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Summary

The COVID-19 pandemic generated highly heterogeneous economic effects across territories, reflecting differences in local production structures and spatial organization. This paper examines the geography of short-run economic fragility during the first wave of the pandemic by identifying spatially-coherent clusters of municipalities exposed to lockdown-induced shutdowns. Using municipal-level data on Italian suspended firms, workers, and value added in Spring 2020, we apply a Ward-like hierarchical clustering approach under spatial constraints that combines socio-economic dissimilarities with geographical proximity. We first analyze Lombardy, the region most severely affected during the initial phase, and then extend the analysis to the entire Italian territory. The results show that clustering based solely on socio-economic variables mainly reflects differences in economic scale, while incorporating spatial information reveals coherent territorial structures. Industrial and peripheral municipalities appear to be more exposed to shutdown measures than large service-oriented urban centers. At the national level, spatial partitions reproduce Italy's hierarchical territorial structure, from the North–South divide to intermediate macro-regions. These findings highlight the role of spatially targeted policies and the importance of pre-existing territorial structures in shaping the economic impact of systemic shocks.

Keywords: COVID-19; Economic fragility; Spatial clustering; Spatial Econometrics

JEL Classification: R12; R15; C38; O18; D22

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Abstract

The COVID-19 pandemic generated highly heterogeneous economic effects across territories, reflecting differences in local production structures and spatial organization. This paper examines the geography of short-run economic fragility during the first wave of the pandemic by identifying spatially-coherent clusters of municipalities exposed to lockdown-induced shutdowns. Using municipal-level data on Italian suspended firms, workers, and value added in Spring 2020, we apply a Ward-like hierarchical clustering approach under spatial constraints that combines socio-economic dissimilarities with geographical proximity. We first analyze Lombardy, the region most severely affected during the initial phase, and then extend the analysis to the entire Italian territory. The results show that clustering based solely on socio-economic variables mainly reflects differences in economic scale, while incorporating spatial information reveals coherent territorial structures. Industrial and peripheral municipalities appear to be more exposed to shutdown measures than large service-oriented urban centers. At the national level, spatial partitions reproduce Italy's hierarchical territorial structure, from the North–South divide to intermediate macro-regions. These findings highlight the role of spatially targeted policies and the importance of pre-existing territorial structures in shaping the economic impact of systemic shocks.

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1 Introduction

The COVID-19 pandemic constituted an unprecedented shock to economic systems, not only due to its global reach, but also due to the nature of the policy responses adopted to contain it (Deng et al., 2021; Gagnon et al., 2023; Goolsbee and Syverson, 2021).

In Italy, the economic downturn was largely induced by non-pharmaceutical interventions that restricted mobility and temporarily suspended production activities. These measures, while necessary from a public health perspective, generated highly heterogeneous economic effects across sectors and territories, a pattern that has been widely documented in the context of the Italian lockdown experience (Cerqua and Letta, 2022; Brunori et al., 2021; Caselli et al., 2022). Understanding how such heterogeneity unfolded in space is, therefore, essential to interpret the geography of economic vulnerability and to design effective place-based policy responses (Iammarino et al., 2019).

Against this background, this article develops an empirical spatial analysis aimed at identifying territorially differentiated patterns of economic fragility during the first wave of the pandemic. We rely on the geographically-informed hierarchical clustering algorithm developed by Chavent et al. (2018) to perform a spatial clustering analysis at the municipal level while combining detailed socio-economic indicators with geographical information (Anselin, 2022).

Using data from the Italian National Statistics Office (ISTAT) on suspended and active firms, workers, and value added during the Spring 2020 lockdown, we apply a Ward-like hierarchical clustering algorithm under spatial constraints (Chavent et al., 2018). This methodology allows us to identify clusters of municipalities that are similar in terms of economic exposure while remaining geographically coherent, thus overcoming the limitations of purely spatial-agnostic partitioning (Morelli et al., 2025, 2026).

A central element of our analysis is the operational definition of economic fragility. We adopt a simple and transparent measure grounded in observable outcomes directly related to lockdown measures (Briguglio et al., 2009; Martin, 2012). Specifically, we define fragile territories as those characterized by large suspension rates in the number of local units and workers, together with substantial shares of suspended value added and revenues relative to the local economic base. This parsimonious definition is designed to retain interpretability and remain closely connected to the institutional design of the restrictions themselves. Although previous studies have explored vulnerability and fragility using broader concepts, ranging from income losses to long-term resilience capacities (Cerqua and Letta, 2022; Iammarino et al., 2019), our focus is on the immediate exposure generated by the shutdown of economic activities (Bonaccorsi et al., 2020; Chetty et al., 2020).

Activities that require physical proximity and on-site work were disproportionately affected by shutdowns, while sectors compatible with remote work experienced milder disruptions (Dingel and Neiman, 2020). These sectoral characteristics are not randomly distributed across space, but reflect long-standing patterns of local specialization, agglomeration economies, and increasing returns (Krugman, 1991, 2009; Iammarino et al., 2019). Territorial responses to shocks are therefore shaped both by economic structure and spatial dependence, consistently with the first law of geography, which states that nearby locations tend to be more similar than distant ones (Tobler, 1970; Anselin and Li, 2020).

Capturing this spatial structure is therefore essential for understanding how economic shocks spread across territories (Blanchard et al., 1992) and for distinguishing between purely sectoral effects and territorially embedded vulnerabilities. Analyses conducted at highly aggregated spatial scales risk masking this heterogeneity, while spatial-agnostic methods may group economically similar but geographically distant locations, limiting their relevance for policy design and territorial targeting (Arbia, 2024).

The contribution of the paper is twofold. First, we conduct a fine-grained analysis of Lombardy, the Italian region most severely affected during the first wave of the pandemic (Brunori et al., 2021; Ascani et al., 2021), both in terms of health outcomes and the intensity of economic shutdowns. Second, we replicate the methodology at the national level, allowing us to assess whether patterns observed at a regional scale re-emerge at broader spatial resolutions. This multi-scale approach (Iammarino et al., 2019; Martin, 2012) makes it possible to identify how large-scale territorial clusters are composed of smaller, internally heterogeneous sub-clusters, and to evaluate the extent to which local patterns of fragility are nested within macro-regional structures.

Using the aforementioned data and methodology, we aim to identify clusters of municipalities with similar socio-economic profiles under both non-spatial and spatially constrained clustering schemes. At this scale, the analysis is designed to explore whether patterns emerge that resemble provincial-level structures, highlighting the role of localized production systems and urban–rural gradients. Comparing spatial and non-spatial approaches further clarifies the extent to which geographically contiguous areas share common exposure profiles beyond purely sectoral similarities.

The initial focus on the Lombardy region allows us to study economic fragility within an administrative area characterized by exceptional internal diversity. Lombardy combines large metropolitan areas, dense suburban systems, industrial districts, agricultural zones, and mountainous municipalities within a relatively compact territory (Eurostat, 2024). During Spring 2020, it was the epicenter of the Italian COVID-19 crisis (Buonanno et al., 2020) and was subject to particularly stringent restrictions on economic activities (Pelagatti and Maranzano, 2021). This makes Lombardy a natural laboratory for analyzing how sectoral composition and spatial proximity interact in shaping local exposure to lockdown measures (Brunori et al., 2021; Caselli et al., 2022).

We then extend the analysis to the entire Italian territory. At this broader scale, the spatially-constrained clustering identifies groups corresponding to well-known macro-areas, such as the Northwest, Northeast, Center, and South and Islands, while also uncovering finer-grained differentiation within some regions. Several large-scale clusters are shown to encompass internally coherent sub-clusters that mirror the patterns detected in the Lombardy case study, suggesting a nested and hierarchical structure of economic fragility.

By jointly analyzing Lombardy and Italy as a whole, this paper highlights how the spatial organization of economic activities mediates the local impact of uniform national restrictions. The multi-scale perspective adopted here demonstrates that macro-regional divides and local-level heterogeneity are not competing explanations but complementary dimensions of the same phenomenon.

