Local inequalities of the COVID-19 crisis

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Abstract

This paper assesses the pandemic's toll on the local economies of one of the hardest-hit countries, Italy. We combine up-to-date quarterly local labor market data with the machine learning control method for counterfactual building. Our results document that the economic effects of the COVID-19 shock are dramatically unbalanced across the Italian territory and spatially uncorrelated with the epidemiological pattern of the first wave. The heterogeneity of employment impacts is associated with exposure to social aggregation risks and pre-existing labor market fragilities. Such diverging trajectories call for targeted policies that promptly address the uneven economic geography of the current crisis.

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1. Introduction

With over 83,000 deaths and more than 2,400,000 cases (as of January 20, 2020), Italy ranks among the worst-hit countries by COVID-19.[1] The Italian government was the first in Europe to declare, on March 9, an unprecedented national lockdown that paralyzed the country. From March 25, productive activities were shut down, except for those deemed 'essential' for the functioning of the country's economic system. On May 4, lockdown rules started to be lifted, and, from June 15, almost all economic activities were finally allowed to re-open, albeit under strict safety protocols. The suspension of restrictive measures continued throughout the summer until the impressive resurgence of the contagion in the fall of 2020 forced the government and regional authorities to issue new social distancing policies, including the reintroduction of restrictive measures targeting economic activities.

The repercussions of this remarkable series of disruptive events on the Italian economy are enormous, and the Italian government tried to attenuate these impacts via the adoption of several emergency measures and fiscal packages.[2] In order to increase workers' protection, the government also issued an *ad hoc* Decree-Law on March 17, which introduced two labor market policies: a special COVID-19 short-time work retroactive compensation scheme and a freezing of layoffs (Casarico & Lattanzio, 2020).

Despite the implementation of a wide range of policy interventions, annual forecasts by the Bank of Italy (December 2020) pointed to a 9 % GDP fall, a reduction of 12.8% in the number of hours worked and a decrease of 1.8 % in the number of persons employed, while earlier estimates (October 2020) by the International Monetary Fund (IMF), suggested an even larger annual GDP drop at 10.6%.[3]

However, credible *ex-post* quantifications of microeconomic and local impacts are still missing. Such a vacuum is hardly surprising as real-time microdata is scarce. On top of data scarcity, rigorous evaluation of the crisis effects is challenging for econometric issues: the COVID-19 exogenous shock virtually left no part of the world unaffected. In econometric jargon, this means that it is hard to find a control group because the treatment affected all units simultaneously or with

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[1] See https://www.worldometers.info/coronavirus/country/italy/.

[2] For a database of fiscal policy responses to COVID-19 in Italy (as well as many other countries), please refer to https://www.imf.org/en/Topics/imf-and-covid19/Fiscal-Policies-Database-in-Response-to-COVID-19.

[3] See here: https://www.bancaditalia.it/pubblicazioni/proiezioni-macroeconomiche/2020/Macroeconomic-Projections-Italy-december-2020.pdf.pdf?language_id=1 and here: https://www.imf.org/en/Publications/WEO/Issues/2020/09/30/world-economic-outlook-october-2020.

short lags.[4] As noted by Chudik et al. (2020), this implies that in most cases, standard evaluation techniques, such as difference-in-difference or the synthetic control method (SCM), are not applicable.[5] This is probably the reason why, although micro literature on the pandemic is flourishing (Adams-Prassl et al., 2020; Baker et al., 2020; Bartik et al., 2020; Benedetti et al., 2020; Bick & Blandin, 2020; Blundell et al., 2020; Buchheim et al., 2020; Cajner et al., 2020; Carvalho et al., 2020; Forsythe et al., 2020; Gourinchas et al., 2020; Von Gaudecker et al., 2020), almost all these policy-relevant works are not based on counterfactual impact evaluation methodologies. A notable exception is the study by Chetty et al. (2020), who employ private real-time anonymized data and an evaluation strategy which exploits between-state heterogeneity in the reopening's timing to document the granular impact of the pandemic and the related policy responses on various economic outcomes in the United States.

Concerning Italy, Ascani et al. (2020) provide evidence of a close relationship between COVID-19 disease patterns and local economies' characteristics. Giammetti et al. (2020) suggest that the lockdown measures adopted by the Italian government would have locked about 52% of total GDP, 30% of which has been locked within indirect value chains. Casarico and Lattanzio (2020) focus on how different categories of workers were affected by the pandemic in the short-term and carry out a first evaluation of the policy responses implemented. Using a linear probability model, they find that workers already in disadvantaged conditions before the shock (young, low-skilled, and seasonal workers) have substantially higher risks of losing their jobs.

These studies underline important local and sectoral components of the impacts of the crisis in Italy. Indeed, in Europe as elsewhere, the current crisis is undoubtedly a regional one, because the economic impacts are unfolding unevenly at the local level, so regional perspectives are essential to understand the unequal impacts of the pandemic (Bailey et al., 2020). At least in the Italian context, however, we are not aware of any paper showing *ex-post* counterfactual evidence on the local

[4] There are some exceptions: in countries and areas where no total lockdowns were implemented, one might exploit staggered or heterogenous policy responses to generate a counterfactual scenario (see the study by Chetty et al. (2020) mentioned below). This is not the case of Italy. Yet, one could argue that since the spread of the contagion, especially in the first wave, was highly heterogeneous and predominantly affected Northern Italian regions, it would be possible to use the Southern regions as a control group or to consider the shock as 'continuous' treatment with different intensity levels. However, we disagree with the premise. The national lockdown implemented during the first wave, and the shutdown of entire sectors, involved the entire country.

[5] To make up for this, Chudik et al. (2020) develop a cross-country econometric model in which the Covid-19 shock is identified using the IMF's GDP growth forecast revisions between January and April 2020, under the assumption that Covid-19 was the main driver of these forecast revisions. In this way, they use the difference in the forecasts as a counterfactual strategy to quantify the economic impact of the shock.

microeconomic effects of the COVID-19 disruption on labor and firm outcomes.

This article quantifies the heterogeneous impacts of COVID-19 on employment and business demography for all 610 Italian local labor markets (LLMs)[6] and investigates the main territorial features of such unevenness. To this end, we leverage up-to-date quarterly LLMs data, collected from the Business Register kept by the Union of the Italian Chambers of Commerce, combined with a counterfactual application of machine learning (ML), namely the newly developed machine learning control method (MLCM). The MLCM draws on the predictive ability of ML algorithms to generate a no-COVID counterfactual scenario (i.e. a 'business-as-usual' scenario) in such a peculiar econometric setting. The use of the MLCM is made possible by constructing a comprehensive time-series cross-sectional database on LLMs.

Thanks to this counterfactual approach, we document that at the end of the third quarter of 2020, the shock has not only already caused a steep decrease in firm entry and a moderate drop in employment and firm exit at the aggregate level but, more importantly, that the effects have been markedly heterogeneous across the Italian territory. In the following step, we use a regression tree to identify the features that matter the most in explaining the heterogeneity of the main outcome variable, i.e. the estimated treatment effect of employment change. We find that the features more significantly associated with employment effects are the share of workers in sectors characterized by a high social aggregation risk and pre-existing labor market fragilities.

The remainder of this paper proceeds as follows. Section 2 describes the data. Section 3 introduces the econometric methodologies. Section 4 reports the treatment effects resulting from the counterfactual analysis, while the subsequent section investigates the main predictors of the estimated impacts. Section 6 concludes.

2. Data

Our primary dependent variable is the log of overall employment. In addition, we also split employment between manufacturing and services, and investigate the impact of COVID-19 on the number of new business registrations (births) and cessations of trading (deaths). All these variables come from the Business Register kept by the Union of the Italian Chambers of Commerce (*Unioncamere*). The Business Register is based on administrative data on the Italian companies gathered by the provincial Chambers of Commerce. It contains information on the registration data of the universe of Italian private non-financial sector firms. The Business Register quarterly data on

[6] 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.

local employment have been made available by the Italian Social Security Institute (INPS) since the third trimester of 2014.

To estimate the impact of COVID-19 on each LLM, we build a comprehensive, balanced panel of all 610 Italian LLMs from 2016 Q3 to 2020 Q3 and employ the random forest algorithm described in Section 3.[7] The counterfactual is estimated by controlling for the industrial structure of each LLM. To this end, we exploit the classification by the Italian National Institute of Statistics (Istat), which splits the Italian LLMs into four classes: without specialization, non-manufacturing, made in Italy,[8] and other manufacturing. Furthermore, in light of the expected plunge in tourism-related employment, we split the non-manufacturing class into touristic and non-touristic. We then control for LLM size, geographical dummies (North-East, North-West, Centre and South), population density, unemployment rate, activity rate, yearly and quarterly fixed effects, and trends in employment, business births, and business deaths. For each of the latter three variables, we control for two lags of the same quarter, the lags of the four preceding quarters, and four lags of the yearly averages. The total number of features included in the counterfactual analysis is 54.

In the second phase of the empirical analysis, the association analysis uses the estimated COVID-19 impact on employment for all LLMs as the outcome of interest to uncover its primary predictors. For this analysis, we collected variables potentially correlated with the employment change due to COVID-19. We use the dependency ratio to control for the population structure and its implications for the productive part of the population. As a measure of the spread of COVID-19, we use the excess mortality estimates provided by Cerqua et al. (2020), updated to 30 September 2020.[9] We also employ two variables which capture the criticality of the tasks performed by employees, the possibility of exposure to the virus and physical proximity to the workplace, all highlighted as relevant factors in the literature (see Barbieri et al., 2020): the share of jobs having a high risk of social aggregation and the share of jobs having a high 'integrated' risk. These variables proxy for the demand-side changes due to peoples' immediate response to the pandemic and are generated on the basis of the work conducted by an *ad hoc* task force,[10] which linked a level of social aggregation

[7] Please note that for business demography variables, instead, the sample starts from 2015 Q1.

