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AUTHOR
MARCO LOMUSCIO
Development Economics and Local Systems, Doctoral School of Social Sciences, University of Trento & University of Florence
marco.lomuscio@unitn.it

Exploring Local Dynamics of COVID-19 in Italy: Local Labour Markets and the Cases of Bergamo and Brescia

ABSTRACT

In containing and mitigating the diffusion of COVID-19, countries are not fully able to pursue local *test, trace and isolate* strategies due to difficulties in detecting place-based infections and positive asymptomatic cases. This paper explores whether and to what extent local labour markets, functional areas defined by employment self-containment indexes and labour mobility data, can grasp the spatial dynamics of COVID-19 diffusion. Local labour markets capture most of the socio-economic interactions of working and residential populations and identify areas in which people are more likely to engage in frequent, face-to-face contacts with neighbours, colleagues, friends and relatives. Through an exploratory spatial data analysis and the estimation of a spatial autoregressive model, this paper examined a sample of 441 municipalities and 20 local labour markets. These territorial units belong to the Lombard provinces of Bergamo and Brescia (Italy), among the worst affected areas of the country in respect to both reported deaths and confirmed infections in the early stages of the pandemic. The findings suggest that municipal variations in mortality rates in 2020 correlate with a range of statistics for local labour markets, namely self-containment indexes, labour market dynamics and commuting behaviours. Overall, this paper shows that local labour markets are a useful scale of analysis in detecting the geography of COVID-19 diffusion in the target sample, and verifies the possibility of capturing the spatial dynamics of the epidemic on a smaller territorial scale than NUTS-3 regions do.

KEY-WORDS

COVID-19, COMMUTING, LOCAL LABOUR MARKET, EXPLORATORY SPATIAL DATA ANALYSIS, ITALY

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1. Introduction

Since December 2019, public authorities and private corporations around the world have expended enormous efforts to contain the COVID-19 virus. To cope with this health emergency and to mitigate the epidemic, mass vaccinations, social distancing, lockdown measures and the adoption of non-pharmaceutical interventions have been implemented wherever available and feasible (Pepe et al., 2020). However, effective control and limitation strategies are still problematic and subject to debate in many regions and countries due to the hardship in detecting and containing the infected population. Indeed, "positive individuals not showing fever ≥ 37.5°C or respiratory symptoms represented 73.9% […] of all infections detected in individuals younger than 60 years of age" (Poletti et al., 2020: 3). Positive and asymptomatic individuals are virus carriers who are not susceptible to containment measures since they remain undetected by public authorities, healthcare workers or contact-tracking apps. Even so, "undocumented infections could be the source of eight out of ten documented cases" (Maugeri et al., 2020: 2).

The hardship of carrying out local *test, trace and isolate* strategies undermines the possibility of isolating COVID-19 outbreaks and forces countries to adopt large-scale mitigation strategies at regional or, more often, national levels (Poletti et al., 2020). Digital solutions, such as contact-tracking apps, have proven to be useful tools in investigating contacts among infected and non-infected people on a local scale (Zastrow, 2020). However, these devices are not fully effective without face-to-face and follow-up interviews, which are time and resource consuming (Hellewell et al., 2020). Additionally, the employment and correct use of these devices are far from being widespread practices among citizens (Rowe, Ngwenyama and Richet, 2020). The implementation of large-scale mitigation strategies entails high social and economic costs, which also affect populations and communities whose lives are not directly threatened by the pathogen, whenever mild countermeasures are already effective.

The employment of fine-tuned spatial scales of intervention is essential for public authorities to develop local response schemes—in combination with already available test, trace and isolate strategies (Ren, 2020)—and to reduce the monetary and non-monetary costs of emergency management. The understanding of spatial dynamics of COVID-19 has been extensively debated, but there has been little empirical research on this issue (Anitori et al., 2020; Daniele, 2020; Franch-Pardo et al., 2020; Musolino and Rizzi, 2020; Ren, 2020), which needs to be furtherly investigated. This paper explores the feasibility of tackling local, sub-provincial COVID-19 outbreaks by leveraging data on labour mobility dynamics in Italian Local Labour Markets (LLMs)—*Sistemi Locali del Lavoro*—and variations in mortality rates at the municipal level. Commuting activities are routinized, day-to-day and home-to-work movements across and within cities, provinces and regions (Colleoni, 2013). In Italy, around half of the population commute every day for work or study: 51.6% of the working population and 31.4% of students commute across two or more municipalities (ISTAT, 2018). LLMs employ commuting data to identify territorial areas in which workers, students and their families are more likely to carry out most of their daily activities and their socio-economic interactions (ISTAT, 2015b). Besides work and study, leisure activities, visits to friends and relatives, grocery shopping and other social and interactive activities occur in residential surroundings (Sandow, 2008), where children, adults and retired people engage in face-to-face, repeated and routinized social interactions. However, face-to-face and repeated social interactions are main drivers of the diffusion of COVID-19 (Surico and Galeotti, 2020). Labour mobility dynamics may be an appropriate source of data for capturing the geographical extent of COVID-19 diffusion over a specified territory (Savini et al., 2020), where residents are more likely to engage in face-to-face interactions with their neighbours, colleagues, friends and relatives. This is true independently from the locations where infections occur—workplaces, schools, groceries, or hospitals—and independently from socio-demographic attributes of infected individuals—gender, age, employment status and degree.

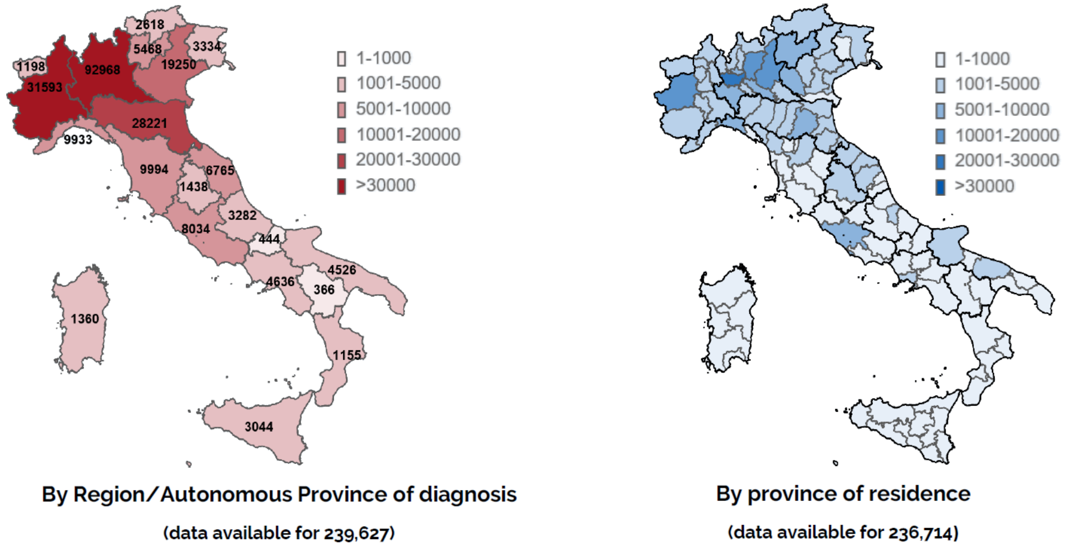
In line with recent studies (Daniele, 2020; Savini et al., 2020; Tortuga, 2020), an exploratory spatial data analysis was performed to investigate variations in mortality rates in the municipalities of the two Italian provinces of Bergamo and Brescia, which are the backbone of Lombardy's economic system (Birindelli, Farina and Rimoldi, 2004) and were among the worst affected areas of the country in early 2020. The investigation was supplemented with an econometric analysis to assess whether and to what extent LLM statistics correlate with the distribution of municipal variations in 2020 mortality rates in the selected sample. This analysis is innovative for at least two reasons. Firstly, it endorses the employment of reported deaths—supplied by the Italian National Institute of Statistics (ISTAT)—to measure the impact of COVID-19 in place of reported infections, since reported infections are downward biased due to unregistered cases. Secondly, it suggests that a comprehensive understanding of COVID-19 spatial dynamics should overcome the limits imposed by administrative boundaries, since "regional administrative boundaries are frequently the result of historical circumstances rather than reflecting present-day social and economic reality and issues" (Radermacher, 2015: 14). LLMs better capture socio-economic dynamics among clusters of municipalities on a smaller geographical scale compared to regions or provinces—NUTS-2 and NUTS-3 regions according to the Nomenclature of Territorial Units for Statistics. As a corollary, LLMs may be smaller and more flexible areas to capture the diffusion dynamics of the COVID-19 virus and, therefore, more suitable regions of intervention to contain and mitigate its effects.

