

# Large plant crises in bad times: do local economies (ever) recover?

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# The importance of large manufacturing firms

- ▶ Despite its continued and steady decline, manufacturing remains a source of jobs, as well as the segment from which is derived a significant portion of the **nation's wealth** - especially through exports, innovation and the strength of its inter-industry linkages (Harris & Moffat, 2019).
- ▶ **High local multipliers:** an added job in the tradable sector in a region has a positive and large effect on the non-tradable - to a lesser extent, also on the tradable - sector of the regional economy (Moretti, 2010).
- ▶ **Local-based incentives** are pervasive in manufacturing, because a mass layoff or a closure of a large firm could not only harm workers in that plant but create a domino effect on the region as a whole, thereby multiplying job losses (Gathmann et al. 2018)

## Why should we care?

- ▶ Large number of employees are generally involved in manufacturing plant closures.
- ▶ Mass layoffs in manufacturing might engender severe 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 or the erosion of shared knowledge.
- ▶ Such local economic shocks might have heterogeneous effects (Eriksson & Hansen, 2013; Hansen & Winther, 2015; Eriksson et al., 2017).

# Aim of the paper

Investigate the impact of a large manufacturing plant closure/downsizing on the affected industry as well as on the whole local economy in Italy during the recent economic crisis.

We also investigate the heterogeneity of these impacts, in particular analysing if they depend on the regional development.

# Main studies

- ▶ **Gathmann et al. (2018)** quantify the spillover effects of mass layoffs. They find sizable and persistent negative spillover effects on the regional economy, but with a relatively small negative impact for the workers affected.
- ▶ **Jofre-Monseny et al. (2018)** find that when a large 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.
- ▶ **Holm et al. (2017)** analyze what happens to redundant skills and workers when large companies close down. They find that getting a job in a skill-related industry or moving to a spinoff firm leads to skill reallocation.
- ▶ **Bisztray (2016)** finds that when a foreign-owned large plant closes down, the firms located nearby are negatively affected by such event.

# Our novelties

- ▶ Long term analysis
- ▶ Investigation of the heterogeneity of the impact depending on economic development
- ▶ Use of a recently developed econometric technique, which is ideal for our research question
- ▶ First time this phenomenon is studied at the time of the Great Recession

# Data

- ▶ Our unit of analysis is the **Local Labour Market**
- ▶ LLM is sub-regional geographical areas where the bulk of the labour force lives and works, and where establishments can find the largest amount of the labour force necessary to occupy the offered jobs.
- ▶ The key criterion to define LLMs is the proportion of commuters who cross the LLM boundary on their way to work.
- ▶ Italy counts 610 LLMs.

# Data

- ▶ We have considered **4 different sources of data** to select treated observations:
  - ▶ The ASIA datasets on local units and firms
  - ▶ Balance-sheet data from AIDA
  - ▶ ‘Tavoli di crisi’ official documents
  - ▶ National and local newspapers.
- ▶ We have created a **large database 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.



# Treated cases

- ▶ 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 between 2008 and 2011 for the main analysis. We excluded the 4 biggest LLMs (Turin, Rome, Naples and Milan).
- ▶ Following the above criteria, we have selected the **24 treated LLMs**
- ▶ The main **dependent variable** is the number of employees.
- ▶ The **control covariates** are the total number of employees, the number of employees in the industry and manufacturing sector, employment rate, unemployment rate, population, share of graduates, per capita income and average size of the economic sectors.

# Methodology

- ▶ We adopt the **nonparametric generalization of the difference-in-differences estimator** proposed by Imai et al. (2020) to estimate the ATT.
- ▶ It requires four steps:
  1. Select for each treated LLM a set of control LLMs that have an identical treatment history and similar trends in the pre-treatment outcome and control covariates.
  2. Refine the matched set,  $M_{i,t}$ , by using the Mahalanobis distance measure with 5 neighbors. We also apply an exact matching on the geographical partition (North, Centre, South).
  3. For each treated LLM, we estimate the counterfactual outcome using the average of the five control units.
  4. Compute the difference-in-differences (DiD) estimate of the ATT

## Evaluation strategy

- ▶ Average Treatment effects among Treated (ATT):

$$\delta(F, L) = E \left\{ \underbrace{Y_{(i,t+F)} \left( X_{i,t} = 1, X_{(i,t-1)} = 0, (X_{(i,t-l)})_{l=2}^L \right)}_{\text{Potential outcome under a treatment change}} + \right. \\ \left. - \underbrace{Y_{(i,t+F)} \left( X_{i,t} = 0, X_{(i,t-1)} = 0, (X_{(i,t-l)})_{l=2}^L \right)}_{\text{Potential outcome without the shock}} \right| X_{i,t} = 1, X_{i,t-1} = 0 \Bigg\}$$

- ▶  $\delta(8, 4)$  represents the average causal effect of a plant closure/downsizing on the outcome, eight years after the treatment, while assuming that the potential outcome only depends on the treatment history up to four years earlier.
- ▶ Compute the DiD estimate of the ATT for each treated observation and then average it across all treated observation.