Our results underscore the importance of combining detailed municipal data with spatially-aware classification methods to capture large-scale and fine-grained territorial responses to systemic economic shocks. In addition, the findings reveal spatially coherent clusters of economic exposure, with industrialized peripheral municipalities displaying systematically higher fragility than large service-oriented urban centers. These patterns emerge consistently across spatial scales.

The remainder of the paper is organized as follows. Section 2 presents the institutional background. Section 3 reviews the literature. Section 4 describes the data and Section 5 outlines the methodology. Section 6 presents the results and the final section concludes.

2 Background and context

The COVID-19 pandemic reached Europe in early 2020, Italy being among the first and most severely affected countries (Mathieu et al., 2020). The rapid spread of the virus placed extraordinary pressure on the national health system and prompted the adoption of unprecedented containment measures (Buonanno et al., 2020; Buonanno and Puca, 2021; Buonanno et al., 2023; Ascani et al., 2021). In this context, the Italian experience represents a particularly relevant case for studying the territorial and sectoral consequences of pandemic-related restrictions.

Among Italian regions, Lombardy occupies a central role both demographically and economically. Located in Northern Italy, Lombardy is characterized by the highest population density in the country and hosts several large urban and metropolitan areas, including Milano, Bergamo, and Brescia. At the same time, the region concentrates a substantial share of national economic activity, with leading positions in terms of gross domestic product, industrial output, and export capacity (Eurostat, 2024). These structural features contributed to making Lombardy the epicenter of the pandemic in Italy, both in terms of infection rates and mortality outcomes (Buonanno et al., 2020). Since the onset of the crisis in 2020, the region has recorded more than 45,000 deaths attributable to COVID-19, highlighting the severity of the shock (see Figures 1 and 2).

Figure 1 illustrates the daily number of deceased individuals by region in Italy during the pandemic, clearly showing the disproportionate impact borne by Lombardy.

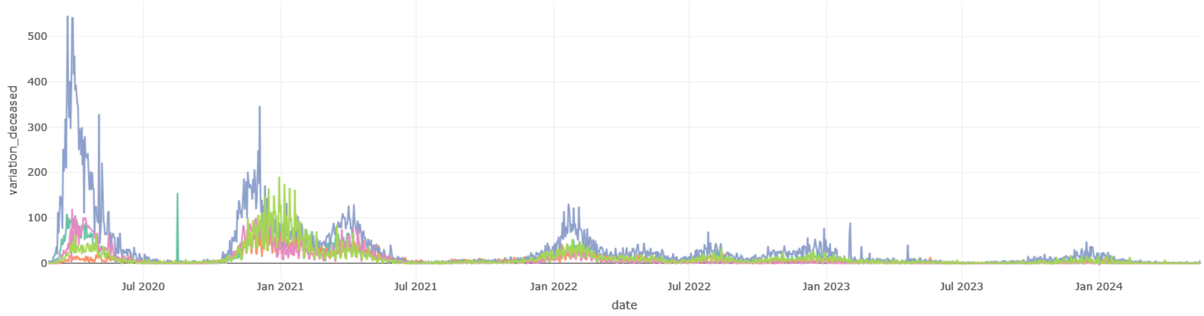

Figure 1: Daily number of deceased individuals by Italian region during the COVID-19 pandemic. Lombardy is highlighted in blue.
Source: Author's elaboration based on data from the "Italy COVID-19 Dashboard" (Chiodin, 2022).

Similarly, Figure 2 documents the evolution of intensive care occupancy, again emphasizing the exceptional strain experienced by the Lombard healthcare system. These patterns are further corroborated by evidence from municipalities on excess mortality.

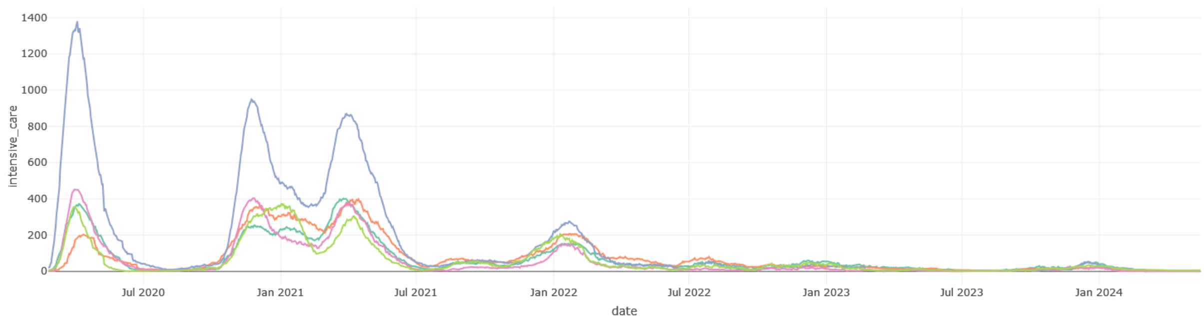

Figure 2: Daily number of individuals in intensive care by Italian region during the COVID-19 pandemic. Lombardy is highlighted in blue.
Source: Author's elaboration based on data from the "Italy COVID-19 Dashboard" (Chiodin, 2022).

In response to the rapid spread of the virus, the Italian government implemented a combination of pharmaceutical and non-pharmaceutical interventions (NPIs), including restrictions on mobility, limits on in-person interactions, and the temporary shutdown of non-essential economic activities (Pelagatti and Maranzano, 2021). These measures were formalized through a sequence of Prime Minister Decrees (Decreti del Presidente del Consiglio dei Ministri, DPCMs), most notably those issued in March 2020 (del Consiglio dei Ministri Italia, 2020b) and November 2020 (del Consiglio dei Ministri Italia, 2020a). The DPCMs classified economic activities according to the ATECO sectoral taxonomy, distinguishing between activities deemed essential and allowed to remain operational, and non-essential activities subject to temporary suspension.

The economic implications of these measures were substantial and uneven in all sectors. According to data provided by the Italian National Statistics Office (ISTAT), approximately 650,000 local industrial units, around 65% of the total, were affected by shutdowns at the national level, while the corresponding share for service activities was lower, at approximately 45%. Figure 3 illustrates the share of suspended local units in industry and services, highlighting marked sectoral differences in exposure to restrictions.