2. SARS-CoV-2 in Italy

The *Severe Acute Respiratory Syndrome Coronavirus 2*, the SARS-CoV-2 or COVID-19 virus, is a coronavirus that heavily affects the upper respiratory system in human beings (Surico and Galeotti, 2020). Due to its viral load, the COVID-19 virus appears to be highly transmissible: estimates of the R_0, the basic reproductive number, range from 1.6 to 3.8 (ISS, 2020a), values higher than for other influenzas or the Ebolavirus, yet lower than for the chickenpox and the smallpox (Surico and Galeotti, 2020). The high transmittal potentiality of this disease has made this virus a global threat due to the capillary diffusion it has had since its first appearance in China. The threat has been exacerbated by the hardship in detecting infected people during the incubation period and in absence of clear symptoms. On a sample of 18,553 Italian positive cases, 5,231 (28.2%) were reported to be asymptomatic, 2,155 (11.6%) displayed few and mild symptoms, 6,828 (36.8%) were affected by minor symptoms, whereas 3,320 (17.9%) and 364 (2.0%) exhibited severe or critical symptoms, respectively—there is no information about the severity of symptoms for 655 (3.5%) positive individuals in the considered sample (ISS, 2020c). Overall, three-quarters of the infected population displays mild or no symptoms at all (Maugeri et al., 2020; Poletti et al., 2020). These are asymptomatic cases who are not tested for COVID-19 positivity unless severe symptoms arise over time or contacts with infected people are confirmed. If not already subject to containment measures, asymptomatic cases result in a latent threat to non-infected populations.

Until late April 2020, Italy had been reported to be the most severely affected country by the COVID-19 virus around the world. After the very first native patient was diagnosed with COVID-19 in the town of Codogno, Lombardy, on the 22nd of February 2020, mild countermeasures had been appointed in several municipalities and provinces in the north of the country. In face of 6,387 confirmed cases and 366 confirmed deaths, more strict measures had been implemented over the entire national territory on the 9th of March 2020. Commercial and industrial activities, as well as public services, had been frozen till the 4th of May 2020, apart from essential ones. From the 4th of May onwards, countermeasures had been gradually eased, making populations' movements more feasible and restrictions more stretched (ISS, 2020b). As of the 22nd of June 2020, 239,627 positive cases and 33,498 confirmed deaths were recorded in Italy. However, the spatial distribution of confirmed cases and deaths within the country proved not to be homogenous throughout the first COVID-19 wave. Figure 1 shows the total number of COVID-19 cases diagnosed in Italy per region and province as of the 22nd of June 2020 (ISS, 2020b).

Figure 1. The total number of COVID-19 cases diagnosed in Italy per region and province as of 22 June 2020



Note: Darker colours identify a higher incidence of COVID-19 cases than light colours.
Source: ISS (2020b).

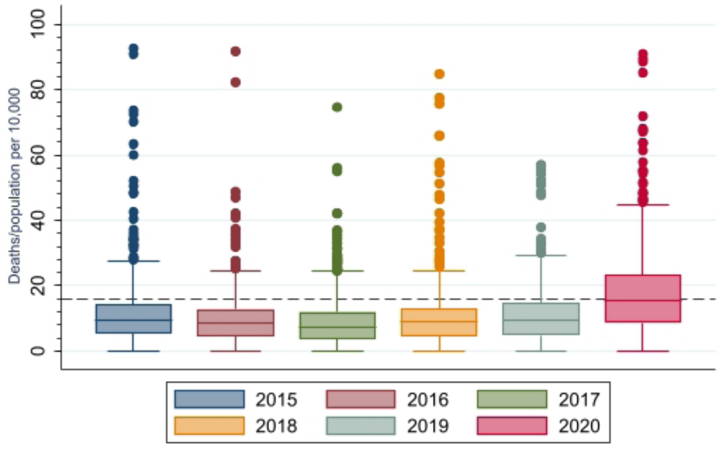
As reported in Figure 1, confirmed cases concentrate in Lombardy, Piedmont, Veneto and Emilia-Romagna, namely northern regions. As of June 2020, Lombardy was the worst affected region in Italy in respect to both confirmed infections and reported deaths (ISS, 2020b), with a cumulative incidence of 925.49 cases per 100,000 inhabitants (ISS, 2020c). The magnitude of COVID-19 in Lombardy makes this region the ideal subject of analysis since the results may be more informative and valuable in critical COVID-19 contexts. The selection of a single-region territorial sample is also preferable given the legal and administrative specificities of healthcare and welfare management in Italy. Even though ordinary laws are issued at the national level, Italian regional administrations are appointed to coordinate and execute several services of public interests on behalf of the central state (Bifulco, 2015). The management of the Italian healthcare system is one of the competencies assigned to regional administrations and it varies from region to region. Dissimilarities in healthcare management turn into different epidemic managements, thus different COVID-19 responses and consequences.

Among the provinces of the same region, health treatments and policies should be considered homogenous. However, Figure 1 shows that reported cases are concentrated in three out of eleven Lombard provinces. 53,891 cases out of 92,968 were localized in the three provinces of Milan, Bergamo and Brescia (ISS, 2020c)—which also accounted for 56.1% of the Lombard population. Yet, 24,211 confirmed cases were reported in the province of Milan, and 10,274 exclusively in the city of Milan (ISS, 2020c). COVID-19 statistics registered in the city and province of Milan may distort the analysis due to the presence of outliers. Therefore, the following analysis focuses only on the two provinces of Bergamo and Brescia and their municipalities, which locate in the north-eastern area of Lombardy.

The two provinces account for 2,384,839 inhabitants, 23.6% of the regional population. 205 municipalities and 1,268,455 inhabitants belong to the province of Brescia, whereas 243 municipalities and 1,116,384 inhabitants to the province of Bergamo, for a total of 448 municipalities (ISTAT, 2020b). Seven municipalities have been excluded from the sample due to an imperfect overlapping between LLMs and provincial administrative boundaries. The definitive sample is thus composed of 441 municipalities, which contain 2,364,853 inhabitants, distributed on a surface of 7,356 square kilometres. Considering the seven excluded municipalities, the selected sample represents 99.2% of the combined populations of the two provinces and 97.7% of their surfaces.