[8] The 'made in Italy' manufacturing LLMs are characterized by industrial districts. Most of them are specialized in the manufacture of food products, furniture, textiles, apparel, leather and footwear.

[9] This data is publicly available here: https://www.stimecomunalicovid19.com/.

[10] In April 2020, Italy's Prime Minister Giuseppe Conte appointed Vittorio Colao, former Vodafone Group CEO, to lead a group of lawyers, economists, and experts, to outline a plan on how to restart the Italian economy after the coronavirus emergency. One of the group's objectives was to reschedule the gradual reopening of economic activities based on two criteria: the risk of social aggregation and the 'integrated' risk.

to each economic sector (2-digit NACE Rev.2 classification) and integrated risks from low to high. Activities at high integrated risk are those associated with the risk of coming into contact with sources of contagion at work, especially those connected to work processes (e.g. human health services, sewerage, public administration and defense), while activities at high risk of social aggregation are those that involve contact with other subjects in addition to the company's workers (e.g. catering, entertainment, hospitality).

As the geography of industries highly exposed to the 'COVID-19 shock' is heterogeneous (Krueger et al., 2020), we create a variable that incorporates the predicted supply-side sectoral shocks to each LLM. Specifically, we generate the share of jobs in suspended economic activities from March to May 2020.[11] In addition, we build the share of temporary contracts as a metric for temporary jobs' local relative importance.[12]

Other economic variables included in this phase of the analysis are income per capita, unemployment rate, the share of innovative start-ups as a proxy for local innovation, and a measure of economic fragility, i.e. the share of firms having employees in *Cassa Integrazione Guadagni Straordinaria* (CIGS), namely the most utilized Italian short-time work program providing subsidies for temporary reductions in the number of hours worked.[13] We also add two variables that consider the densities of health care personnel and hospitals: i) the number of hospital beds per 1,000 inhabitants, and ii) the share of workers employed in the NACE 2-digit sectors 'human health activities' and 'residential care activities'.

Lastly, as mobility is one of the critical aspects linked to the epidemiological spread of COVID-19, we take this into account by using three variables:

- the number of road accidents per 10,000 inhabitants;
- the share of population living in peripheral areas;
- the index of relational intensity (IIRFL) within the local labor market. The higher the IIRFL, the greater the inter-municipal turbulence in terms of flows.

In the online Appendix, Table A1 includes a more detailed description of all the variables, while

[11] The selection of these activities was carried out on the basis of the NACE Rev.2 classification.

[12] Even if this variable refers to 2015, we argue that this is a valid proxy for 2020, as there is evidence of a strong temporal persistence in the variation of this variable across locations (Caselli et al., 2020).

[13] CIGS targets firms experiencing economic shocks, broadly defined: it can be a demand or revenue shock, a company crisis, a need for restructuring or reorganization, a liquidity or insolvency issue, etc. CIGS is a subsidy for partial or full-time hour reductions, replacing approximately 80% of the worker's earnings due to hours not worked, up to a cap (Giupponi & Landais, 2020).

Table A2 provides descriptive statistics. The availability of these indicators will allow us to identify the LLM characteristics that matter the most in explaining the treatment effects' heterogeneity.

3. Methods

Our empirical exercise consists of two tasks – a counterfactual analysis and an association analysis. For both steps, we harness ML's predictive power, but with a key difference. In the counterfactual analysis, the ultimate aim is causal inference; when looking at impact predictors, instead, we tackle a purely predictive problem. The choice of the algorithm employed in each phase is in line with the different goals of the two analyses: the trade-off between accuracy and interpretability (Hastie et al., 2009; Murdoch et al., 2019) is solved in favor of the former in the counterfactual analysis, and of the latter in the association analysis. Below, we discuss the two methodologies and their different purposes and empirical frameworks separately.

3.1 Counterfactual analysis: the machine learning control method

To tackle the econometric challenges related to the pandemic shock's pervasive nature and establish causality, we draw on the newly developed MLCM to generate a counterfactual scenario in which the COVID-19 crisis never hit Italy. In other words, we employ the MLCM to address the fundamental problem of causal inference, i.e. the impossibility of observing the potential outcome in the no-treatment scenario, a curse that affects all LLMs.

Although ML algorithms primarily deal with out-of-sample predictions or 'prediction policy problems' (see Kleinberg et al., 2015), more recently, they have been combined with causal inference approaches (Athey & Imbens, 2016; Athey et al., 2017; Athey et al., 2019; Belloni et al., 2017; Varian, 2016; Wager & Athey, 2018). Varian (2016) was among the first to note that counterfactual building is essentially a predictive task, which is exactly the task at which ML excels. In a panel or time series setting, he noted that one could exploit pre-treatment observations to generate an artificial control group that acts as a counterfactual in the no-treatment, 'business-as-usual' scenario. This way, one could readily retrieve treatment effects as the difference between the observed outcome and the ML-generated potential outcome. Varian called this straightforward counterfactual method the 'train-test-treat-compare' process. This process is similar to the SCM developed by Abadie et al. (2010), with the key difference that it does not require the availability of untreated units, as it draws on pre-treatment information to generate a credible estimate of the 'outcome for the treated if not treated'.

Early empirical applications of this intuitive methodology for counterfactual building have recently appeared (Abrell et al., 2019; Benatia, 2020; Benatia and de Villemeur, 2020; Bijnens et al., 2019; Burlig et al., 2020; Cerqua et al., 2020; Souza, 2019). Except Burlig et al. (2020) and Souza (2019), all the other studies cannot rely on an original control group in their research design because they only observe treated units in settings with simultaneous treatment, just as in our case.

Benatia (2020) and Cerqua et al. (2020) are the most closely related to this study because they both investigate the causal effects of the COVID-19 crisis. Benatia (2020) applies a neural network model to study the impact of containment measures on the demand reduction in New York's electricity markets; Cerqua et al. (2020) employ three different ML routines (LASSO, random forest, and stochastic gradient boosting) to derive municipality-level excess mortality estimates during the COVID-19 pandemic in Italy.

In the spirit of this nascent evaluation approach, we apply the MLCM to pursue our causal inference analysis of COVID-19 local economic impacts in Italy. Our artificial control group comes from an ML predictive model developed to forecast a post-treatment counterfactual for each LLM. In this way, under the crucial assumption of stable trends in the absence of the shock, we can assess the LLM-specific causal impact of the exogenous shock by comparing the observed post-shock trajectory with the most credible trajectory the LLM unit would have followed in a no-shock scenario. A critical requirement for this approach's validity is that the predictive ML model must not include predictors that may be affected by the treatment (Varian, 2016). We avert this issue by employing only pre-2020 features in our counterfactual building. Finally, the use of the MLCM is made possible from the construction of a comprehensive time-series cross-sectional database on LLMs (see Section 2).

We apply a powerful and popular ML algorithm: the random forest.[14] The random forest is a fully non-linear technique based on the aggregation of many decision trees. In particular, random forest builds many trees (1000, in our case) based on bootstrapped training samples and, at each split of a tree, uses only a random subset of the predictors as split candidates, thus introducing a double layer of decorrelation of the trees from one another (Hastie et al., 2009).

Drawing from the routine already implemented by Cerqua et al. (2020), our counterfactual analysis is based, for each outcome variable, on the following 7-step methodological sequence:

1) We randomly split the pre-2019 quarterly dataset into a training sample, made up of 80% of the

[14] We also tested the forecasting performance of another well-known ML technique, the Least Absolute Shrinkage and Selection Operator (LASSO), but it was always inferior to that of the random forest.

LLMs, and a test set, consisting of the remaining 20%;[15]

2) We train our random forest algorithm on the training set and perform a 10-fold cross-validation to select the best-performing tuning hyperparameter;[16]
3) We test the out-of-sample predictive performance on the corresponding pre-2019 testing sample;
4) We test model accuracy on the entire 2019 sample and compare its predictive performance with that of a before-after analysis, which has become a common and intuitive metric to gauge the magnitude of the pandemic's impact;
5) We repeat the same routine on the entire pre-2020 dataset and finally predict, for the first three quarters of the 2020 sample, employment levels, business births, and business deaths in a 'no-COVID' ('business-as-usual') scenario;
6) We derive individual treatment effects for all LLMs as the difference between the observed 2020 outcomes and the ML-generated potential outcomes;
7) We map the individual treatment effects of the LLM-level economic impacts of COVID-19.

The critical assumption behind this MLCM routine is that the difference between our observed and counterfactual economic outcomes is the causal impact of the COVID-19 shock. We deem it plausible given the massive disruption to the economy brought about by the sudden unexpected arrival of the pandemic. Finally, please note that, by 'COVID-19 shock', we mean the *economic* shock, i.e. we refer not only to the epidemiological spread of the virus *per se*, but also to the national lockdown and the social distancing policies and restrictive measures targeting economic activities that were adopted to contain the health crisis. This implies that, via our counterfactual approach, we capture the total *net* impact on each LLM, that results from different degrees and combinations of supply and demand shocks generated by the dynamic interactions between the pandemic and intrinsic characteristics of the affected areas.

