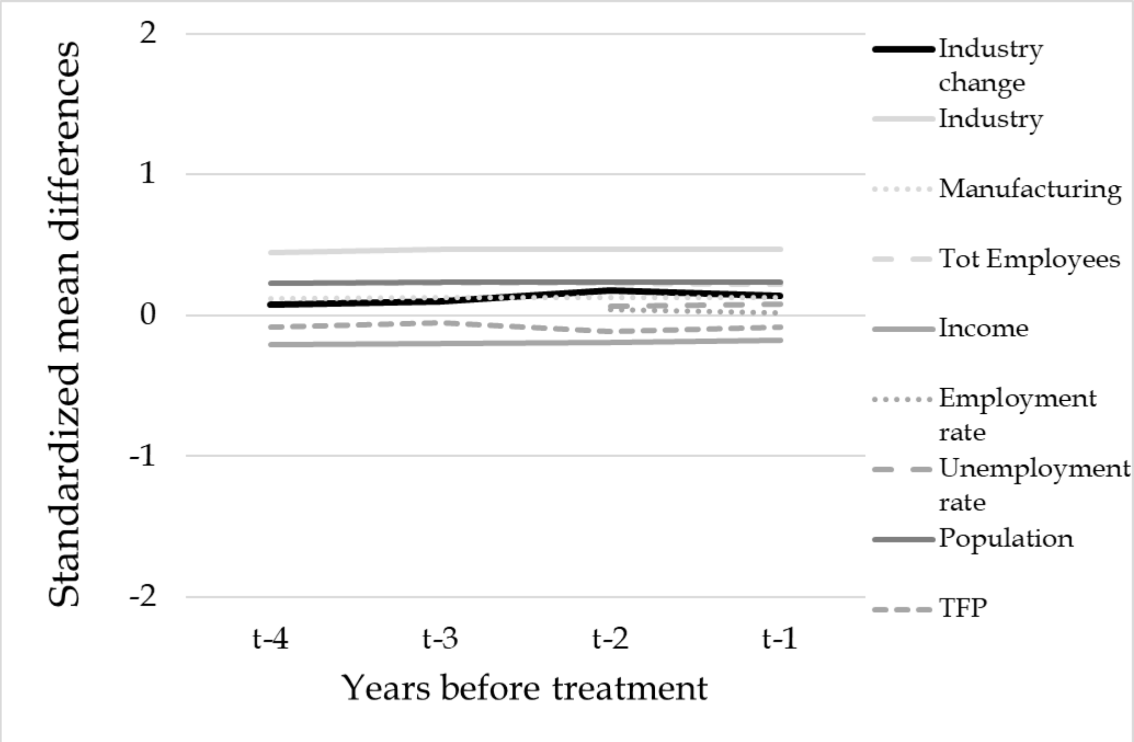
Husqvarna	30	Closure	2014	Biandronno	Varese	147	114
Agustawestland	30	Delocalization	2015	Lonate pozzolo	Busto arsizio	215	153
Keller	30	Closure	2015	Villacidro	Villacidro	473	466
Berloni	31	Mass layoff	2014	Pesaro	Pesaro	114	383
Roland acquaviva	32	Closure	2014	Acquaviva picena	San Benedetto del Tronto	101	109

Table A3. Short-term analysis

	Years after treatment				
	t+0	t+1	t+2	t+3	t+4
Industry	-0,228*** (0,036)	-0,228*** (0,037)	-0,243*** (0,035)	-0,235*** (0,042)	-0,236*** (0,044)
Rest of manufacturing	-0,001 (0,007)	-0,003 (0,012)	-0,006 (0,016)	0,005 (0,016)	0,010 (0,020)
Tertiary	-0,002 (0,003)	-0,005 (0,005)	-0,010 (0,006)	-0,007 (0,008)	-0,004 (0,013)
TFP	-0,003 (0,058)	0,075 (0,068)	0,057 (0,059)	0,029 (0,070)	-0,011 (0,071)
Per capita income (€)	-0,917 (48,267)	-22,933 (88,120)	-33,090 (118,559)	-48,495 (162,137)	-46,729 (209,185)
Local units	-0,885 (1,189)	-2,239 (1,279)	-2,200 (1,458)	-2,814 (1,996)	-2,050 (2,293)
Blue-collar workers wages (€)	0,175 (1,853)	-1,487 (2,771)	-2,261 (3,935)	-2,549 (4,318)	-2,412 (5,017)
White-collar workers wages (€)	0,277 (2,191)	0,993 (2,887)	-0,081 (3,991)	-0,442 (4,853)	0,704 (5,575)

Notes: ***p<0.01, **p<0.05, -p<0.1

Figure A1. Short-term covariate balancing



Notes: We also control for the weekly earnings of native white-collar and blue-collar workers. These variables do not show up in the Figure because they are available only from 2007. This means that we can control for only one pre-treatment year. However, the 1-year pre-treatment standardized mean difference in weekly earnings between treated and control LLMs is close to 0.