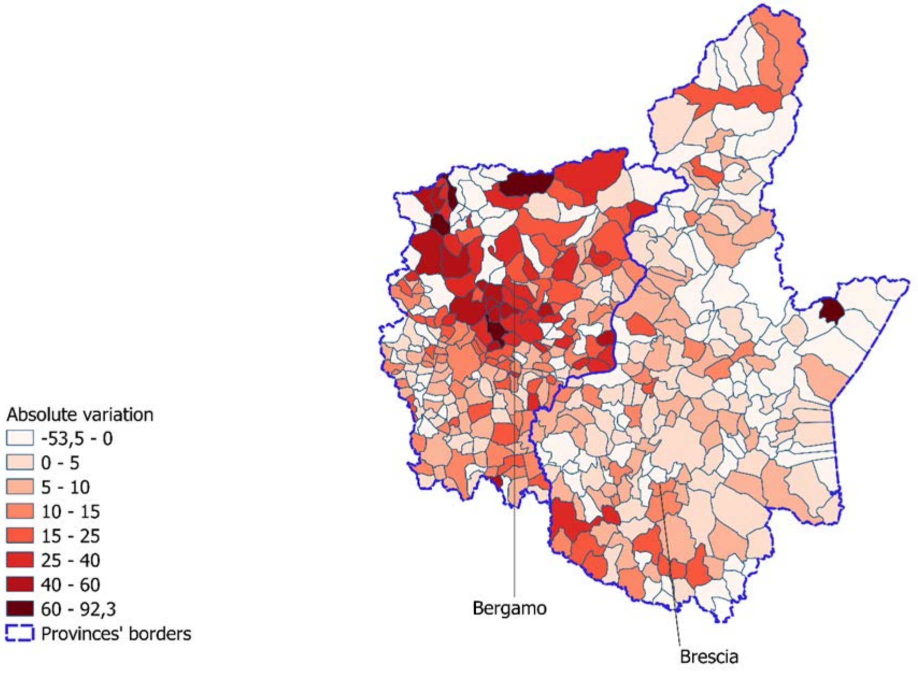
Figure 2 illustrates the non-parametric distribution of the computed mortality rates per municipality and per year. The average 2020 mortality rate equals 18.37, while the average 2015-2019 mortality rate is 10.42. Even before the implementation of lockdown measures in Italy, this corresponds to a 76.3% increase in the 2020 mortality rate, with respect to an overall 2020 population increase of 0.3% compared to the average 2015-2019 population. As highlighted by the dashed black line, the median value for the 2020 mortality rates, which equals 15.45, is higher than the third quartiles' values of each previous year. Furthermore, 2020 mortality rates show higher variability than 2015-2019 mortality rates. Apart from the outliers, the 2020 interquartile range and the distance between minimum and maximum values for the 2020 mortality rates are wider compared to the other years.

Figure 2. Distribution of mortality rates per municipality per year



Note: The colours refer to mortality rates from 9 February to 14 March for the years 2015 to 2020.
Source: Author's elaboration with STATA on data by ISTAT (2020b; 2020d).

Figure 3. Variations in 2020 mortality rates per municipality in Bergamo and Brescia provinces



Note: Variations are expressed as the differences among 2020 mortality rates and the average 2015-2019 mortality rates, from 9 February to 14 March. Lighter colours identify negative or lower municipal variations, while darker colours identify higher, positive municipal variations. The provinces' borders are highlighted in blue.

Source: Author's elaboration with QGis Software on data by ISTAT (2020b; 2020d).

Figure 3 portrays the variations in mortality rates over the territory of the two provinces at the municipal level. The variations also fluctuate towards negative values for those municipalities where the mortality rate decreased in the considered period. The left side of Figure 3 corresponds to the province of Bergamo, while the one on the right side to the province of Brescia. In Bergamo's province, as shown by the choropleth map, high positive variations have been registered in 2020 mortality rates. The map suggests that these high mortality rates mainly cluster in the northern half of the province territory, although in the same area both positive and negative variations co-exist. Unlike the southern half of Bergamo's province, which is morphologically flat, the northern area is mainly mountainous and crossed by valleys. Indeed, mountain municipalities are more isolated, less connected and less populated than municipalities at the bottom of the same valleys (Consolandi and Rodeschini, 2020).

For those mountain municipalities in which negative mortality rates' variations were registered, it is assumed that geographic and social isolations limited the diffusion of COVID-19, at least in its first wave. However, in some other mountain municipalities, COVID-19 consequences were traumatic; this may be due to the age structure of these communities' populations and the absence of close, adequate healthcare services (Consolandi and Rodeschini, 2020).

Variations in Brescia's province are lower than the ones registered in Bergamo's province. More precisely, the eastern area of the province accounts for negative or mild positive variations, which implies that 2020 mortality rates are lower, in line or slightly higher than the average 2015-2019 mortality rates. Yet, in the lower bound of this province, municipalities' absolute variations tend to increase. Peculiarly, despite the spatial contiguity between the two provinces, mortality rates' variations diverge alongside border municipalities.

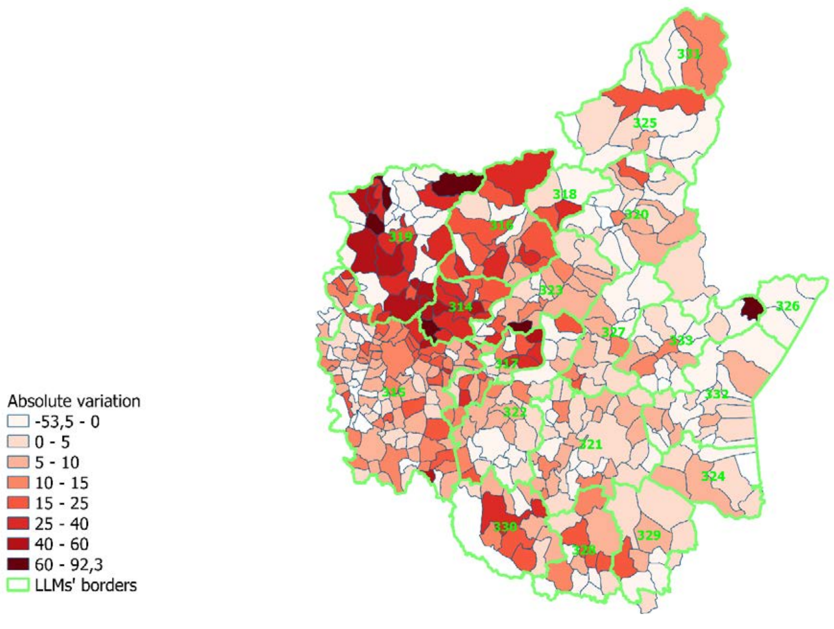
3. Local Labour Markets

Local Labour Markets are functional areas defined by employment self-containment indexes and labour mobility data which are made up of several municipalities, their fundamental territorial units (ISTAT, 2015a). These areas capture workers and students' daily movements over a specified territory, regardless of supra-municipal administrative boundaries (ISTAT, 2015b). Indirectly, LLMs tend to capture most of the socio-economic interactions of the working and residential population, which gravitate towards work and residential surroundings (ISTAT, 2015b; Casado-Díaz, Martínez-Bernabéu and Rowe, 2017). There, people manage most of their social and economic interactions and they are more likely to engage in frequent face-to-face contacts. However, close and repeated contacts among infected and non-infected people are exactly what most favours the spreading of the COVID-19 virus. Accordingly, LLM contours may be sufficiently informative in respect to the extent of COVID-19 outbreaks and place-based diffusion patterns.

LLMs are clusters of municipalities defined by self-containment indexes, employment dynamics and commuting behaviours; they are territorial partitions that reflect socio-economic functions on a smaller scale of analysis than NUTS-3 regions do. In Italy, these sources of data have been employed since 1981 (ISTAT, 2015b). The flexibility of LLMs in capturing socio-economic activities over a target territory and their development over time (Sforzi, 1999) makes them a perfect candidate to explore COVID-19 spatial dynamics.

Italian LLMs are identified through the employment of three metrics: the spatial contiguity and the cohesion among municipalities, the intensity and the direction of commuting flows among municipalities, and the dimensions of residential and working populations (ISTAT, 2015a). LLMs are calibrated to maximize employment and commuting homogeneity across municipalities. The specific criteria adopted by ISTAT to identify LLMs are: (i) the self-containment indexes for both labour supply and demand, and (ii) the dimension of the working population (ISTAT, 2015b). On the one hand, self-containment indexes are measures of internal cohesion as a function of employment dynamics and commuting behaviours: "Supply-side self-containment describes the extent to which local residents of an area access jobs in that area rather than commute elsewhere for work; demand-side self-containment describes the extent to which local jobs are filled by local residents rather than workers who commute in from surrounding areas" (Beecham and Slingsby, 2019: 1218). On the other, ISTAT established that each LLM must contain at least 1,000 working inhabitants. By following these criteria, ISTAT detected 683 LLMs in Italy in 2001 and 611 in 2011 via census data. 20 of these 2011 LLMs mainly locate in the two provinces of Bergamo and Brescia and contain all the 411 municipalities; each municipality belongs to a single LLM.