3.2 Association analysis: the employment change regression tree

To estimate the relationship between the estimated employment outcomes and potentially relevant

[15] We apply the random splitting of the sample at the LLM level, not on *LLM-year* pairs so that there is no data leakage, i.e. the same LLM only appears either in the training or the testing set.

[16] We use cross-validation to solve the bias-variance trade-off and maximize the out-of-sample performance of the random forest algorithm. (Hastie et al., 2009). Specifically, we employ 10-fold cross-validation on the *training* sample to select, among different alternatives (*p/2*, *p/3*, and *p/6*), the optimal value of the tuning hyperparameter *m*, i.e. the number of features *p* randomly sampled as candidates at each split.

covariates linked to economic, mobility, and pandemic-related LLM features, we harness the efficacy and power of another well-known ML algorithm: the regression tree.

First and foremost, bear in mind that here we abandon the causal inference setting to go back to the original ML habitat, i.e. the realm of pure prediction. What we want to do in this analysis is to get an idea of the factors which matter most in predicting the heterogeneous local economic impact of the pandemic.

Regression trees are an ideal tool to fulfill this purpose for two reasons: i) differently from complex, black-box ML methods such as random forest, regression trees allow an intuitive understanding of the mechanism through which the outcome variable of interest is linked to its most relevant predictors, thus producing an easy-to-interpret output which can be particularly valuable when the model must be shared to support public decision-making (Andini et al., 2018; Lantz, 2019); ii) regression trees are extremely flexible methods that can easily capture, in the sequence of splits, the entire range of potential non-linearities and interactions between the features, without imposing any parametric functional form to the underlying data-generating process.

From a technical point of view, this ML algorithm divides the data into progressively smaller subsets to identify significant patterns that are then used to predict the continuous output. Compared to standard regression tree analyses, two necessary clarifications are in order. First, we do not divide our sample into a training and testing set. The reason is straightforward: instead of testing for the out-of-sample accuracy of our regression tree model, we want to investigate the main predictors of our outcome variable, i.e. the estimated treatment effect for employment change in 2020 Q3, on the full sample of Italy's LLMs. Second, and related, we do not apply cross-validation to select the hyperparameter of the regression tree method (named 'complexity parameter', *cp*).

Therefore, we run a basic regression tree model of the employment effects to uncover the most relevant predictors of treatment effect unevenness at the local level. Notably, the associations emerging from the regression tree should not be interpreted in a causal sense, but rather as a way to uncover significant correlations between the most important features and the outcome variable of interest.

4. Counterfactual analysis

We begin by reporting in Table 1 the random forest technique's predictive performance compared to the intuitive before-after method often adopted to gauge the magnitude of the COVID-19 shock.

[17] The before-after analysis estimates the impact of COVID-19 as the difference between the trend of a given outcome (in this case, employment) in 2020 (after the pandemic's arrival) and the pre-pandemic average figures of the past year(s). The underlying assumption is that, without the pandemic, the trend would have been flat, i.e. the number of employees would have remained constant.

As signaled by the Mean Squared Error (MSE) and Median Squared Error (MEDSE) of the various methods, random forest predictions substantially outperform this intuitive methodology in the out-of-sample predictive test on the 2019 sample. Using MSE as the reference metric, the predictive gain of the random forest performance is of more than 26% compared to last year's figures, and of 77% compared to the three-year (2016-2018) average of the outcome variable. MEDSE performances are even more dramatically unbalanced in favor of the random forest. This test demonstrates that data-driven methodologies lead to far more accurate predictions of potential outcomes in a given, 'ordinary' year.

Table 1 – Predictive performances for 2019 (log) overall employment levels

Predictive method	**MSE**	**MEDSE**
Corresponding quarter – Last year (2018)	0.0011209	0.0005058
Corresponding quarter – 3-year average (2016-2018)	0.0036044	0.0024622
Random forest	0.0008268	0.0001938

Notes: Estimates on the 2019 full LLM sample (2440 observations; 610 per quarter). MSE stands for Mean Squared Error; MEDSE for Median Squared Error.

Having established that ML algorithms exploit past information to predict future outcomes much better than standard methods, we take a quick look at the aggregate treatment effects of the coronavirus crisis for the employment outcome. By the end of the third quarter of 2020, the pandemic has entailed a 1.86 % decrease in overall employment in Italy, compared to what employment levels would have been had the pandemic never reached the country.

As we mainly focus on the local heterogeneous impact of COVID-19, in the following sections, we

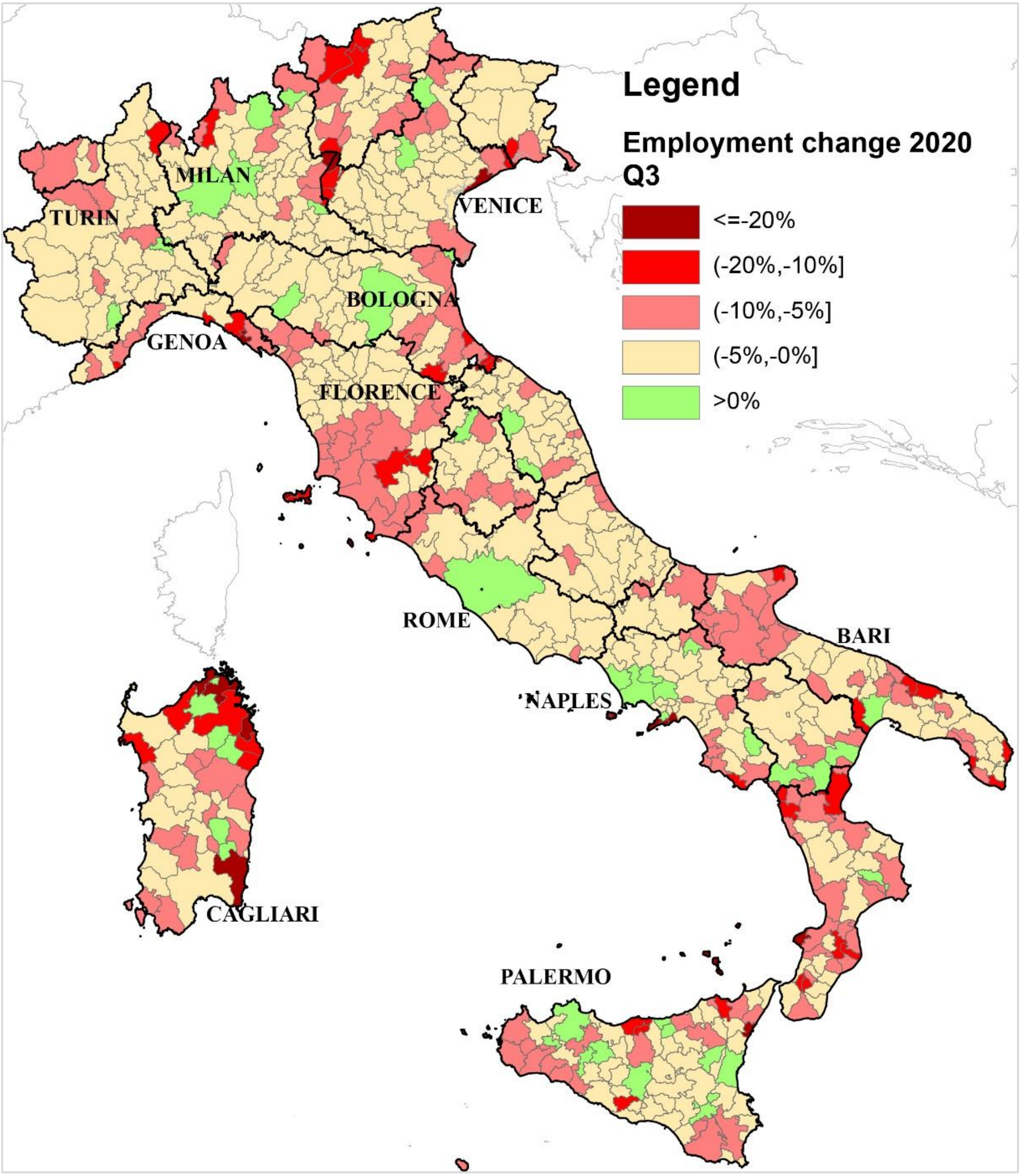
[17] Examples of this approach in the Italian context can be found in Casarico and Lattanzio (2020), as well as here: https://www.lavoce.info/archives/68205/cosi-il-coronavirus-ha-contagiato-limprenditorialita/ (in Italian), here: https://www.bancaditalia.it/media/notizie/2020/Nota-Covid-19.11.2020.pdf?language_id=1 (in Italian) and here: https://www.lavoce.info/archives/71202/nuove-imprese-chiuse-dalla-pandemia/ (in Italian).

first map LLM-specific treatment effects and then gauge the heterogeneity in COVID-19 impacts across local economies.

4.1 Employment

Figure 1 shows the map of the 2020 Q3 employment change at the LLM level. The degree of treatment effect heterogeneity is striking. Except for a few small clusters, the crisis does not seem to unfold along well-defined spatial dimensions or the North-South axis. Nevertheless, some local economies have been hit much harder than others, with impacts ranging from drops larger than 20% in some LLMs of Lombardy, Veneto, Liguria, Calabria, Sicily and Sardinia, to small decreases or even mildly positive effects in Piedmont, Marche, Umbria, Lazio, Abruzzo and Molise. What is even more striking is the *within-region* heterogeneity, which shows how, in all Italian regions, some LLMs fared much better than others despite being geographically close and often contiguous. From an economic geography perspective, our findings suggest that the spatial dimension played a minor role as a transmission channel of the crisis's impacts and suggests a far more prominent role of LLM-specific sectoral characteristics and labor market features. Figure A1 (see the online Appendix) displays the temporal evolution of the employment effects over the first three quarters of 2020: only in the third quarter of 2020, do the impacts appear, and local trajectories start to diverge.