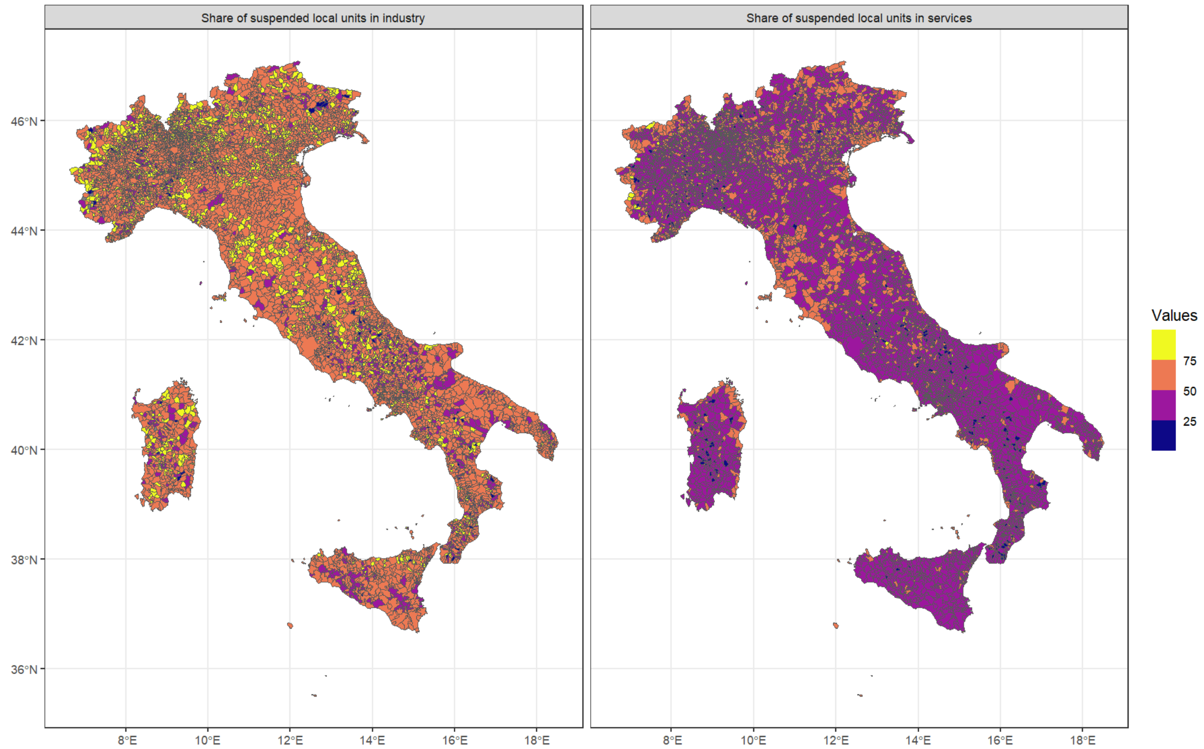

Figure 3: Share of suspended local units over total units in industry (left panel) and services (right panel) following the implementation of DPCM restrictions
Source: Author's elaboration based on ISTAT (2020) data.

To contextualize the national sectoral exposure to shutdown measures, Table 1 reports the number and share of local units suspended in Italian regions, distinguishing between manufacturing and services. This national evidence provides a useful context for our municipal-level analysis of Lombardy.

As shown in Table 1, shutdown measures affected manufacturing activities more severely than services in all Italian macro-areas. At the national level, about 65% of the local manufacturing units were suspended, compared to roughly 45% in services. Some territorial heterogeneity also emerges (Maranzano et al., 2025; Monturano et al., 2025a,b). The Northern and Central regions generally display higher suspension rates in manufacturing, often exceeding two-thirds of the local units, while the Southern and Insular regions show slightly lower shares. In services, instead, differences between regions are more limited, with suspension rates mainly ranging between 40% and 48%. These patterns highlight the strong sectoral asymmetry of the restrictions and suggest that regions with a larger industrial base, such as Lombardy, were structurally more exposed to the economic consequences of the shutdown policies.

Table 1: Suspended local units by region and sector following the COVID-19 restrictions.

Region	**Manufacturing**			**Services**		
	Suspended	Total	Susp./Tot.	Suspended	Total	Susp./Tot.
Northwest						
Piemonte	52607	82044	64.12%	121623	266861	45.58%
Valle d'Aosta/Vallée d'Aoste	1969	2877	68.44%	4242	9044	46.90%
Liguria	16320	26310	62.03%	48401	106138	45.60%
Lombardia	127307	192606	66.10%	301910	677517	44.56%
Northwest (total)	198203	303837	65.23%	476176	1059560	44.94%
Northeast						
Bolzano/Bozen	6382	10665	59.84%	18044	36592	49.31%
Trento	6929	10413	66.54%	15225	33546	45.39%
Veneto	69680	101935	68.36%	154890	319493	48.48%
Friuli-Venezia Giulia	13033	19979	65.23%	31997	69782	45.85%
Emilia-Romagna	57885	88165	65.66%	138215	302136	45.75%
Northeast (total)	153909	231157	66.58%	358371	761549	47.06%
Center						
Toscana	58543	82001	71.39%	127950	262271	48.79%
Umbria	10090	15785	63.92%	24937	54627	45.65%
Marche	23985	34036	70.47%	47275	100322	47.12%
Lazio	42778	69746	61.33%	165026	392710	42.02%
Center (total)	135396	201568	67.17%	365188	809930	45.09%
South						
Abruzzo	14132	22848	61.85%	36645	82033	44.67%
Molise	2810	4776	58.84%	6993	17360	40.28%
Campania	39934	64952	61.48%	136144	306293	44.45%
Puglia	32969	54573	60.41%	95005	213960	44.40%
Basilicata	4681	8097	57.81%	11592	29415	39.41%
Calabria	12642	21434	58.98%	40417	94136	42.94%
South (total)	107168	176680	60.66%	326796	743197	43.97%
Insular						
Sicilia	29847	52522	56.83%	98313	232511	42.28%
Sardegna	13613	21923	62.10%	38278	88481	43.26%
Insular (total)	43460	74445	58.38%	136591	320992	42.55%
Italy	638136	987687	65%	1663122	3695228	45%

Source: Author's elaboration based on ISTAT (2020) data. **Note**: Suspended local units refer to establishments whose activities were temporarily halted following the COVID-19 containment measures introduced by the March 2020 DPCM. Susp./Tot. denotes the share of suspended local units over the total number of local units in each region and sector.

Against this institutional and economic background, the present study aims to identify and characterize fragile subareas of Lombardy by exploiting detailed municipal-level information on the suspension of economic activities during the pandemic. Fragility is assessed using indicators that capture exposure to lockdown measures, constructed from the number of suspended local units and workers, and from the share of value added associated with suspended companies (see Section 4).

The analysis adopts a spatial clustering approach based on the methodology proposed by Chavent et al. (2018), which integrates socio-economic dissimilarities with geographical proximity within a Ward-like hierarchical clustering framework. This methodology allows us to identify homogeneous groups of municipalities based on their fragility degree while explicitly accounting for geographical information among areas.

Consistent with the definition of socioeconomic fragility introduced in Section 1 and in accordance with Serra et al. (2022), fragile areas are identified as territories where high rates of suspension of firms and workers coincide with substantial shares of suspended economic performance, measured in terms of value added. This definition reflects two complementary insights. First, territories with a larger concentration of non-essential activities are inherently more exposed to future shocks that may require renewed shutdowns, increasing the risk of employment losses and economic downturns. Second, the spatial configuration of economic activity, shaped by geography and local production specialization, can generate pronounced heterogeneity in vulnerability within the same region, effectively partitioning Lombardy into zones that differ markedly in their exposure to crisis-related disruptions.

By combining sectoral information with spatial clustering techniques, this study seeks to contribute to a more nuanced understanding of territorial economic fragility, providing a basis for place-based policy interventions aimed at strengthening resilience to future systemic shocks. Recent spatial analyses at the municipal level for Italy also highlight the importance of local socioeconomic disparities in shaping policy outcomes and territorial heterogeneity (Maranzano et al., 2025).

3 Literature review

3.1 Regional resilience and systemic shocks

A large body of research on systemic economic shocks consistently documents that vulnerability and recovery are unevenly distributed across space, reflecting persistent structural differences between regions. Work in spatial econometrics and regional growth shows that shocks propagate through interconnected territorial systems and that regional trajectories are shaped by spatial dependence, spillovers, and long-term structural asymmetries (Sensier et al., 2016; Blanchard et al., 1992). The spatial concentration of economic activity itself reflects long-standing agglomeration forces and increasing returns, as formalized in the new economic geography literature (Krugman, 1991, 2009). Parallel strands of the literature offer conceptual advances in defining economic resilience. Briguglio et al. (2009) introduce a clear distinction between economic vulnerability, defined as structural exposure to external shocks, and resilience, interpreted as the policy-induced capacity to absorb and recover from shocks. Building on this distinction, Martin and Sunley (2015) provides a comprehensive evolutionary framework of regional economic resilience, focusing on path dependence, industrial structure, and adaptive capacity as key determinants of territorial responses to shocks. This perspective is closely related to the evolutionary interpretation proposed by Boschma (2015), who stresses the role of related variety, knowledge networks, and institutional context in shaping regional adaptive capacity. Rose (2004) propose a behavior-based definition of resilience, emphasizing endogenous adaptive responses of firms and households. More recent empirical contributions such as Fingleton et al. (2015) analyze regional employment resilience in the UK, showing that shocks can have persistent effects and that spillovers are stronger among geographically proximate regions. Their results highlight systematic differences between urban and peripheral regions, with service-oriented metropolitan areas exhibiting distinct resilience patterns. On the European scale, Di Filippo et al. (2020) highlight the role of openness, specialization, and factor mobility in shaping heterogeneous responses. Evidence within the country is provided by Di Caro (2017), who perform a spatial analysis of regional employment resilience in Italy using NUTS-2 data, distinguishing between engineering and ecological resilience and showing that regional responses are shaped by both structural characteristics and spatial interactions.