Figure 4. Variations in 2020 mortality rates per municipality per Local Labour Market



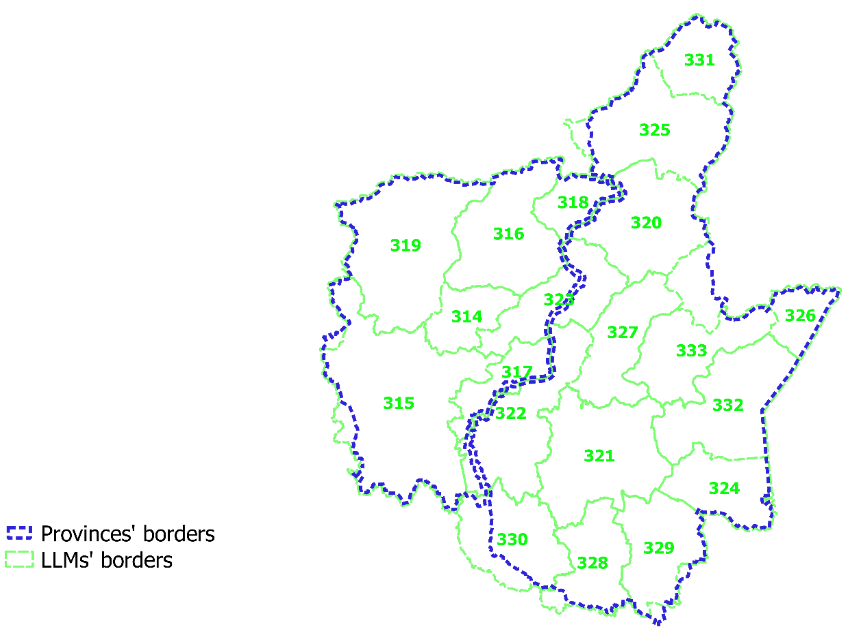
Note: Variations are expressed as the differences among 2020 mortality rates and the average 2015-2019 mortality rates, from 9 February to 14 March. Light colours identify negative or lower municipal variations, while dark colours identify higher, positive municipal variations. LLMs' borders in light green, LLMs numbered from 314 to 333 following the ISTAT enumeration.

Source: Author's elaboration with QGis Software on data by ISTAT (2020c; 2020d).

Figure 4 shows a combined representation of the 441 municipalities and the 20 LLMs that locate in the two provinces. The biggest LLM in the sample is LLM 315—Bergamo's—which accounts for 123 municipalities and 254,257 commuters. The smallest one is LLM 326, which gathers 3 municipalities and 1,384 commuters. As a whole, the 20 LLMs account for 873,859 resident workers, 847,525 jobs and 665,240 internal commuters. 15 LLMs are embedded in industrial district environments and their firms mainly operate in mechanic, metallurgic, petrochemical and textile industrial sectors. Only LLMs 325 and 331, located in the extreme North of Brescia's province, are devoted to non-manufacturing economic activities, such as tourism in mountain areas.

The worst-hit area by COVID-19 corresponds to the LLM 314—Albino's—located north of the city of Bergamo, at the core of the homonymous province. This LLM contains the town of Nembro, sadly famous for the magnitude of COVID-19 impact on elders (Consolandi, 2020). Apart from LLMs 323 and 330—Darfo Boario's and Orzinuovi's—and few other municipalities, the overlap between provinces and LLMs is mostly perfect, as displayed in Figure 5.

Figure 5. Overlayered provinces and LLMs



Note: Provincial borders are intentionally offset to better represent the overlap, otherwise unclear.
Source: Author's elaboration with QGis Software on data by ISTAT (2020c).

4. Data and methodology

4.1 Data

To explore COVID-19 spatial dynamics, three different sources of data are necessary: (i) the residential population per municipality and per month from 2015 to 2020 (ISTAT, 2020b); (ii) the reported deaths per municipality and per day from 2015 to 2020 (ISTAT, 2020d); and (iii) LLM statistics on labour mobility, employment dynamics and economic performances for all LLMs which belong to the target territorial area (ISTAT, 2020c). Data are accessible and available for all the municipalities and LLMs of the two provinces, retrievable by ISTAT databases.

Several aspects need to be taken into consideration before displaying the analysis and its findings. Maugeri et al. (2020) argued that the employment of officially reported infections may lead to biased results since asymptomatic positive cases are not captured from the surveillance systems. Moreover, the number of reported infections fluctuates with respect to the number of implemented swabs and serological assays. To avoid biased results, this paper leverages the number of reported deaths and the computed 2020 mortality rates' variations, as previously done in Tortuga (2020) and ISTAT (2020a).

Nevertheless, the implementation of reported deaths to assess the impact of COVID-19 is not uncontroversial, since ISTAT details the total number of deaths per day, without reporting the corresponding cause of death (ISTAT, 2020d). The absolute values of such 2020 variations are due to a series of joint causes, among which COVID-19. These variations can originate from: (i) the direct effects of COVID-19 symptoms; (ii) the indirect effects of COVID-19 symptoms on already-ill patients, who nevertheless die of preceding diseases; (iii) the indirect effect of COVID-19 emergency, which subtracts resources to the everyday functioning of the healthcare systems (ISTAT, 2020a); (iv) the increase of corollary deaths, such as suicides or domestic violence due to lockdown measures; (v) the reduction of other causes of fatalities, such as car accidents, leisure or workplace injuries; (vi) other undetected and latent factors. Assessing the causal inference of the COVID-19 epidemic on positive mortality rates' variations is out of this paper's scope. However, since no other shock is reported in the first months of 2020, these variations are assumed to be at least correlated with COVID-19 under a ceteris paribus rule.

Data on residential population are retrievable at Demo.ISTAT (ISTAT, 2020b), disaggregated monthly at the municipal level. Mortality rates—measured as the ratio between reported deaths and residential populations times 10,000—and their variations have been computed for each municipality and each year, for a timeframe that ranges from the 9th of February to the 14th of March 2020. Assuming the virus was already spreading globally in January (Zehender et al., 2020), given the introduction of lockdown measures at the national level on the 9th of March, the selected timeframe is meant to capture municipal variations in mortality rates throughout the month before the introduction of labour mobility restrictions. However, the Italian National Institute of Health reported an average 6-day timeframe between hospitalization and death for positive deceased patients in COVID-19 first-wave months (ISS, 2020d). This considered, the selected timeframe extends till the 14th of March 2020 to capture deaths caused by infections contracted before the lockdown but registered only after the 9th of March.

LLM data are also retrievable from ISTAT databases. Partially updated in 2015, they date back to the 2011 census. The selected datasets comprise variables on the number of municipalities and the intersection with other administrative bodies, the magnitude and directions of labour mobility, the LLM labour demand and supply, the self-containment indexes, LLM industrial performances, the socio-demographic attributes and the LLM surface and residential density.

4.2 Methodology

This study combines an exploratory spatial data analysis (ESDA) and the estimation of a spatial autoregressive (SAR) model (Anselin, 1996). The ESDA addresses the spatial autocorrelation among municipalities in respect to labour mobility and variations in mortality rates. The task is performed via the GeoDa Software to investigate both global and local Moran indexes (Moran, 1948; Anselin, 1995; 1999). Mortality rates are computed at the municipal level, whereas the labour mobility indicators are obtained from the LLM database by ISTAT and assumed to be homogenous among the municipalities of the same LLM. The Moran's I statistic offers a measure of global spatial autocorrelation, computed as the cross-product statistic of a standardized variable and its spatial lagged form (Moran, 1948; Cliff and Ord, 1973). Unlike the *global* counterpart, the univariate *local* Moran's I aims at detecting clusters and outliers among the selected territorial units of analysis (Anselin, 1995)—in this case, the 411 municipalities.