Figure 1 – Employment change 2020 Q3



We then inspect the geographic distribution of the employment and epidemiological outcomes engendered by COVID-19. Figure A4 in the online Appendix presents a visual comparison between the economic vs. epidemiological effects of COVID-19 in Italy. Looking at the maps, the geographic distribution of impacts does not mirror the COVID-19 epidemiological spread during the first wave, which is proxied by excess mortality estimates from February 21, 2020, to September 30, 2020. To test the spatial correlation between these outcomes, we measure their overall spatial relationship across all LLMs using the bivariate Moran's I. This index ranges from -1 (perfect negative spatial correlation) to 1 (perfect positive spatial correlation), and we obtained a Moran's I coefficient close to 0 (-0.089), which suggests a lack of significant spatial correlation between employment and epidemiological outcomes.

It is worth noting that the documented employment impacts are net of the Italian government's protective measures. This means that without these protective measures (the layoff freeze and CIGS extensions in particular), local impacts would have likely been even more sizeable.

4.2 Employment by sector

If LLMs' regional or spatial location is not a primary driver, where does the heterogeneous impact on overall employment originate? Sectoral specialization of LLMs is part of the answer. As shown in the maps of employment change in manufacturing and services, depicted in Figure 2 below, the tertiary sector was much more severely affected than the manufacturing one and appears to be the leading cause of the overall employment change observed in Figure 1.[18] This is not unexpected, as workplace closures primarily affected economic activities in the tertiary sector. At the same time, a large share of manufacturing firms could avert the shutdown thanks to being comprised in the list of 'essential activities' that the government decided to keep open to guarantee the basic functioning of Italy's economic system. The tertiary sector is also notably the one with the highest prevalence of temporary jobs and seasonal workers, which could only marginally benefit from the layoff freeze measure. Given these facets, it comes as no surprise that employment losses primarily affected LLMs specialized in services.

Figures A2 (for manufacturing) and A3 (for services) in the online Appendix also provide the evolution of impacts by quarter: while the manufacturing sector experienced only a moderate negative trend over the year, the services sector suffered a massive blow during the third quarter, in line with the trajectory of overall employment illustrated in Figure A1.

4.3 Business demography

We then look at how COVID-19 affected business demography outcomes. At the national level, by the end of the third quarter of 2020, the crisis determined a 20.99% decrease in business births and a 2.11% decrease in business deaths. Figure 3 disaggregates these country-level estimates and maps the cumulative impact of COVID-19 for business births change (i.e. firm entries) and business deaths change (firm exits) over the first three quarters of 2020.

The impact on business births is particularly acute and, with almost no exception, involves the entire national territory. This anomalous plunge happened despite the so-called *Decreto Rilancio* (May 14, 2020), which included a set of protective measures intended to support investments in start-ups (Fini & Sobrero, 2020). By contrast, the impact on firm exits is more polarized and

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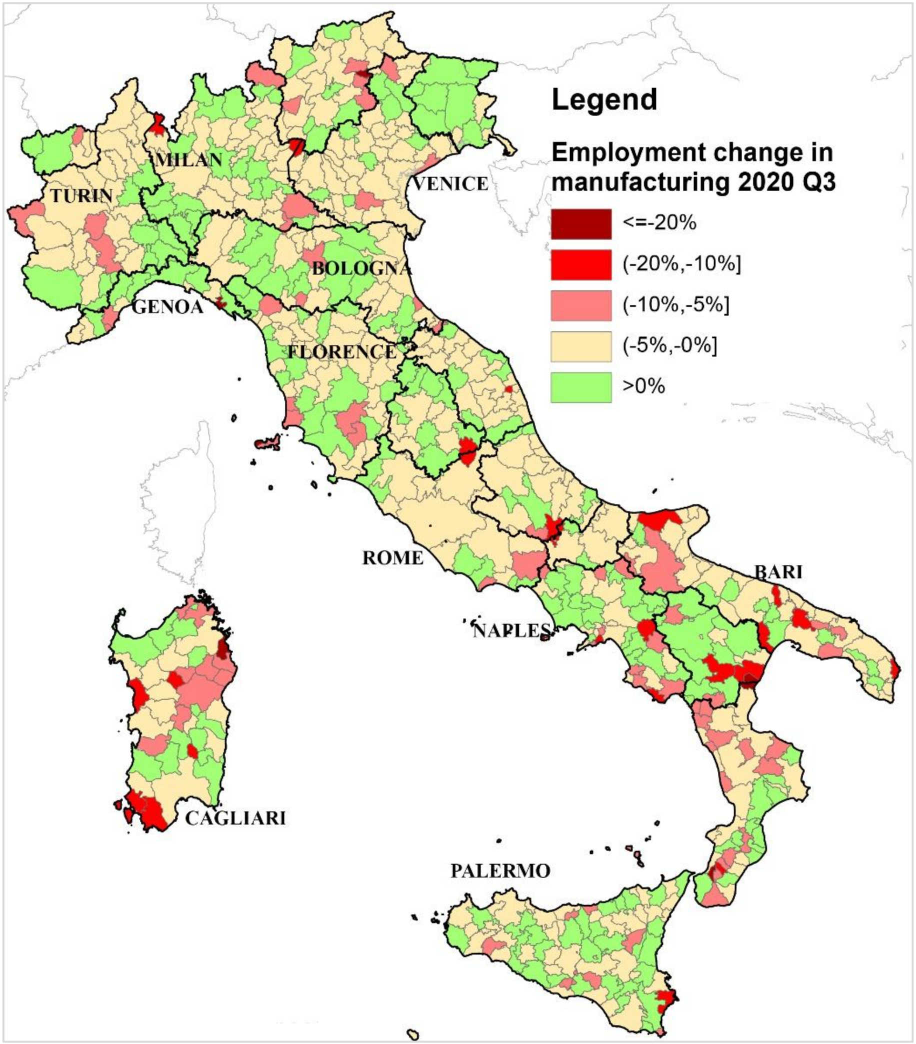
[18] This is confirmed by the national-level estimates, which reveal an aggregate 0.28% decrease in manufacturing compared to a 2.13% decrease in services.

geographically dispersed, with several regions experiencing substantial reductions in cessations of trading, e.g. Emilia-Romagna and Marche, whereas others (Lazio, Abruzzi, Basilicata and, in particular, Sardinia) saw a significant increase in firm exits. Sardinia's case is emblematic as tourism, arguably the hardest-hit sector, plays a vital role in its economy.

The generalized drop in the number of newly-born firms across the country is particularly troublesome because start-ups and young firms are usually the most innovative ones, thus pointing to dire forecasts about the potentially long-lasting effects of the fall in business births in terms of aggregate productivity growth. Moreover, this lost generation of firms creates a persistent dent in overall employment as subsequent years will be characterized by a lower number of firms (Sedláček, 2020). This is all the more worrying in Italy, a country whose economic dynamism – its ability and willingness to allocate resources efficiently – has been steadily declining in the last quarter of a century (Rossi & Mingardi, 2020). The results on firm closures, instead, should be interpreted with caution, as many firm exits could have been 'frozen' by the supportive measures adopted by the government, and may occur in the following months.