Despite these advances, most existing studies rely on predefined administrative regions or ex ante urban–rural classifications, limiting their ability to detect endogenous spatial regimes of economic vulnerability at the municipal level.

Following the COVID-19 pandemic, a rapidly growing literature has analyzed the economic consequences of lockdowns and mobility restrictions (Jay et al., 2020; Bargain and Aminjonov, 2021; Wang et al., 2024; Bonaccorsi et al., 2020). From a macroeconomic perspective, sector-specific disruptions can spread through production linkages and demand spillovers, generating economy-wide contractions even when initial restrictions affect only selected industries (Acemoglu et al., 2012; Guerrieri et al., 2022).

A related strand of research emphasizes how the feasibility of remote work shaped the spatial distribution of economic disruptions, with areas specialized in telework-compatible occupations experiencing milder short-term impacts (Dingel and Neiman, 2020; Bonacini et al., 2021; Davis et al., 2024). In March 2020, around 80% of cases were located in ten NUTS-3 provinces in Northern Italy, spanning Lombardy, Veneto, and Emilia-Romagna, which also account for a large share of high value-added and export-oriented activities (Ascani et al., 2021). Brunori et al. (2021) documents sharp spatial and sectoral heterogeneity in economic losses using high-frequency indicators, administrative data, and difference-in-differences designs. Many activities typically associated with higher-skill and higher-income occupations were shifted to remote work, strongly mitigating the effects of containment measures. In contrast, sectors most affected by lockdowns were those where physical proximity is intrinsic to production, especially activities involving direct customer interaction (e.g. retail, hospitality, personal services). These sectors generally employ lower-skill and lower-income workers who cannot substitute on-site work with remote arrangements. As a result, restrictions directly led to more severe losses in labor income and increased economic vulnerability among socioeconomically fragile groups (Barbieri et al., 2022; Borsati et al., 2023). In addition, reductions in high-income individuals' spending, driven primarily by health concerns, translated into sharp revenue losses for small in-person service businesses, which in turn laid off low-income workers (Chetty et al., 2020). Similar longitudinal perspectives on the psychological and social dimensions of resilience during the pandemic are explored by Egozi-Farkash et al. (2025), who highlight how individual and community attachment orientations interact with systemic shocks. Bonaccorsi et al. (2020) provide a network-based analysis of the economic and social effects of COVID-19 lockdowns in almost 3,000 Italian municipalities using near-real-time mobility data from the Facebook's Data for Good program. The mobility-network perspective reveals inter-municipal interactions through measures such as network efficiency and node centrality. Complementing this approach, Pierri et al. (2023) uses machine learning to predict economic resilience across Italian territories, reinforcing the importance of local structural characteristics. These contributions show that the contractions were stronger in municipalities with lower per capita income and higher inequality, while also pronounced in areas with stronger fiscal capacity. This suggests a segregation effect by which poorer individuals and municipalities characterized by higher inequality bear a large share of the economic costs of lockdowns, even when aggregate fiscal indicators appear strong.

Works such as Ascani et al. (2021), Capello and Caragliu (2022), and Fazio and Modica (2022) focus on regional resilience and recovery patterns, highlighting how pre-pandemic structural conditions, including sectoral composition and labor market structure, are key determinants of post-shock performance. These studies emphasize how COVID-19 acted as a systemic shock amplifying pre-existing territorial inequalities.

3.2 Urban vs rural resilience in periods of crisis

A substantial strand of the literature investigates whether urban and rural areas respond differently to large economic shocks. Several studies rely on cross-sectional regressions explaining regional growth rates to assess the role of structural characteristics and territorial disparities. For instance, Glaeser (2011), Partridge (2010), and Ezcurra and Rios (2019) show that urban areas tend to display higher adaptive capacity due to agglomeration economies, diversified economic structures, and better access to services. These analyses typically find that rural and peripheral areas are more vulnerable to persistent downturns. Similarly, Chelli et al. (2023) investigate long-term regional disparities in Italy, highlighting how historical trajectories shape the well-being and structural vulnerability of different territories.

More recent empirical evidence, including Duran and Fratesi (2023) and Capello and Caragliu (2021), applies spatial econometric techniques and comparative regional analyzes to crisis periods such as the Great Recession and COVID-19. These studies find that urban resilience is often linked to service-oriented economic structures and digital adaptability, while rural and suburban areas with a stronger industrial base may suffer more from supply-chain disruptions and mobility constraints. Recent work by Dueñas and Campi (2024) further illustrates how regional resilience is shaped by sectoral clusters such as exporting industries, while Champlin et al. (2023) and Du et al. (2024) emphasize the importance of city networks and spatio-temporal activity patterns in maintaining social and structural resilience during systemic shocks. Furthermore, the role of network connectivity and complexity in determining territory-wide vulnerability is explored by Reggiani (2022) and Cardinale et al. (2022), who argue that architectural connectivity is a key driver of systemic resilience.

Nevertheless, most of these approaches rely on ex ante territorial classifications (e.g. urban vs rural) or predefined administrative units and therefore do not allow for the endogenous identification of heterogeneous vulnerability regimes within regions. In addition, they typically focus on regional aggregates (NUTS-2 or NUTS-3) that potentially mask substantial intra-regional heterogeneity.

These limitations motivate the need for a finer-grained, spatially explicit approach capable of identifying homogeneous groups of municipalities based jointly on economic structure and geographical proximity. By endogenously detecting spatially coherent clusters, our contribution advances the literature beyond binary urban–rural comparisons and provides a micro-territorial perspective on economic fragility.

3.3 Spatial modeling and clustering approaches

Empirical analysis of systemic shocks increasingly relies on spatial modeling to capture the inherent geographical dependencies of economic and health phenomena. Bourdin and Levratto (2024) highlight how the COVID-19 pandemic exploited economic integration and mobility, spreading rapidly through densely populated urban centers and exacerbating geographical inequalities. This uneven spatial footprint requires a shift from aggregate national policies to region-specific interventions. In the Italian context, Cutrini and Salvati (2021) find that economic forces such as urban agglomeration and industrial districts significantly predict infection intensity, with spatial models consistently outperforming spatial-agnostic ones.

A critical challenge in these models is accounting for spatial heterogeneity, the tendency for structural relationships to vary across space. Spatial clustering serves as a fundamental tool for identifying latent territorial regimes. Kopczewska (2022) provide a comprehensive taxonomy of these methods, distinguishing between unsupervised learning approaches for territorial partitioning and supervised approaches that extend classical econometrics. The identification of spatially constrained homogeneous areas is further advanced by Benedetti et al. (2020), who propose a hierarchical algorithm based on Dynamic Time Warping to group territories with similar epidemic trends, showing that universal lockdown policies are often sub-optimal compared to localized, data-driven strategies. Similarly, Mare et al. (2025) utilize spatial Durbin Error Models to reveal how socio-economic factors such as poverty and urbanization generate spatial clusters of behavior, including vaccine hesitancy.

Although our work focuses on identifying structural fragility profiles through clustering, the literature suggests a natural extension toward integrating these partitions directly into modeling and inferential frameworks. Recent developments in clusterwise spatial regression demonstrate the statistical relevance of this step. For example, Sugasawa and Murakami (2021) and Cerqueti et al. (2025b) propose models in which regression coefficients vary between spatially contiguous clusters, allowing joint estimation of cluster membership and local spillovers. Further refinements include fuzzy clustering in panel data to capture regional differences in demand (Cerqueti et al., 2025a) and LASSO-based variable selection within clusters to handle high-dimensional spatial datasets (Mari et al., 2023).

Finally, the robustness of spatial partitions depends on the stability of the underlying estimators. Nardelli and Salvini (2025) emphasize that large-scale spatial datasets are prone to local outliers and misspecification of the model; using Local Influence Functions, they identify municipalities exerting disproportionate influence on global parameters. By adopting a spatial clustering framework at the municipal level, our analysis provides a non-parametric identification of local fragility regimes, complementing existing spatial econometric approaches.