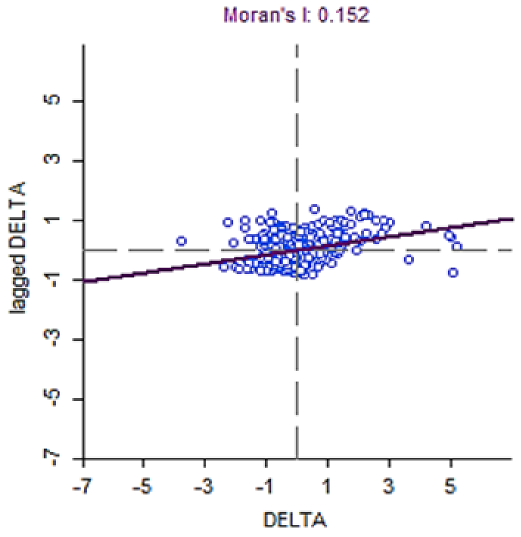
The ESDA procedure is supported by the estimation of a cross-sectional SAR model to tackle the behaviour of mortality rates among contiguous territorial units (Drukker et al., 2013; Drukker, Prucha and Raciborski, 2013). Indeed, while the ESDA explores whether and to what extent municipalities are spatially autocorrelated, by offering a first graphical representation of COVID-19 impact, the procedure does not inform the researcher about the relationships between the dependant variable—variations in mortality rates in 2020 per municipality—and LLM statistics, such as self-containment indexes or relational cohesion. To understand spillover effects, OLS estimators in linear regression are usually not consistent with a spatial lag of the dependent variable (Kelejian and Prucha, 1998). A naïve check with OLS estimators was performed; however, residuals proved to be spatially autocorrelated. Therefore, the model's parameters are estimated with a quasi-maximum likelihood (QML) procedure, whose estimators are robust when the normality of the residuals' distribution is violated (Lee, 2004).

5. Global and local spatial autocorrelation

To investigate the distribution of mortality rate variations over the selected territory, the analysis focuses on the spatial autocorrelation among continuous municipalities. The Moran's I is a global measure of spatial autocorrelation for the entire selected territory (Moran, 1948). Figure 6 shows the Moran scatter plot and the Moran's I for the 441 selected municipalities. The investigated variable is the variation in mortality rate at the municipal level— DELTA—and its spatial lagged form—lagged DELTA.

The Moran's I scores 0.152, which implies a significant and positive spatial autocorrelation—0.152 is also the slope coefficient of the fitting line. The hypothesis of spatial randomness is rejected—the standard deviation equals 0.0157 at 99,999 permutations, with a pseudo-p-value of 0.00001. However, the Moran's I and the Moran scatter plot do not provide any information about the local indicators of spatial autocorrelations, the presence of clusters and the detection of outliers (Anselin, 1995; 1996). Accordingly, even though this procedure confirms the existence of overall spatial autocorrelation in the selected sample, it does not offer a geo-referenced representation of the explored phenomenon.

Figure 6. Moran's I statistic and Moran scatter plot

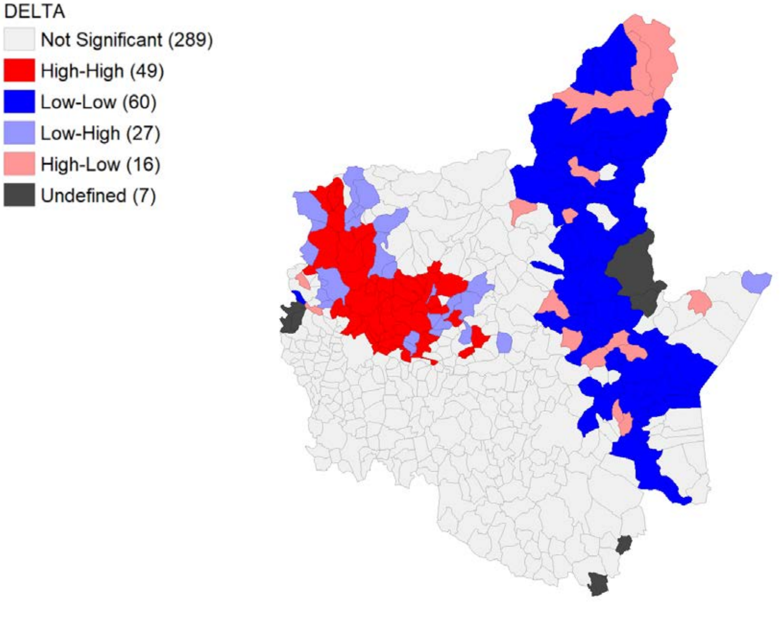


Note: The x-axis represents the variations in mortality rate at the municipal level, while the y-axis represents its lagged form. Blue dots represent each observation, or each municipality. The purple line linearly fits the cloud of dots; the value of the Moran's I statistic is the slope coefficient of the fitting line.

Source: Author's elaboration with GeoDa Software on data by ISTAT (2020b; 2020d).

More details are added by the local analysis carried out with a univariate local Moran's I. As shown in Figure 7, which displays how and where the municipalities are spatially autocorrelated considering a p-value of 0.05, two isolated clusters of municipalities emerge, although with opposite features. The bright red cluster corresponds to contiguous municipalities where high positive variations in 2020 mortality rates had been registered in the selected time span. On the contrary, municipalities that belong to the blue cluster are associated with low mortality rate variations. The red cluster, composed of 49 municipalities, corresponds to the core of Bergamo's province and is entirely located within its provincial borders. It comprises the municipalities of the northern metropolitan area of Bergamo and the ones located in the Val Brembana and the lower Val Seriana valleys. On the right side of the representation, the blue cluster locates in the eastern territory of Brescia's province and depicts a blue belt that extends from north to south, at the border with Veneto and Trentino Alto-Adige regions. The blue cluster is made up of 60 municipalities, which—again—entirely pertain to the same province. Seven municipalities remain *undefined* due to the imperfect overlap among territorial units of analysis. The software assigns light blue and light pink colours to outlier municipalities—27 and 16, respectively—at clusters' borders, which is typical of spatial heterogeneity. 289 municipalities are not significant for the Moran's I statistic; among these 289 municipalities lie the cities of Bergamo and Brescia, administrative centres of the two provinces. Figure 8 displays the significance map of the univariate local Moran's I and reports the p-values of each territorial unit.

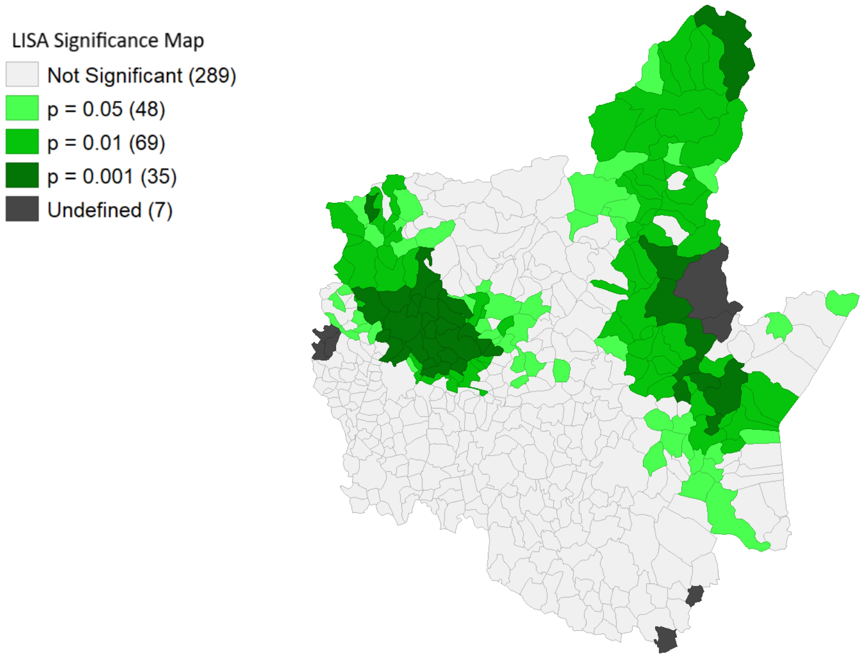
Figure 7. Univariate local Moran's I statistic



Note: Bright-red coloured cluster gathers municipalities with high positive 2020 mortality rates' variations, while blue coloured cluster gathers municipalities with low positive 2020 mortality rates' variations.