Figure 2 – Employment change 2020 Q3 by sector

Manufacturing



Services

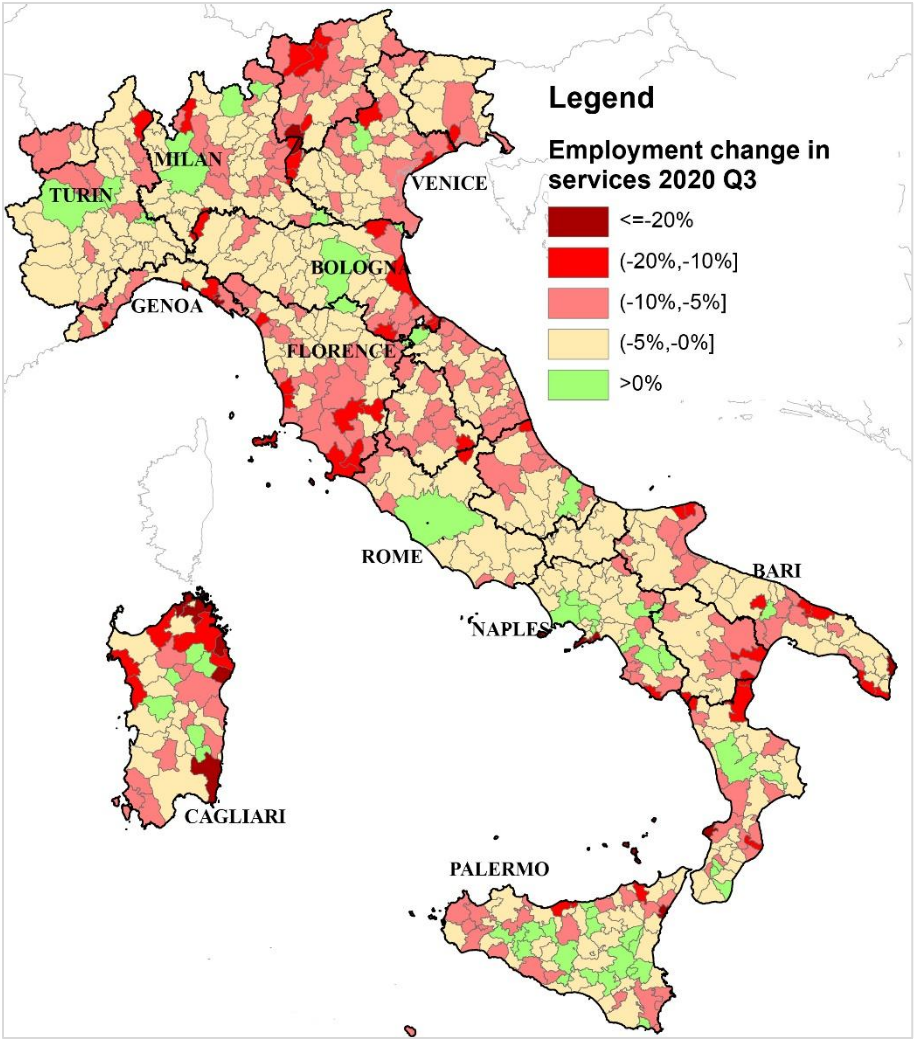
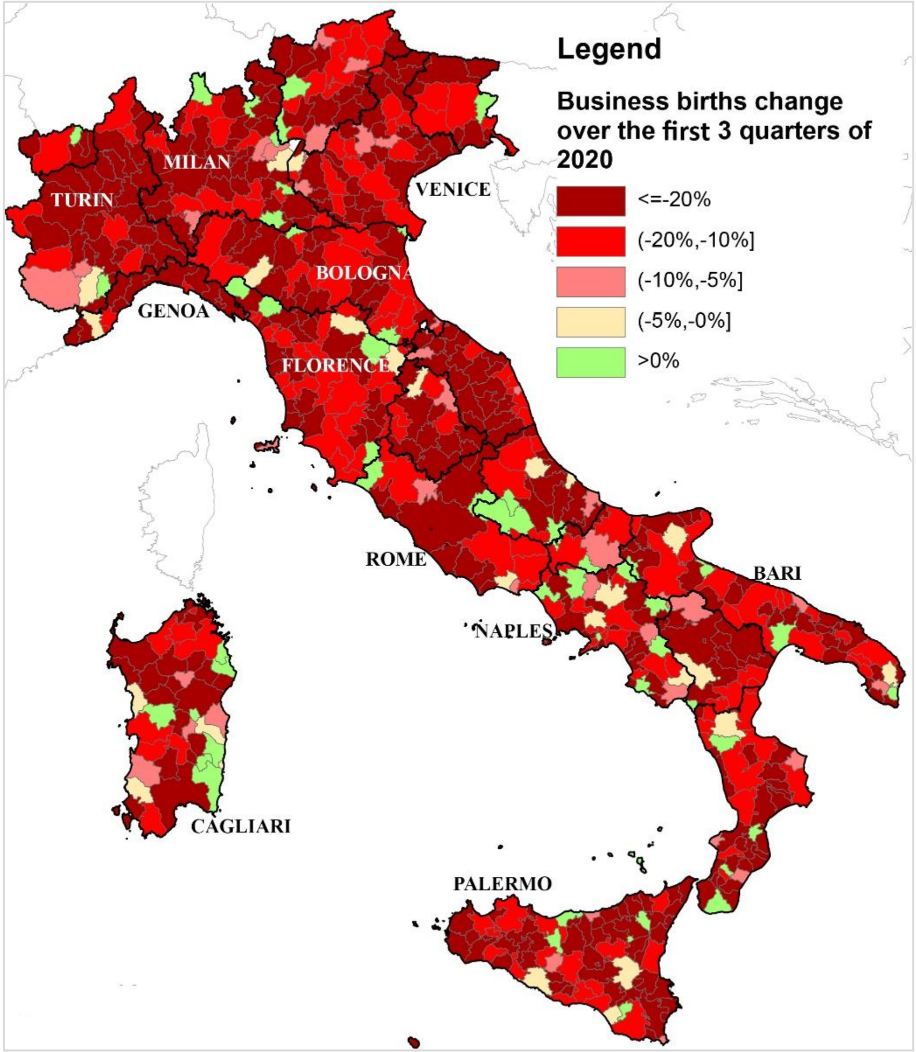
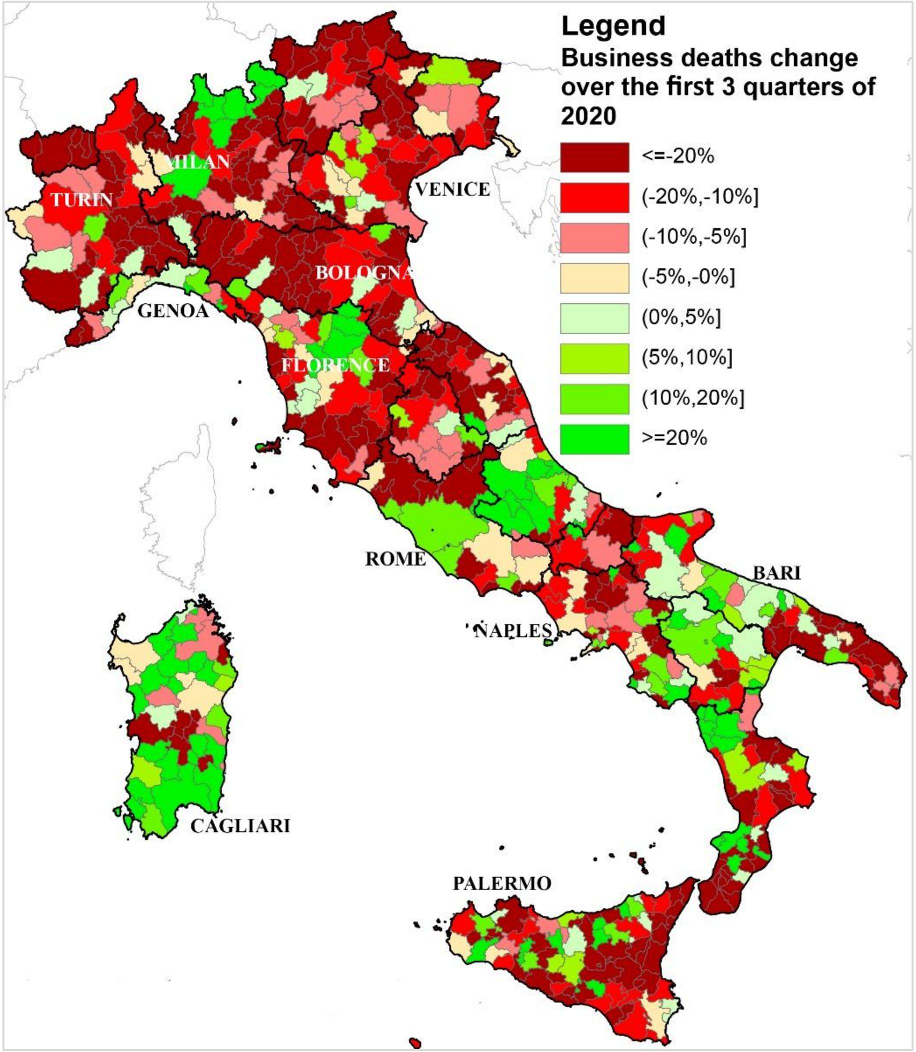


Figure 3 – Business births and deaths change 2020 Q1-Q3

Business births



Business deaths



5. Association analysis

The counterfactual analysis revealed a substantial heterogeneity of the pandemic economic effects. Such heterogeneity does not stem from regional or intra-regional clusters but is partly driven by the LLMs sectoral specialization. Nevertheless, we want to go further than this and understand the factors that matter the most in generating such a fragmented landscape. Therefore, in this section, we use a regression tree to examine the main predictors of our primary variable of interest, employment.