4 Dataset and descriptive statistics

We rely on a publicly available, highly granular dataset at the municipal level for Italy provided by ISTAT (2020), based on administrative registers linked to the official classification of essential and non-essential activities introduced by the national DPCMs during Spring 2020 (del Consiglio dei Ministri Italia, 2020b). The data set provides a detailed picture of the immediate economic disruption induced by containment measures, allowing a fine-grained spatial assessment of their heterogeneous territorial impact.

Specifically, ISTAT (2020) collects information on:

- the number of firms (local units) that were suspended and those that remained active during the shutdown period;
- the number of employed workers suspended and active during the shutdown period;
- the value added generated by suspended and active local units.

These indicators directly capture the intensity of the economic shutdown at the local level and therefore provide a suitable proxy for short-term territorial exposure to lockdown measures.

All firms are classified by sector, distinguishing between industry and services, which enables us to capture sector-specific exposure to lockdown policies. The complete data set covers $n = 7{,}903$ Italian municipalities. In this work, our initial focus is on the subsample of $n = 1{,}522$ municipalities located in the Lombardy region, the economic center of the country, and the area most severely affected during the first wave of the pandemic.

Figure 4 illustrates the spatial distribution of suspended economic activity across municipalities. For both industry and services, the maps report the number of local units, the associated value added, and the number of employed persons affected by the shutdown. To enhance comparability between municipalities and variables, all indicators are normalized with respect to the maximum observed value. Because Milano represents a strong outlier in terms of economic size (see Figure A1 in Appendix A), the municipal values are normalized with respect to Brescia and exclude Milano, allowing a clearer visualization of the spatial heterogeneity among the remaining municipalities.

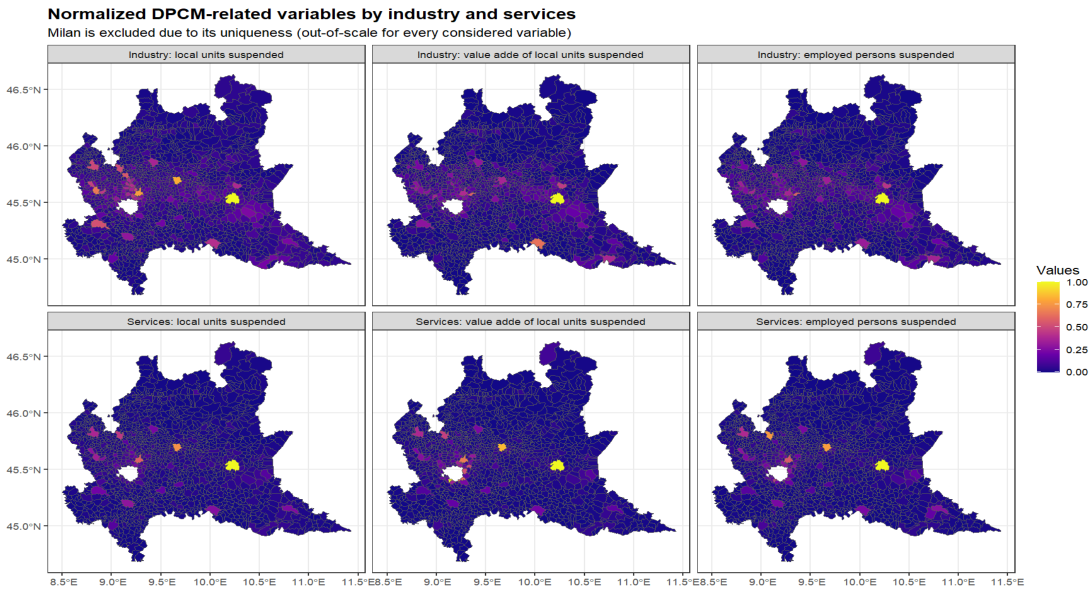

Figure 4: Spatial distribution of suspended activity indicators.

Note: Panels report the number of local units (left), value added (center), and employed persons (right) for industry (top) and services (bottom). Values are normalized with respect to the maximum observed value (Brescia), excluding Milano. Source: Author's elaboration based on data from (ISTAT, 2020).

A visual inspection of these maps reveals substantial spatial heterogeneity across municipalities, motivating the need for spatially constrained clustering methods. These municipal indicators define the feature space used in the spatial cluster analysis described in Section 5.

5 Empirical strategy

5.1 Analysis approach

This section describes the empirical strategy adopted to identify homogeneous groups of municipalities according to their exposure to COVID-19 lockdown measures implemented through the DPCMs in Spring 2020. The methodology is applied first to the Lombardy region and subsequently extended to the entire Italian territory in order to assess whether the geographical patterns identified at the regional level generalize at the national scale.

Clustering analysis relies on a set of socio-economic indicators designed to capture both the intensity and the composition of the economic shock induced by shutdown measures. In particular, we consider 12 variables related to DPCM constructed from (i) value added, (ii) number of workers employed, and (iii) number of local units, distinguishing between suspended and active activities, and accounting separately for the industrial and service sectors.

For the Lombardy-specific analysis, Milano is a clear outlier in terms of economic size, activity concentration, and employment levels (see Figure A1). Including Milan in the clustering procedure would mechanically drive cluster formation and obscure the heterogeneity structure between the remaining municipalities. Milano is therefore treated as a stand-alone cluster and excluded from the clustering exercise applied to the rest of the region.

To ensure comparability across municipalities and variables, all socio-economic indicators are normalized using the double normalization procedure described below. This transformation preserves relative differences while preventing scale effects from dominating the distance calculations.

5.2 Double normalization of socio-economic variables

Before computing the socio-economic dissimilarity matrix, all variables undergo a two-step normalization procedure aimed at accounting for differences in municipal size and reducing the influence of extreme values, following standard practices in regional and spatial data pre-processing (Kaufman and Rousseeuw, 2009; Hennig et al., 2015; Cerqueti and Mattera, 2025).

Step 1: density transformation. Each variable is first expressed as a density with respect to the municipal surface:

$$Y_i^* = \frac{Y_i}{Area_i}, \qquad \forall i = 1, \dots, n, \tag{1}$$

where Y_i denotes the original value of the variable for municipality i, $Area_i$ is the surface area in km^2 of the municipality and n is the total number of municipalities in the dataset. This transformation allows comparisons across municipalities of very different geographical size.

This type of density adjustment is commonly used in regional analysis to make territorial indicators comparable across heterogeneous spatial units (Fotheringham et al., 2009, 2015; Arbia and Nardelli, 2024).

Step 2: robust standardization. To mitigate the effect of skewed distributions and outliers (Huber, 1996; Wilcox, 2012), density-transformed variables are standardized using a robust quantile-based approach:

$$Y_i^{**} = \frac{Y_i^* - \text{Median}(Y_i^*)}{Y_{0.75}^* - Y_{0.25}^*} = \frac{Y_i^* - \text{Median}(Y_i^*)}{\text{IQR}(Y^*)}, \qquad \forall i = 1, \ldots, n, \tag{2}$$

where $Y_{0.25}^*$, $\text{Median}(Y_i^*)$ and $Y_{0.75}^*$ denote the 25°, 50° and 75° quantiles of the distribution of Y_i^*, respectively, and $\text{IQR}(\cdot)$ is the interquartile range.

This double normalization ensures that socio-economic variables entering the distance matrix are comparable between municipalities, robust to extreme values, and reflect differences in economic intensity rather than sheer size Cerqueti and Mattera (2025).

5.3 Ward-like hierarchical clustering: fundamentals

We now introduce the spatial clustering methodology adopted in the empirical analysis. We rely on a Ward-like hierarchical clustering framework extended to explicitly account for spatial proximity. This approach allows us to identify groups of municipalities that are internally homogeneous in terms of socio-economic characteristics while also preserving geographical coherence.