Source: Author's elaboration with GeoDa Software on data by ISTAT (2020b; 2020d).

Figure 8. Significance map of the univariate local Moran's I statistic

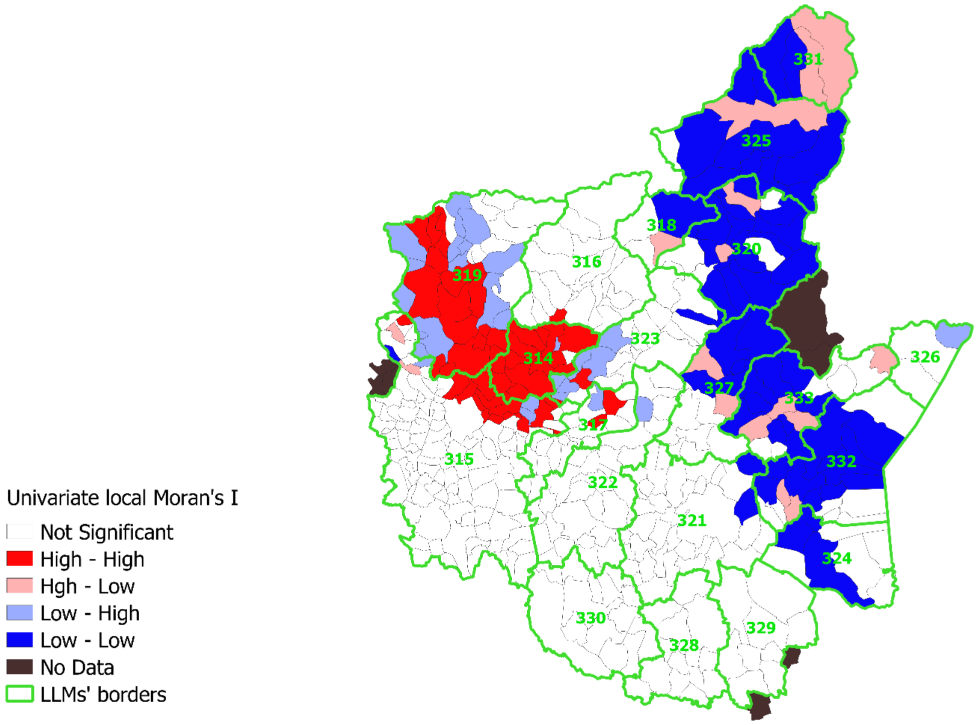


Note: Registered p-values for the Univariate Local Moran's I for each municipality.
Source: Author's elaboration with GeoDa Software on data by ISTAT (2020b; 2020d).

Interestingly, each of the two detected clusters pertains to a single province, but they do not cross the respective provincial borders. Yet, none of the two clusters covers the entire provincial territory. This suggests that a deeper comprehension of COVID-19 impact should address a more accurate and smaller territorial unit than a NUTS-3 does. The variations in mortality rates registered in 2020 in respect to the average 2015-2019 mortality rates are not homogenous among the municipalities of the same province. The adoption of the LLM spatial scale of analysis might solve this issue. A first graphical representation of the overlap between the results of the univariate local Moran's I and the LLM partition is offered in Figure 9.

As shown in Figure 9, 32 red-coloured municipalities out of 49—spatially autocorrelated municipalities displaying high positive 2020 mortality rates' variation—exclusively pertain to LLMs 314 and 319. Similarly, although displaying a fuzzier pattern, 56 blue-coloured municipalities out of a total of 60 concentrate in LLM 320, 325, 327, 332 and 333. Interestingly, in all the remaining LLMs, municipalities are not significant to the univariate local Moran's I statistic and, thus, are not considered spatially autocorrelated in respect to the response variable DELTA.

Figure 9. Overlayered univariate local Moran's I and LLMs



Note: LLMs' borders in light green, superimposed on the Univariate Local Moran's I statistic's map.
Source: Author's elaboration with QGis Software on data by ISTAT (2020b; 2020c; 2020d).

6. Econometric analysis

6.1 Model specification and estimation

So far, the ESDA outlined that: (i) the overall sample is spatially autocorrelated in respect to variations in 2020 mortality rates at the municipal level; (ii) two clusters, characterized by opposite behaviours in respect to the response variable, locate respectively in only one of the two provincial territories, without covering them entirely and without crossing over their provincial administrative boundaries; (iii) spatially autocorrelated and clustered municipalities locate into 10 out of 20 LLMs. The ESDA suggests that LLMs may be appropriate sub-provincial territorial partitions that somehow grasp the spatial dynamics of COVID-19 impact. The econometric analysis addresses the existing interactions between the response variable DELTA and the socio-economic dimensions of LLMs, dimensions that are assumed to be homogenous among all the municipalities of each LLM.

A cross-sectional SAR model is specified and estimated by employing QML estimators. A naïve linear regression model was initially specified and estimated through an OLS procedure, but residuals proved to be spatially autocorrelated. A SAR model followed, and ML estimators were initially employed, being these more statistically efficient (Kelejian and Prucha, 1998; Drukker et al., 2013). Post-estimation tests, however, demonstrated this second model's residuals not being normally distributed. Therefore, a QML procedure for parameters estimation was performed to get standard errors robust to non-normality. To avoid issues in interpreting one-unit changes in regressors' coefficients due to different scales and units of measurement, all the regressors have been standardized. In order to take into account spillover effects, a spatial weighting matrix was specified on a second-order contiguity criterion basis, as already done in the ESDA analysis. Here is the specification of the cross-sectional SAR model.

$$DELTA = \beta_0 + \beta_1 Z_{SC\_DOM} + \beta_2 Z_{SC\_OFF} + \beta_3 Z_{IIRCLCONN} + \beta_4 Z_{SUP2011} + \beta_5 Z_{POSTI\_LAVORO} + \beta_6 Z_{SOCIO\_DEM} + \beta_7 Z_{MANIFATTURA\_PES} + \beta_8 W_{DELTA} + e$$

Where:

- DELTA is the response variable, the computed variation in the 2020 mortality rate per municipality compared to the average 2015-2019 mortality rates.
- SC_DOM, the self-containment index for labour demand, measures how much of the labour demand is filled by the LLM—a ratio between within-LLM-working residents over LLM jobs. It ranges from a minimum of 0 to a maximum of 1.
- SC_OFF is the self-containment index for labour supply, which measures how much the labour supply is absorbed by the LLM—a ratio between within-LLM-working residents over total employed LLM residents. It ranges from a minimum of 0 to a maximum of 1.
- IIRCLCONN measures the consistency of LLM municipalities' relations; it is computed as the observed number of connections among pairs of LLM municipalities over the highest possible number of connections.
- SUP_2011 measures the LLM extent in square kilometres from 2011 census data.
- POSTI_LAVORO measures the total working population of an LLM, independently from workers' intra- or extra-LLM residency.
- SOCIO_DEM captures territorial, urban and socio-demographic attributes of LLM residential populations. This variable was created by ISTAT (2015c) and classifies LLMs in three categories by taking into account the residential density, the urban structure, the ageing index, the total-age dependency ratio, the population age structure, the child-elderly ratio and the active-population turnover index. It takes value 1 when a young, active population lives in extended, dense, urban and suburban neighbourhoods, porously crossed by commuting routes. It takes

value 2 when LLM municipalities are low-density, family-friendly small towns in peripheral and internal areas. It takes value 3 when LLM municipalities, mainly populated by aged citizens and characterized by slow population growth, located in rural and/or mountain areas.