# Assumptions

## ► Assumption 1

- **Absence of the carryover effect:** it 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.  $(X_{i,t-l})_{l=L+1}^{T-1}$ . This implies that we allow for the possibility that past treatments affect future outcomes up to  $L$  years.

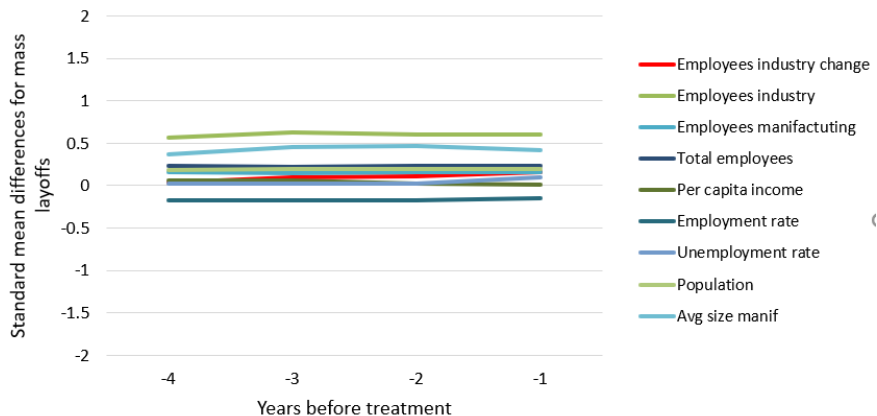
## ► Assumption 2

- **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.

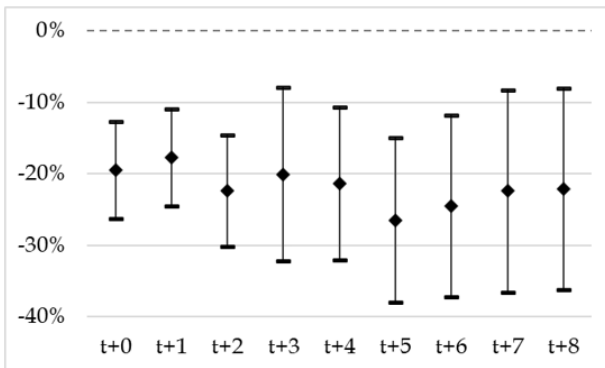
## ► Assumption 3

- **Parallel trend assumption** after conditioning on the treatment, outcome and covariate histories.

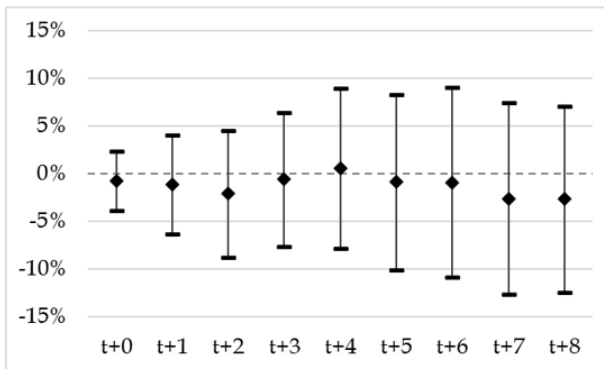
# Covariate balancing



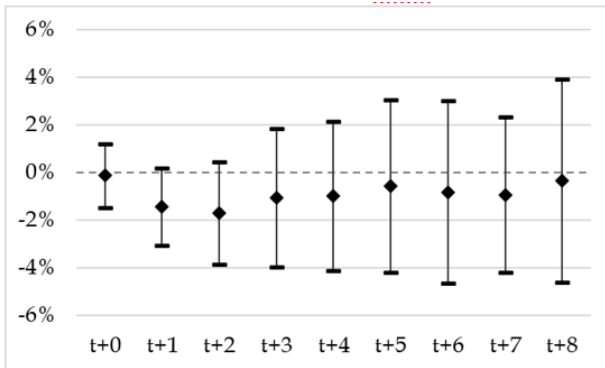
# Long-term analysis - industry



# Long-term analysis - manufacturing



## Long-term analysis - tertiary





# Effect heterogeneity by sector

Table 5. Effect heterogeneity by sector

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

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

# Mass layoff impact on other outcomes

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

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

# Robustness checks

- ▶ We test the sensitivity of the results modifying the specification of the estimator. In particular, our results are robust:
  - ▶ using 10 neighbors in the *size.match* argument
  - ▶ using 3 neighbors in the *size.match* argument
  - ▶ using the *inverse probability weighting* as refinement method
  - ▶ using the *propensity score matching* as refinement method
  - ▶ we also run a **placebo test** using as treatment cases firms which have faced a deal with the government for new buyers/subsidies.

# Conclusions

- ▶ The negative shock on a large plant opens a scenario that deserves a comprehensive and accurate analysis: in addition to know how many workers leave the company undergoing downsizing or closure, it is crucial to know **how LLMs react** to negative shocks.
- ▶ The results show that a shock in the tradable sector has a negative and persistent effect only on the same industry of the LLM affected.
- ▶ This effect is persistent also for LLMs with a more solid economic system.
- ▶ The impact on the rest of the local economy is negative but statistically non-significant.
- ▶ These results demonstrate how the Italian LLMs are not flexible to shocks with low dynamic adjustments.