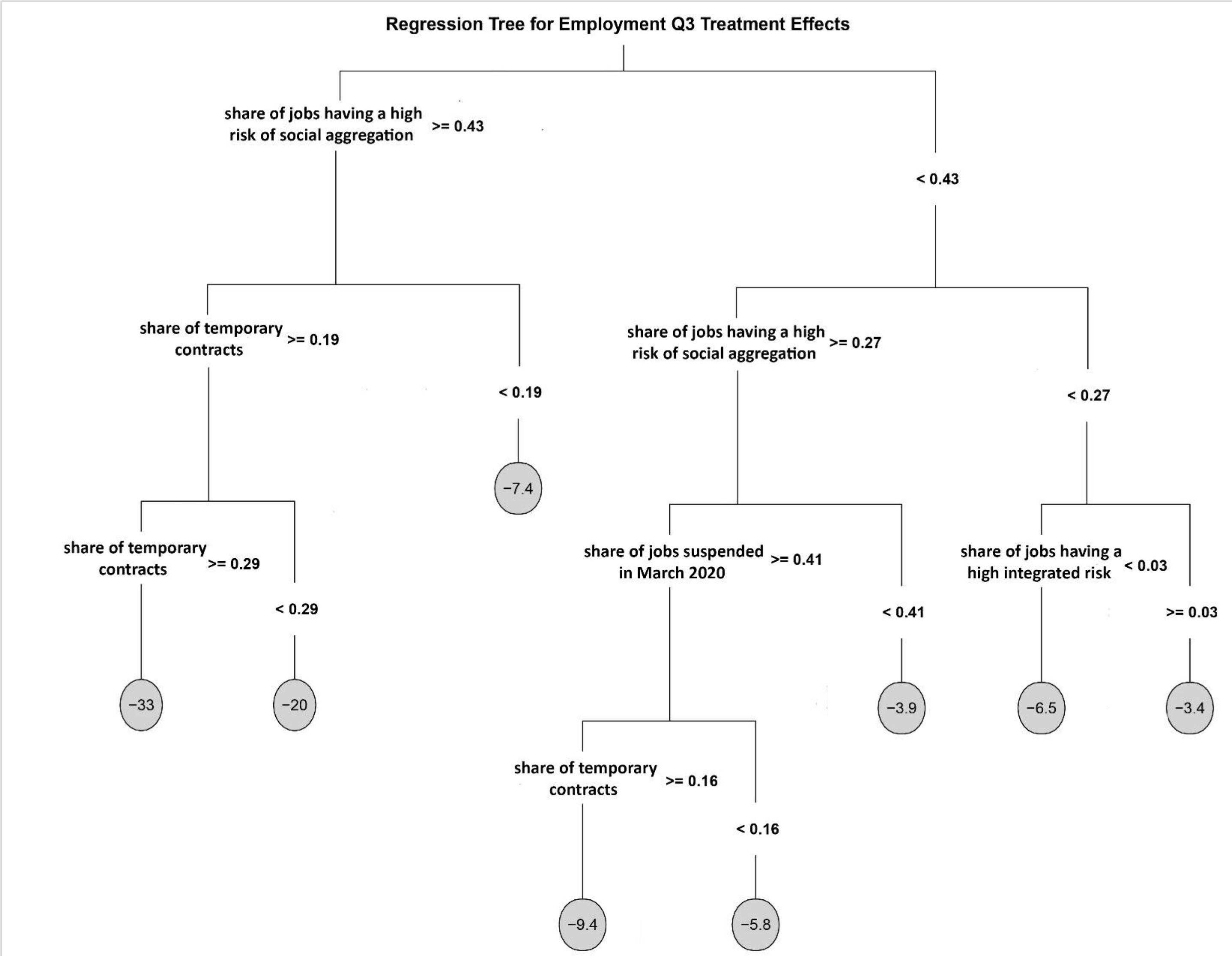
Figure 4 illustrates the regression tree of the LLM-specific overall employment treatment effects. The tree reveals interesting patterns. First, the few variables that generate the tree belong exclusively to two variable groups: aggregation risk features and labor market characteristics. Second, the most severely affected LLMs are those in which there is a high share of jobs at a high risk of social aggregation and a high share of jobs suspended in March 2020, and, even more importantly, a high share of temporary contracts. For instance, the tree predicts that LLMs with a share of jobs having a risk of aggregation equal to or higher than 43% and a share of temporary contracts equal to or higher than 29%, will experience a 33% drop in employment.

Exposure to high aggregation and proximity risk seems to be a primary discriminant of impacts across LLMs with different shares or 'workers at risk' (Barbieri et al., 2020). In turn, the relevance of the labor market attributes in generating the regression tree provides empirical support for the above discussion on the unequal exposure of different workers' categories and types of contracts in the face of the crisis, in line with the heterogeneous findings of Casarico and Lattanzio (2020) for Italy and Blundell et al. (2020) for the UK. This analysis also suggests that emergency measures and fiscal packages were by design effective only for specific categories of workers and types of contracts. By contrast, more fragile categories (think of seasonal workers and occasional jobs) proved to be more vulnerable to the crisis's labor market consequences.

In sum, LLMs characterized by economic sectors having high social aggregation risks and fragile labor markets saw sharp drops in overall employment levels.

Finally, as a sensitivity check, we replace our variables on the share of jobs having a high risk of social aggregation, the share of jobs having a high 'integrated' risk, and the share of jobs in suspended economic activities with alternative measures of the expected sectoral shocks: the demand- and supply-side changes. These two variables weight the expected supply and demand sectoral shocks reported in del Rio-Chanona et al. (2020) by each LLM's sectoral composition (see Tables A1 and A2 in the online Appendix for definitions and descriptive statistics). The corresponding regression tree is presented in Figure A5. The tree confirms the predominant role of demand and supply changes and the extensive overlap between the two alternative sets of variables capturing the magnitude of local sectoral shocks.

Figure 4 – Regression tree on employment change 2020 Q3



6. Conclusion

We have documented the striking local inequalities of the coronavirus crisis across the Italian territory. The heterogeneous employment effects are associated with LLM-specific features such as sectoral specialization, exposure of economic activities to high social aggregation risks, and pre-existing labor market vulnerabilities. These associations track well the patterns of demand and supply shocks that drive the detected treatment effects (del Rio-Chanona et al., 2020). By contrast, there is no discernible spatial correlation between the economic and epidemiological patterns of the pandemic.

We deem the local dimension of the crisis to be policy-relevant, especially in light of the current political debate on the allocation of the forthcoming resources earmarked by the European Union under the *NextGenerationEU* initiative. While a broad glance at the national level can capture the generalized drop in firm entries, it overlooks the uneven geography of the effects on employment levels and business deaths.

Coupled with the relevant role played by labor markets' insecurity emerging from the association analysis, our findings call for more research to untangle and monitor the local economic impacts of the pandemic, and for a place-based approach in the policy response to the crisis. As national policies and top-down plans will be insufficient to lead the recovery (Bailey et al., 2020), policymakers should not neglect the local evolution of this unprecedented shock.

Therefore, to such diverging trajectories should correspond *ad hoc*, well-targeted policy interventions based on a decentralized perspective that considers the territorial profile and sectoral specialization of local economic systems (Ascani et al., 2020). Only in this way will it be possible to mitigate the far-reaching repercussions of the COVID-19 upheavals on local economies and prevent the unfolding crisis from further exacerbating pre-existing territorial disparities.

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Online Appendix

Table A1 – Definition of the variables included in the analysis

Variable name	Definition	Time period	Source
	Counterfactual analysis		
Employment	Overall employment of private non-financial sector firms	2014 Q3 – 2020 Q3	Business Register
Employment in manufacturing	Overall manufacturing employment	2014 Q3 – 2020 Q3	Business Register
Employment in services	Overall services employment	2014 Q3 – 2020 Q3	Business Register
Business births	Companies that have registered in the period under review	2014 Q1 – 2020 Q3	Business Register
Business deaths	Companies that went out of business in the period under review	2014 Q1 – 2020 Q3	Business Register
Economic classification dummies	Without specialization, non-manufacturing (touristic), non-manufacturing (non-touristic), made in Italy, other manufacturing	2011	Istat
Geographical dummies	North-East, North-West, Centre, South		Istat
Population density	Resident population per unit area	2014-2019	Istat
Unemployment rate	Resident population aged 15+ not in employment but currently available for work	2014-2019	Istat
Activity rate	The number of people employed and those unemployed as a % of the total population	2014-2019	Istat
	Association analysis		
Employment change Q3 2020	Treatment effect of the COVID-19 crisis on overall employment levels	2020 Q3	Estimated via the MLCM
Unemployment rate	Resident population aged 15+ not in employment but currently available for work	2019	Istat
Excess mortality estimates	Municipality-level excess mortality estimated by applying ML techniques to all-cause deaths data	From Feb 21, 2020 to Sep 30, 2020	Cerqua et al. (2020)
Share of jobs having a high risk of social aggregation	Number of employees exposed to a medium-high or high risk of social aggregation divided by the number of employees	2019	Own calculations using Business Register data

Table A1 – Continued

Share of jobs having a high integrated risk	Number of employees exposed to a medium-high or high integrated risk divided by the number of employees	2019	Own calculations using Business Register data
Share of temporary contracts	Number of employees with temporary contracts in October divided by the number of employees in October	2015	Istat
Share of jobs in suspended economic activities	Share of jobs in activities suspended in March 2020 by the Italian Government due to the spread of the pandemic	2017	Istat
Income per capita	The amount of money earned per person	2018	Ministry of Economy and Finance
Share of innovative start-ups	The ratio between innovative start-ups and the universe of firms registered in the Business Register	Average (2016-2019)	Business Register
Share of firms having employees in CIGS	The number of firms with employees in CIGS divided by the universe of firms registered in the Business Register	Average (2015-2018)	Ministry of Labor and Social Policies
Number of road accidents per 10,000 inhabitants	The number of road accidents with injuries to persons divided by resident population * 10,000	2019	Istat
Dependency ratio	The ratio of those typically not in the labor force (the dependent part, ages 0 to 14 and 65+) and those typically in the labor force (the productive part, ages 15 to 64)	Jan 1, 2020	Istat
Share of population living in peripheral areas	Share of population living in areas defined by Istat as peripheral or ultra-peripheral	Jan 1, 2020	Istat
Index of relational intensity (IIRFL)	The percentage of flows within an LLM that connect different municipalities on the total of flows within the LLM. This indicator ranges from values close to 0 to 100 (case in which all the workers of the municipalities of the LLM go to work in another municipality). The higher the indicator, the greater the inter-municipal turbulence in terms of flows	2011	Istat
Number of hospital beds per 1,000 inhabitants	Number of hospital beds divided by resident population * 1,000	2018	Ministry of Health
Share of workers employed in health care occupations	Share of jobs in the NACE 2-digit sectors ‘human health activities’ and ‘residential care activities’	2019	Own calculations using Business Register data

Table A1 – Continued

Supply-side changes	Supply-side changes due to the closure of non-essential industries and workers not being able to perform their activities at home	2019	Own calculations using forecasts by del Rio-Chanona et al. (2020)
Demand-side changes	Demand-side changes due to people's immediate response to the pandemic, such as reduced demand for goods or services that are likely to place people at risk of infection	2019	Own calculations using forecasts by del Rio-Chanona et al. (2020)

Notes: To determine the flow of registrations in a given period – e.g. 2nd trimester 2019 – the firms' universe extracted from the archive on June 30 is compared with that extracted in the previous quarter (March 31). Firms that are present in the 2nd (1st) quarter but not in the 1st (2nd) are classified as new registrations (companies that went out of business). Outcome variables in bold.