- MANIFATTURA_PES is a dummy variable that takes value 1 if heavy industry sectors, such as petrochemical and metallurgic ones, are leading industries in the LLM area; otherwise, it takes value 0.
- W_{DELTA} is the spatial lag of the response variable DELTA.

Summary statistics of non-standardized variables are reported in Table 1. The model does not include a spatially autoregressive error term since it proved to be statistically non-significant in all previous model's specifications.

Table 1. Summary statistics for 441 observations, non-standardized variables

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
DELTA	8.064	16.252	-53.480	92.343
SC_DOM	0.790	0.054	0.669	0.861
SC_OFF	0.736	0.082	0.620	0.861
IIRCLCONN	70.420	17.859	31.984	100
SUP_2011	548.079	265.888	140.888	935.780
POSTI_LAVORO	111,980	124,064	1,290	300,509
SOCIO_DEM	1.492	0.837	1	3
MANIFATTURA_PES	0.778	0.416	0	1

Source: Author's elaboration with STATA on data by ISTAT (2020c; 2020d).

Table 2 reports the estimation of the model's coefficients with the QML procedure, whose regressors have been standardized. Their interpretation is implemented by the effects' analysis, reported in Table 3 since the spatial lag of the response variable also influences the covariates and the coefficients reported by the software. Table 3 confirms the results of the SAR model estimation with respect to the sign and magnitude of the effects. Interestingly, all the average direct effects are higher than the average indirect ones, implying that own-municipality, intra-LLM effects impact more on the conditional mean of DELTA in each of the sample municipalities than spillover effects.

Table 2. SAR linear regression model with QML estimators

	Coef.	*95% Conf. interval*	
Labour-demand self-containment index (Z_{SC_DOM})	3.905*** (1.509)	0.946	6.863
Labour-supply self-containment index (Z_{SC_OFF})	-5.906 *** (1.957)	-9.742	-2.070
Intra-LLM relational consistency index ($Z_{IIRCLCONN}$)	-3.701*** (1.354)	-6.355	-1.046
LLM surface – Km² (Z_{SUP_2011})	-15.166*** (4.569)	-23.034	-7.299
LLM working population (Z_{POSTI_LAVORO})	16.455*** (4.569)	7.500	25.410
LLM socio-demographic index (Z_{SOCIO_DEM})	2.502* (1.438)	-0.317	5.321
Heavy-industry prevalence ($Z_{MANIFATTURA\_PES}$)	-1.638** (0.853)	-3.309	0.334
Spatial lag of DELTA (W_{DELTA})	0.412*** (0.105)	0.205	0.620
Cons.	5.050*** (1.044)	3.004	7.097
Obs.	441		
Pseudo R^2	0.153		
Log pseudo-likelihood	-1814.1649		

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Author's elaboration with STATA on data by ISTAT (2020c; 2020d).

The coefficient of the spatial lag of the response variable is positive and statistically significant, implying spatial autocorrelation between DELTA in one municipality and DELTA in neighbouring municipalities. All employed regressors are statistically significant, even though SOCIO_DEM and MANIFATTURA_PES at 10% and 5% significance levels, respectively. With the exclusion of SC_DOM, POSTI_LAVORO and SOCIO_DEM regressors, which are positively correlated, the others are negatively correlated to the response variable DELTA. The pseudo R^2 reported by the STATA software is 0.153.

Table 3. Direct, indirect and total effects on the conditional mean of DELTA

	dy/dx	*Std. Err.*	*z*	*P>z*	*95% Conf. Interval*	
Direct						
Z_SC_DOM	3.943	1.516	2.600	0.009	0.971	6.914
Z_SC_OFF	-5.963	1.965	-3.040	0.002	-9.814	-2.113
Z_IIRCLCONN	-3.737	1.359	-2.750	0.006	-6.401	-1.072
Z_SUP_2011	-15.314	4.016	-3.810	0.000	-23.184	-7.444
Z_POSTI_LAVORO	16.616	4.577	3.630	0.000	7.644	25.587
Z_SOCIO_DEM	2.526	1.450	1.740	0.081	-0.316	5.369
Z_MANIFATTURA_PES	-1.654	0.860	-1.920	0.055	-3.340	0.033
Indirect						
Z_SC_DOM	2.197	0.994	2.210	0.027	0.248	4.146
Z_SC_OFF	-3.323	1.447	-2.300	0.022	-6.158	-0.488
Z_IIRCLCONN	-2.082	0.908	-2.290	0.022	-3.861	-0.303
Z_SUP_2011	-8.534	3.286	-2.600	0.009	-14.974	-2.094
Z_POSTI_LAVORO	9.259	3.718	2.490	0.013	1.972	16.546
Z_SOCIO_DEM	1.408	0.923	1.530	0.127*	-0.401	3.217
Z_MANIFATTURA_PES	-0.921	0.593	-1.550	0.120*	-2.084	0.241
Total						
Z_SC_DOM	6.140	2.210	2.780	0.005	1.808	10.471
Z_SC_OFF	-9.286	2.920	-3.180	0.001	-15.009	-3.564
Z_IIRCLCONN	-5.819	1.968	-2.960	0.003	-9.675	-1.963
Z_SUP_2011	-23.848	5.770	-4.130	0.000	-35.156	-12.540
Z_POSTI_LAVORO	25.875	6.736	3.840	0.000	12.673	39.076
Z_SOCIO_DEM	3.934	2.249	1.750	0.080	-0.473	8.342
Z_MANIFATTURA_PES	-2.575	1.371	-1.880	0.060	-5.261	0.111

Note: The table reports the average effects of listed variables on DELTA, computed with delta method; * = p > 0.1.
Source: Author's elaboration with STATA on data by ISTAT (2020c; 2020d).

6.2 Discussion

The labour-demand self-containment index tends to one—its maximum—when the number of within-LLM-working residents equals the number of LLM jobs. This is to say that if the number of within-LLM-working residents is lower than the number of jobs offered in each LLM, the residual labour supply comes from extra-LLM commuters. Differently, the labour-supply self-containment index tends to one—again, its maximum—when the number of within-LLM-working residents matches the total number of employed LLM residents. This is to say that if the number of within-LLM-working residents is lower than the total number of employed LLM residents, a fraction of employed LLM residents commutes outside their respective LLM municipalities (ISTAT, 2015a; 2015b). Jointly considered, the two indexes show that municipalities that belong to less attractive labour markets, whose job demand is mainly filled by working residents, display high DELTA values.

The interpretation of self-containment indexes' regressors is enriched by the analysis of the intra-LLM relational consistency index and the working population per LLM. The intra-LLM relational consistency index measures the relational consistency of LLM municipalities, and it is negatively correlated with DELTA. The relational consistency can be interpreted as the strength of municipal networks within their respective LLM. High relational consistency implies a highly interconnected network of municipalities within each LLM: the more workers of LLM municipalities commute towards other municipalities of the same LLM, the higher the intra-LLM relational consistency index. POSTI_LAVORO measures the total working population of each LLM. The model estimation suggests that LLMs and, consequently, municipalities that attract more workers also register high DELTA values. This interpretation is confirmed by Table 3, which reports the highest values for direct, indirect and total effects for the POSTI_LAVORO variable.