Let n denote the number of observational units. Let $D = [d_{ij}]_{i,j=1,\ldots,n}$ be a symmetric dissimilarity matrix summarizing pairwise distances between observations, and let w_i be the weight associated with unit i, for $i = 1, \ldots, n$. In the empirical application, we adopt uniform weights, that is, $w_i = 1/n$.

A partition of the data set into clusters K is denoted by $\mathcal{P}_K = (\mathcal{C}_1, \ldots, \mathcal{C}_K)$, where each $\mathcal{C}_k$ is a non-empty subset of observations and $\cup_{k=1}^K \mathcal{C}_k = \{1, \ldots, n\}$.

For a given cluster $\mathcal{C}_k$, its inertia (i.e., the total dispersion of a set of statistical units with respect to the Euclidean distance) is defined as

$$I(\mathcal{C}_k) = \sum_{i \in \mathcal{C}_k} \sum_{j \in \mathcal{C}_k} \frac{w_i w_j}{2 \sum_{i \in \mathcal{C}_k} w_i} d_{ij}^2, \tag{3}$$

and the corresponding within-cluster inertia (i.e., cumulated throughout the clusters) of the partition $\mathcal{P}_K$ is given by

$$W(\mathcal{P}_K) = \sum_{k=1}^{K} I(\mathcal{C}_k). \tag{4}$$

Ward (1963) hierarchical clustering starts from the finest partition consisting of n singleton clusters and proceeds iteratively by merging, at each step, the pair of clusters that leads to the smallest increase in within-cluster pseudo-inertia. As a result, the algorithm constructs clusters so as to minimize the overall within-cluster heterogeneity, that is, lower pseudo-inertia corresponds to more homogeneous clusters.

5.4 Ward-like hierarchical clustering under spatial constraints

To explicitly incorporate spatial proximity, we consider two distinct dissimilarity matrices defined over the same set of n geo-referenced units:

1. $D_0 = [d_{0,ij}]$: it captures the socio-economic dissimilarity between units (e.g. distances based on economic structure or exposure to shutdown measures), computed using Euclidean distances on the normalized variables;

2. $D_1 = [d_{1,ij}]$: it captures the geographical dissimilarities, measured as geodetic distances (or Great Circles) between municipal centroids.

This approach follows the growing literature on spatially-constrained clustering, which integrates attribute similarity and geographical proximity in territorial classification problems (Rey, 2004; Guo, 2008; Rey and Anselin, 2009).

Because D_0 and D_1 can be expressed on very different scales (for example, monetary or structural distances versus physical distances in kilometers), each matrix is rescaled by its maximum value so that all dissimilarities lie in the interval $[0, 1]$. This normalization ensures that neither component mechanically dominates the clustering outcome due to scale effects.

To combine the two dissimilarity matrices, Chavent et al. (2018) introduced a further hyperparameter $\alpha \in [0, 1]$ in addition to the number of clusters K. The parameter α governs the relative importance of socio-economic versus geographical information in cluster formation. When $\alpha = 0$, clustering is based exclusively on socio-economic dissimilarities, whereas when $\alpha = 1$ clusters are formed solely on the basis of spatial proximity.

Furthermore, let us consider a generic partition obtained using $\mathcal{P}_K^\alpha = (\mathcal{C}_1^\alpha, \ldots, \mathcal{C}_K^\alpha)$ that depends on both the number of clusters K and the mixing parameter α. Consequently, the mixed pseudo-inertia (i.e., a generalization of the the concept of inertia to the case of non-Euclidean dissimilarities) of a generic cluster $\mathcal{C}_k^\alpha$ is defined as a convex combination of the attribute-based and spatial components, that is,

$$I(\mathcal{C}_k^\alpha) = (1-\alpha) \sum_{i \in \mathcal{C}_k^\alpha} \sum_{j \in \mathcal{C}_k^\alpha} \frac{w_i w_j}{2 \sum_{i \in \mathcal{C}_k^\alpha} w_i} d_{0,ij}^2 + \alpha \sum_{i \in \mathcal{C}_k^\alpha} \sum_{j \in \mathcal{C}_k^\alpha} \frac{w_i w_j}{2 \sum_{i \in \mathcal{C}_k^\alpha} w_i} d_{1,ij}^2. \quad (5)$$

where w_i represents the weight associated with the i-th observation (with $i = 1, ..., n$), $\mu_k^\alpha = \sum_{i \in C_k^\alpha} w_i$ is the total weight of the partition C_k^α, $d_{0,ij}^2$ is the normalized $n \times n$ dissimilarity between observations i and j in D_0, and $d_{1,ij}^2$ is the normalized geographical distance for units i and j.

In the same spirit of the Ward's hierarchical approach, as the mixed pseudo inertia of cluster C_k^α decreases, the units belonging to that cluster are more homogeneous (i.e., $\downarrow I_\alpha(C_k^\alpha)$ then $\uparrow$ homogeneity within C_k^α). When considering a partition into K clusters, the overall homogeneity is measured by the mixed within-cluster pseudo inertia, denoted by $W(\mathcal{P}_K)$, which is computed as

$$W_\alpha(\mathcal{P}_K^\alpha) = \sum_{k=1}^{K} I_\alpha(\mathcal{C}_k^\alpha). \tag{6}$$

The geographically-informed (or spatial) hierarchical clustering algorithm formulated by Chavent et al. (2018) extends the Ward's minimum-variance principle to settings where both attribute similarity and geographical proximity jointly determine cluster formation. Recall that in the hierarchical clustering framework, a high degree of homogeneity for the partition $\mathcal{P}_K$ is achieved by forming clusters that minimize the mixed within-cluster pseudo inertia. Similarly, the Ward-like spatial hierarchical algorithm proceeds as in the standard case (Ward, 1963) (i.e., it is implemented by evaluating alternative partitions for different numbers of clusters), but the cluster aggregation is guided by the minimization of W_α, thereby ensuring that the resulting clusters balance socio-economic similarity and geographical coherence.

5.5 Choice of the tuning hyperparameters

A critical aspect of this methodology is the selection of reasonable values for the two hyperparameters, that is, the number of clusters K and the mixing parameter α. To pursue this goal, we follow the procedure described by Kaufman and Rousseeuw (2009); Chavent et al. (2018), which consists of three steps.

First, using only the socio-economic dissimilarity matrix D_0, we identify a preliminary optimal number of clusters K_0^* based on standard criteria, such as the elbow method and the inspection of the dendrogram.

Second, fixing $K = K_0^*$, we run the spatial hierarchical clustering for different values of α and select α^* such that the normalized proportions of explained pseudo-inertia associated with D_0 and D_1 are as close as possible:

$$\alpha^* = \arg\min_\alpha \left| \tilde{Q}_{D_0}(\mathcal{P}_K^\alpha) - \tilde{Q}_{D_1}(\mathcal{P}_K^\alpha) \right|. \tag{7}$$

The above criterion reflects the best trade-off between preserving the clustering structure driven by the feature space and ensuring spatial coherence of the resulting clusters; in other words, it determines the value of α for which socio-economic and spatial information contribute symmetrically to the partitioning, relative to what would be explained by each component alone. In practice, this value α^* can be identified by graphical inspection of the empirical difference as a function of α, selecting the value at which the distance reaches its minimum.

Finally, fixing $\alpha = \alpha^*$, we determine the final optimal number of clusters $K^*_{\alpha^*}$ using the combined dissimilarity matrix $D(\alpha^*)$, again relying on dendrogram inspection and inertia-based criteria (Morelli et al., 2026; Zammarchi and Maranzano, 2024).

6 Results

6.1 Clustering without spatial information

We start considering the results obtained from the hierarchical clustering procedure in the municipalities of Lombardy (normalized values are reported in the Appendix A, in Figure A2) based exclusively on socio-economic information, that is, by setting the spatial mixing parameter to $\alpha = 0$.

Figure 5 reports the resulting partition into $K = 8$ clusters, with the municipality of Milan treated as an outlier and excluded from the clustering process.