Table A2 – Descriptive statistics

Variable name	Mean	SD	Min	Max
Counterfactual analysis				
Employment (log)	9.31	1.25	5.95	14.41
Employment in manufacturing (log)	7.53	1.61	3.37	12.65
Employment in services (log)	8.89	1.29	5.51	14.22
Business births	55.97	236.18	0	5173
Business deaths	44.63	202.79	0	9685
Share of LLMs without specialization	0.19	0.39	0	1
Share of touristic LLMs	0.14	0.34	0	1
Share of non-manufacturing (non-touristic) LLMs	0.23	0.42	0	1
Share of *made in Italy* LLMs	0.31	0.46	0	1
Share of manufacturing LLMs	0.14	0.35	0	1
<=10,000 inhabitants	0.08	0.28	0	1
(10,000; 50,000]	0.46	0.50	0	1
(50,000; 100,000]	0.25	0.43	0	1
(100,000; 500,000]	0.18	0.39	0	1
> 500,000 inhabitants	0.03	0.16	0	1
Activity rate	48.26	6.66	30.15	63.91
Unemployment rate	11.85	6.17	1.19	39.08
Population density	0.21	0.30	0.01	3.17
Association analysis				
Employment change Q3 2020 (%)	-5.17	5.50	-44.73	6.78
Unemployment rate (%)	10.99	5.91	1.19	36.19
Excess mortality estimates (%)	7.99	19.72	-34.30	148.07
Share of jobs in suspended economic activities	0.47	0.08	0.25	0.79
Income per capita (€)	12705	3588	5882	22118
Share of firms having employees in CIGS	0.0008	0.0007	0	0.0046
Share of population living in peripheral areas	0.29	0.40	0	1
Share of temporary contracts	0.19	0.08	0.10	0.56
Number of road accidents per 10,000 inhabitants	2.18	1.20	0	6.94
Index of relational intensity (IIRFL)	25.70	14.48	0.2	66.1
Dependency ratio	0.58	0.05	0.43	0.78
Share of innovative start-ups	0.003	0.003	0	0.017
Share of jobs having a high risk of social aggregation	0.23	0.11	0.06	0.76
Share of jobs having a high integrated risk	0.06	0.03	0.01	0.37
Number of hospital beds per 1,000 inhabitants	2.43	3.16	0	24.27
Share of workers employed in health care occupations	0.0253	0.0265	0	0.3530
Supply-side changes (used in the sensitivity check)	-0.27	0.06	-0.51	-0.10
Demand-side changes (used in the sensitivity check)	-0.21	0.08	-0.08	-0.61
Number of LLM-quarters (whole sample)	10,370			
Number of LLMs	610			

Figure A1 – 2020 Employment change by quarter

Quarter 1 Quarter 2 Quarter 3

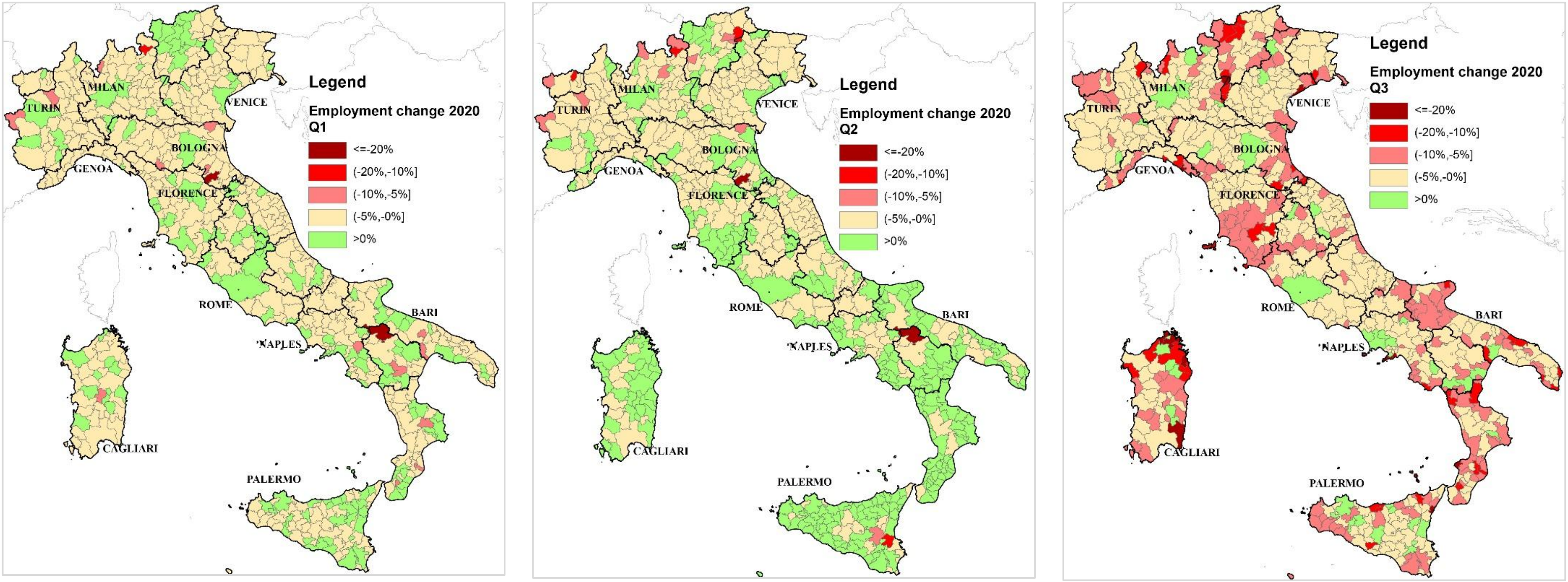
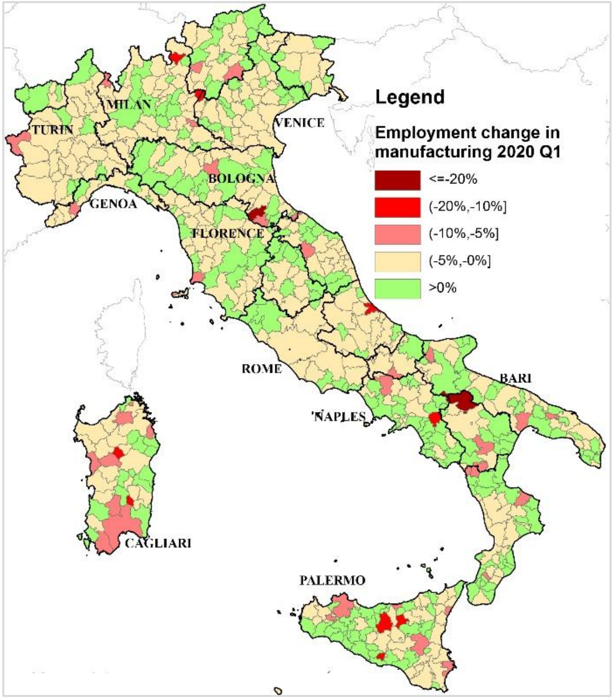
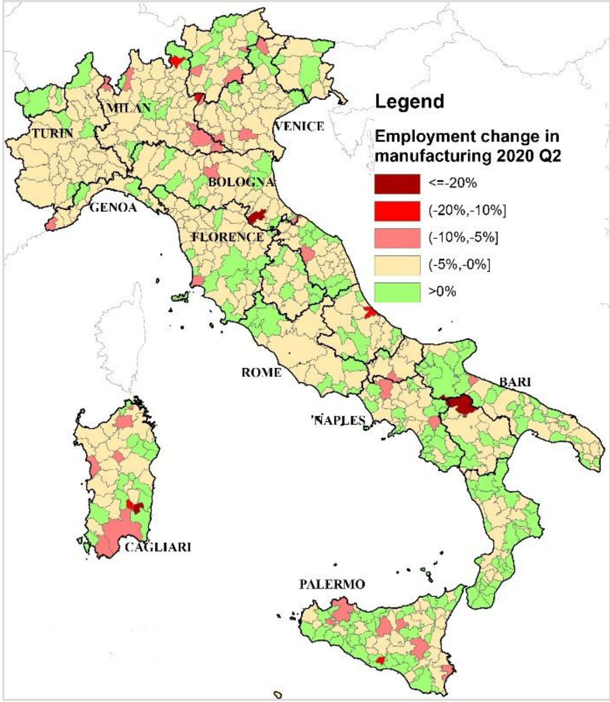