The variable SUP_2011 grasps the geographical extent of each local labour market in square kilometres. Ceteris paribus, the regression coefficient suggests that more extended LLMs registered lower variations in the response variable. This result is confirmed by the effects' analysis, which shows that standardized LLM surfaces have a statistically significant and negative effect on the conditional mean of DELTA. This is true either for the effect of the LLM surface on the conditional mean of the dependent variable in the same municipality—own effect—or for the effect of SUP_2011 on the conditional mean of the dependent variable in neighbouring municipalities—spillover effect. Compared to the other regressors, the LLMs' surface generates one of the highest marginal effects on the response variable.

SOCIO_DEM, the LLM socio-demographic index, captures urban and demographic features of the municipalities of each LLM, as in ISTAT (2015c). As reported in Table 2, the higher the LLM socio-demographic index, the higher is the dependent variable, somehow implying that rural areas suffered higher and positive 2020 mortality rates' variations than other urban or suburban regions. This is in line with Consolandi and Rodeschini (2020), who argued that mountain municipalities may have suffered more the impact of COVID-19 due to their demographic structures—the share of aged citizens over the total population is higher in mountain communities than in other areas—and their distance from adequate healthcare services. It should be noted that the indirect effect of the socio-demographic index on the conditional mean of the dependent variable is not statistically significant. However, its direct and total effects are both positive and statistically significant, suggesting that the SOCIO_DEM total effect is mainly driven by its own-municipality effect.

At the industry level, MANIFATTURA_PES registers whether LLMs specialize in petrochemical, mechanical and metallurgic industrial sectors, and it is specified in the SAR model as a dummy variable. Apart from LLM 322, which is not an industrial district, this dummy variable approximates the economic structure of each LLM since it detects both industrial agglomerations in the form of industrial districts (Sforzi, 1999), and the prevalence of heavy industry sectors among the LLM economic activities. The SAR model estimation reports a negative and statistically significant coefficient for the heavy-industry dummy. Like the LLM socio-demographic index, the marginal effects are in line with the regression's outputs, even though the indirect effect of the heavy-industry dummy variable on the conditional mean of neighbouring municipalities' DELTA is not statistically significant. It suggests that municipalities located in heavy industry districts registered lower variations in the 2020 mortality rate. This may be due to the peripheral collocation of industrial districts in respect to urban agglomerations, the plants' density within those districts as well as the sizable dimensions of the productive plants—a suitable characteristic for improved workplace social distancing among employees.

Overall, the SAR model so far estimated offers a first exploratory image of the geography of COVID-19 in its first wave in Italy, by taking into account variations in 2020 mortality rates per municipality, labour mobility and economic performances of LLM regions. By leveraging on the econometric analysis' outputs, LLMs can be classified as *closed* and *open* ones. Closed LLMs display high values of both labour self-containment indexes, high values of intra-LLM relational consistency and intra-LLM commuting flows. Closed LLMs can be thought of as peripheral, vast, non-attractive and self-reliant local markets embedded in industrial districts, whose dynamics are hardly related to fluctuations in other LLMs' environments. On the contrary, open LLMs experience substantial in- and out-commuting flows, which span across municipalities of different LLMs. Open LLMs are attractive, urban, small-scale and non-specialized labour markets, whose labour demand is fulfilled by extra-LLM workers and commuters.

All regressors considered, the econometric analysis shows that municipalities which belong to closed LLMs exhibit lower 2020 variations in mortality rates compared to municipalities that belong to open LLMs. As already explained in Section 4.1, in this paper positive 2020 variations in mortality rates are assumed to be at least correlated with the COVID-19 epidemic under a ceteris paribus rule. The analysis suggests that the impact of COVID-19 on closed LLMs is less traumatic than for open LLMs' areas. However, due to the very same isolation which in some cases preserves closed LLMs from the spreading of COVID-19, other closed LLMs experienced traumatic consequences from the diffusion of the pathogen. Indeed, the demographic structure of these LLMs and the distances from healthcare services generate favourable conditions for the diffusion of COVID-19 and its negative externalities.

7. Conclusions and implications

Albeit in an exploratory fashion, this paper has shown that LLMs are a useful scale of analysis in detecting the spatial geography of the COVID-19 virus in the two provinces of Bergamo and Brescia. This paper has verified the possibility of capturing the epidemic in its spatial diffusion on a smaller territorial scale than the NUTS-3 regions do. Additionally, it has demonstrated that the methodology is viable and potentially extendable to wider regions and territorial units. Indeed, routes, intensity, size and self-containment measures of labour mobility are crucial elements for the development of an advanced comprehension of the spatial dynamics of COVID-19.

By rejecting the null hypothesis of spatial randomness, the analysis of the Moran's I statistic confirmed the presence of spatial autocorrelation among the selected sample of 441 municipalities. Two clusters of contiguous municipalities, for a total of 109 municipalities, and 43 outliers were detected by employing the univariate local Moran's I. The procedure emphasized the presence of 49 contiguous municipalities with high positive variations in 2020 mortality rates in the northern metropolitan area of the city of Bergamo, and a second cluster made up of 60 municipalities with low positive variations in 2020 mortality rates, which was located east in the province of Brescia. Both these clusters are located entirely in only one of the two provinces, respectively, and did not cross over provincial borders.

By specifying and estimating a cross-sectional SAR model with QML estimators, the econometric analysis proved the spatial distribution of 2020 mortality rates' variations at the municipal level to be consistent with the LLM geographical scale. The employed regressors adequately grasped the variability of DELTA, the response variable, as confirmed by the goodness-of-fit measure. Variations in 2020 mortality rates at the municipal level are significantly associated—both positively and negatively—with labour markets' self-containment indexes, attractiveness, dimensions, extents and basic socio-economic indicators. As a whole, municipalities that belong to an *open* LLM display higher positive variations in 2020 mortality rates than the others do. Indeed, municipalities that belong to *closed* LLMs are less subject to external commuting activities and tend to exhibit lower variations in 2020 mortality rates. However, the condition of social and geographical isolation can turn against the residential population, who is distant from appropriate healthcare services—as it happened in some mountain municipalities or villages.

Limits in detecting infections and asymptomatic virus carriers via surveillance systems and digital contact-tracking apps require further efforts in grasping the spatial dynamics of COVID-19 diffusion. This paper has demonstrated the usefulness of data on labour mobility, a key resource for the definition of a fine-tuned spatial scale of analysis and intervention to counteract COVID-19. By employing LLM statistics, healthcare and public authorities may be able to define more appropriate perimeters to contain and mitigate COVID-19, regardless of the places in which the infections occurred, the individual attributes of the infected population, the sources of the infections and the nature of the displayed symptoms. Indeed, by operating at the sub-provincial level, it would not be necessary to extend containing measures to populations not directly threatened by the pathogen. Consequently, the overall social and economic costs of lockdown measures would be lowered thanks to targeted strategies at the LLM level.

8. Limitations

A final remark goes to possible limitations of this work. Firstly, the LLM dataset dates back to 2011. Despite the updates, the most reliable source of information on LLM statistics is nine years old. Indeed, as shown by the 1991 and 2001 censuses, the number of LLMs fluctuates over time as well as their own indicators. In any case, this is still the most accurate representation of LLMs in Italy. Secondly, the reported deaths are not informative as to the cause of death. The lack of this information is only partially filled by the de-trending operation—which aims at extracting the 2020 variations in mortality rates by subtracting the average 2015-2019 mortality rates—and by the selection of the timeframe. As discussed previously, the association between positive mortality rates' variations in 2020 and the epidemic is merely assumed. Thirdly, the two provinces of Bergamo and Brescia have been chosen through reason-based criteria, they are not randomly selected. The results obtained by investigating these two provinces may be biased by unmanageable features, whose impacts cannot be traced and, hence, controlled for. Finally, since there are no intermediate public administrations between the municipal and provincial levels, operating at the LLM scale of intervention implies the existence of sound emergency governance among designated authorities, whose cooperation should not be taken for granted. As a consequence, unsupportive authorities may hinder COVID-19 coping strategies at the LLM level.

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