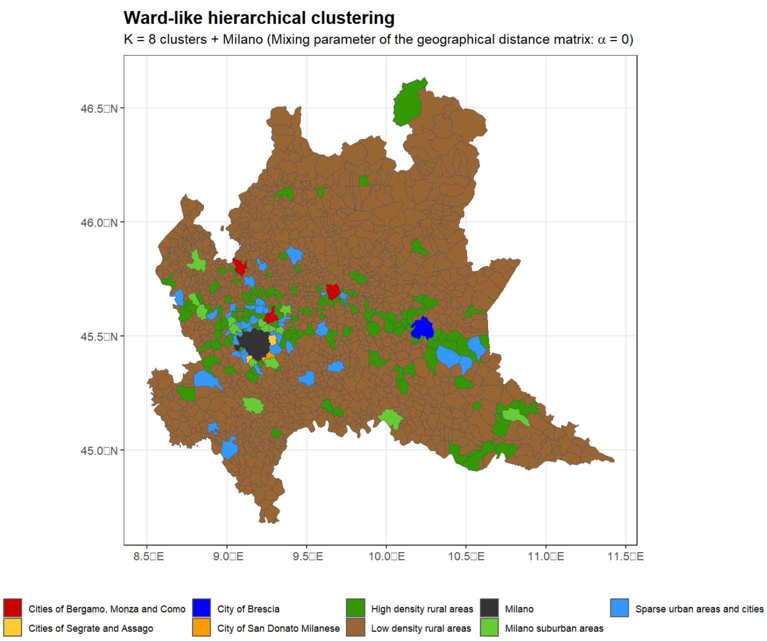

Figure 5: Clusters obtained from hierarchical clustering based solely on socio-economic dissimilarities ($\alpha = 0$), with $K = 8$ clusters and Milano treated as an outlier.

When spatial information is not incorporated, the clustering procedure primarily reflects differences in the socio-economic scale of municipalities. In particular, large urban centers, such as Brescia, Bergamo, Monza, and Segrate, (respectively: darkblue, red, yellow in 5), are clearly separated from rural municipalities, regardless of whether the latter are characterized by relatively high or low population density. This outcome is consistent with the tendency of agglomeration economies and urban concentration processes to generate strong disparities in economic scale between territories, which makes large and diversified urban systems different from smaller local economies (Glaeser, 2011; Iammarino et al., 2019). In the absence of geographical constraints, the algorithm therefore tends to isolate municipalities with large economic size and concentration of activities.

The spatial configuration of the resulting clusters exhibits a pronounced alignment along the A4 motorway corridor, which spans from Torino (North-West) to Trieste (North-East) horizontally crossing the whole Lombardy. This pattern reflects the concentration of major industrial and service activities along one of the main infrastructural axes of the region, which connects the Eastern and Western parts of Lombardy and separates the Po Valley from the Alpine areas. This configuration mirrors the well-documented spatial organization of production systems and transport accessibility in Northern Italy, where economic activity is strongly structured around major mobility corridors and industrial belts (Maranzano et al., 2025; Bergantino et al., 2026). This configuration, which we refer to as an "A4 law", highlights the strong role played by economic intensity and accessibility when clustering is driven exclusively by socio-economic similarity.

At the same time, the partition does not clearly distinguish between municipalities located in the Alpine areas to the North and those located in the Po Valley to the South. This absence of separation is notable given the well-established structural contrasts between these two macro-areas in terms of settlement patterns, economic organization, and productive specialization, suggesting that socio-economic similarity alone cannot fully capture the underlying geographical heterogeneity (Di Caro, 2017; Iammarino et al., 2019).

6.2 Clusters with spatial constraints

Then, we consider the hierarchical clustering procedure based on the convex combination of socio-economic and geographical dissimilarities, thus accounting for spatial proximity among municipalities.

For the sake of brevity, in the main manuscript, we mainly focus on the partitions induced by the algorithm and the subsequent policy interpretations. In the Appendix A, we report an extended set of results regarding the choice of the hyperparameters following the procedure described in Section 5.5. Specifically, Figure A4 reports the dendrogram obtained for spatially informed clustering with a mixing parameter set to $\alpha = 0.10$, while Figure A5 illustrates the proportion of pseudo-inertia explained by the partition and its normalized counterpart as functions of α for clusters $K = 8$. We note that the value $\alpha = 0.10$ represents a compromise that balances the contribution of socio-economic and geographical information, ensuring that neither component dominates the clustering structure.

Figure 6 reports the spatially constrained clustering solution obtained with $\alpha = 0.10$ and $K = 8$, again treating Milano as an outlier.

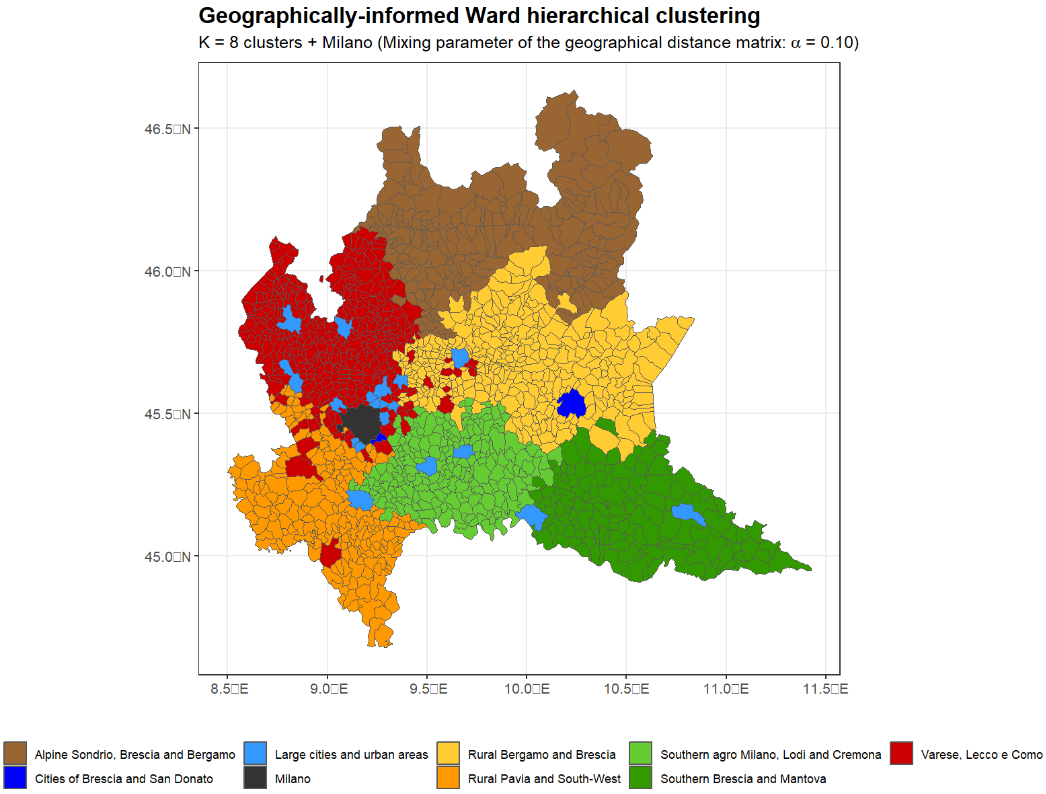

Figure 6: Clusters obtained from hierarchical spatial clustering with $\alpha = 0.10$, $K = 8$, and Milano treated as an outlier.

The introduction of spatial information yields clusters that are more geographically cohesive and easier to interpret in territorial terms.

The first group, labeled *"Rural Pavia and the South-West"* (orange in 6), is composed of predominantly rural and sparsely populated municipalities. These areas experienced a limited number of suspended activities in both industry and services, although not the lowest in all clusters. Value added and overall output are low in both sectors and the number of workers affected by closures is small in absolute terms. Nevertheless, suspended firms account for approximately two-thirds of all local units.

The cluster identified as *"Southern agro Milano, Lodi and Cremona"* (light green in 6) shares several characteristics with the previous group but displays a more balanced distribution between industrial and service sector workers. In this case, the number of workers involved in closures and the number of suspended firms are almost identical across sectors, while the value added associated with suspended activities is higher.