Figure A2 – 2020 Employment change in manufacturing by quarter

Quarter 1



Quarter 2



Quarter 3

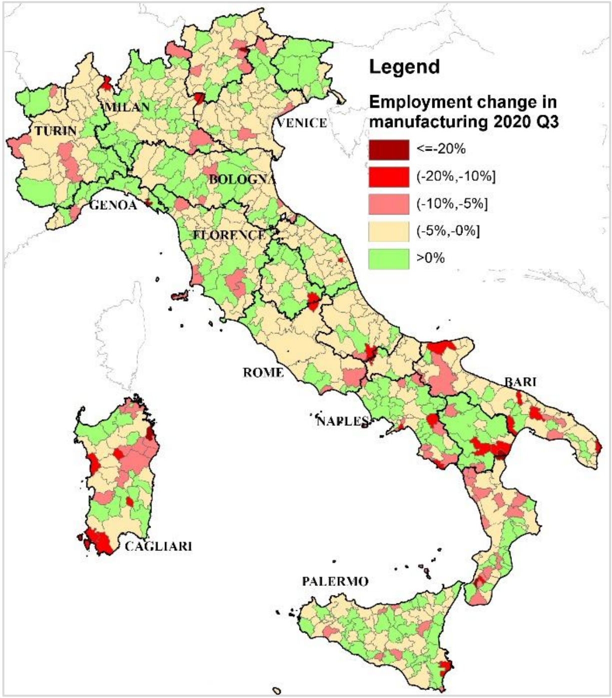
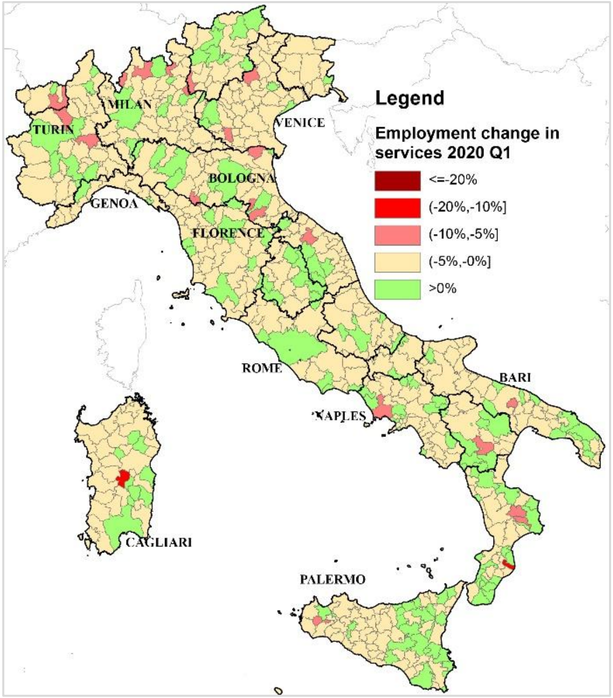
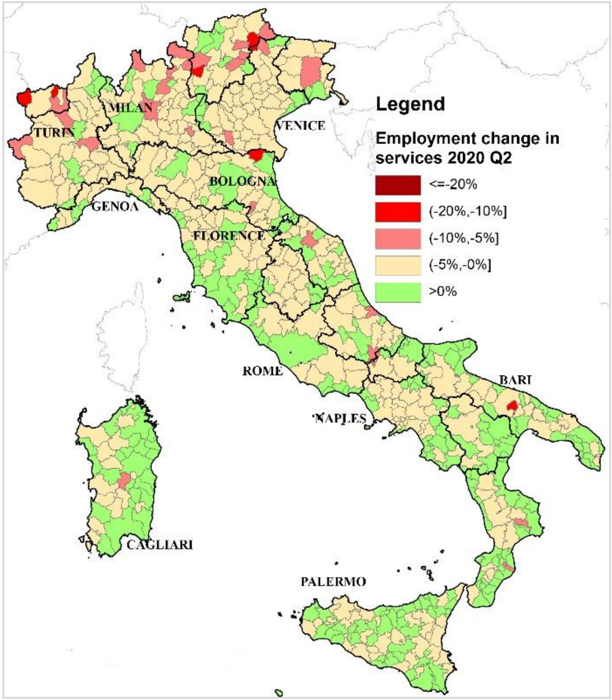


Figure A3 – 2020 Employment change in services by quarter

Quarter 1



Quarter 2



Quarter 3

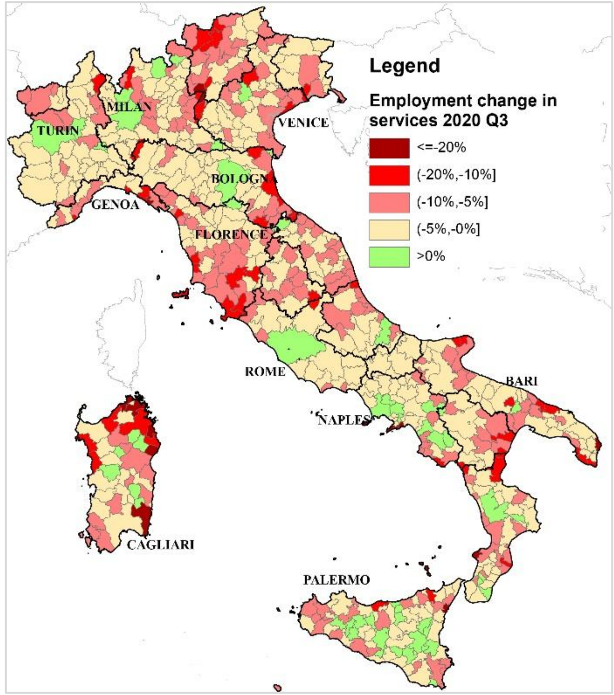
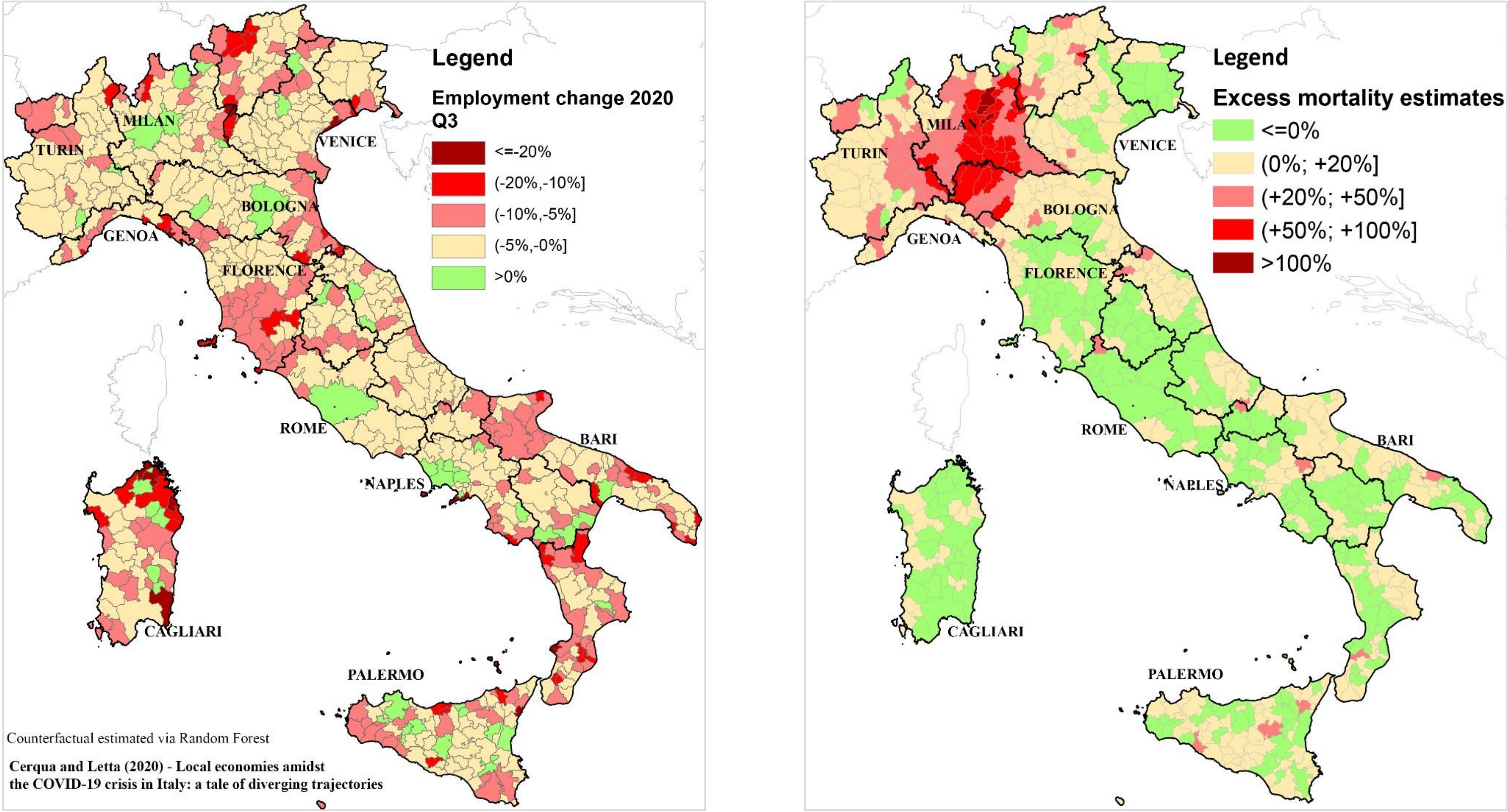


Figure A4 – Economic versus epidemiological impacts of the COVID-19 pandemic across Italy

Employment change 2020 Q3 | Excess mortality (21 Feb 2020 – 30 Sep 2020)



Notes: Municipality-level excess mortality estimates are from Cerqua et al. (2020).

Figure A5 – Regression tree on employment change 2020 Q3 using demand- and supply-side changes reported in del Rio-Chanona et al. (2020)