The *"Alpine Sondrio, Brescia and Bergamo"* (brown in 6) cluster consists of rural municipalities with very small populations. Although the number of workers involved in closures is very low, approximately two-thirds of industrial firms were suspended. At the same time, a substantial share of service firms, employing most workers, remained active, with closure rates between 44% and 48%.

The cluster labeled *"Varese, Lecco and Como"* (red in 6) includes small municipalities characterized by high population density, often functioning as intermediate urban centers closely connected to larger cities. The share of suspended service firms is around 46%, while suspended service workers represent 39% of the total. The value added associated with suspended industrial firms is relatively high, approximately 63%. These municipalities often function as intermediate urban systems within the polycentric structure of Northern Italy (Iammarino et al., 2019; Salvati and Carlucci, 2016).

The *"Southern Brescia and Mantova"* (dark green in 6) cluster is composed of rural municipalities with larger populations compared to the previously discussed rural groups. These areas experienced more severe industrial disruptions, with 44% of total local units suspended, compared to 36–40% in the first three groups. The industrial sector was particularly affected, with approximately 70% of workers and value added involved in suspensions, while the service sector recorded suspension rates between 30% and 35%. This reflects the well-known manufacturing specialization of several areas that form part of the larger system of Northern Italian industrial districts (Di Caro, 2017; Bianchi et al., 2024).

In the *"Rural Bergamo and Brescia"* (yellow in 6) cluster, industrial firms experienced shutdown patterns similar to other rural clusters, but service activities were more heavily affected, with suspension rates close to 49%. Approximately 70% of industrial workers and 41% of service workers participated in shutdowns, both values being relatively high compared to other groups.

The *"Large cities and urban areas"* (light blue in 6) cluster includes major urban centers in Lombardy, with the exception of Brescia and San Donato Milanese. Despite the strong presence of industrial activities, suspended industrial workers account for 47% of the total, while suspended service workers represent approximately one-third. The share of suspended firms is comparable to that observed in other clusters; however, the value added affected by suspensions is lower, at 38% in industry and 30% in services. This pattern is consistent with evidence showing that service-oriented urban economies were generally less exposed to shutdown measures compared to manufacturing-intensive territories (Bonaccorsi et al., 2020; Ascani et al., 2021; Maranzano et al., 2025).

Finally, the cluster labeled *"Cities of Brescia and San Donato"* (dark blue in 6) is characterized by high shares of suspended firms, 57% in industry and 41% in services, combined with relatively lower proportions of workers involved in shutdowns, equal to 50% in industry and 29% in services. A similar pattern emerges for value added, with 27% in industry and 32% in services. Milano, treated as a separate outlier, displays a comparable pattern in the service sector, with limited suspensions of firms and workers, while experiencing more pronounced disruptions in industrial activities.

6.3 Spatial clustering results for Italy

This section presents the results of the spatial clustering analysis conducted on $n = 7{,}903$ Italian municipalities, based on the same fragility indicators related to the suspension of economic activities during the COVID-19 pandemic used for the Lombardy analysis. The analysis exploits detailed municipal-level data and explicitly incorporates geographical coordinates, allowing us to investigate how sectoral exposure to lockdown measures translates into coherent spatial patterns throughout the country.

We begin by illustrating the spatial distribution of the standardized variables used in the clustering procedure. Figure A3 in the Appendix A reports the normalized indicators for Italy, highlighting substantial heterogeneity between municipalities. Even at this descriptive stage, clear macro-territorial gradients emerge, suggesting that exposure to the suspension of economic activities followed structured spatial patterns rather than being randomly distributed.

This evidence is consistent with the long-standing territorial organization of the Italian economy, characterized by persistent macro-regional divides and strong spatial clustering of productive structures (Iammarino et al., 2019; Chelli et al., 2023). Rather than emerge purely from the pandemic shock, these patterns reflect structural differences in the specialization, productivity, and settlement systems throughout the country.

We then compare the clustering results obtained without and with the inclusion of spatial information. Figure 7 shows the clusters identified by a hierarchical clustering algorithm based solely on socio-economic dissimilarities, for different values of the number of clusters K (with the tuning parameter $\alpha = 0.02$). Although this approach successfully groups municipalities with similar levels of exposure to economic shock, the resulting clusters are often geographically fragmented. Municipalities belonging to the same cluster can be located far apart, reflecting similarities in sectoral composition, but offering limited insight into territorially grounded patterns.

Although the optimal mixing parameter is numerically small (i.e., $\alpha = 0.02$), this indicates that spatial structure is already partly embedded in the socio-economic dissimilarities (Tobler, 1970; Anselin and Li, 2020), across Italian municipalities (Cerqueti et al., 2025b; Maranzano et al., 2025). The balancing criterion equalizes the normalized explained pseudo-inertia associated with the socio-economic and geographical components (Chavent et al., 2018). Consequently, only a limited spatial penalization is required to obtain clusters that jointly reflect economic similarity and geographical coherence.

Such fragmentation is typical when clustering is based exclusively on sectoral similarity, as municipalities with comparable economic structures may belong to very different territorial systems. This confirms that ignoring spatial dependence may obscure the role of geographically embedded production networks and regional development trajectories (Fingleton et al., 2015).

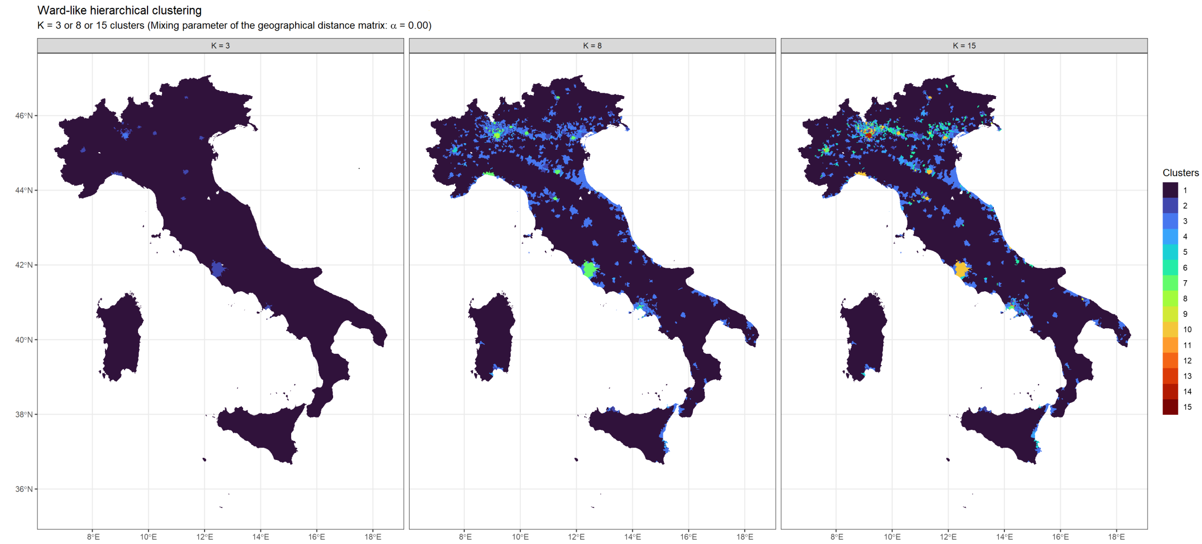

Figure 7: Clusters obtained from hierarchical clustering without spatial information ($\alpha = 0.02$), for $K = 3, 8, 15$.

In contrast, Figure 8 reports the clustering results obtained when spatial coordinates are incorporated into the algorithm. Accounting for geographical proximity leads to markedly different outcomes: clusters become spatially contiguous and display a strong correspondence with well-known territorial divisions, broadly reflecting the persistent macro-regional structure of the Italian economy, including the North–South divide and the differentiation between industrial centers and peripheral areas (Lagravinese, 2015; Monturano et al., 2025a,b). This result indicates that spatial dependence plays a crucial role in shaping the economic exposure of municipalities to pandemic-related restrictions.

The interpretation of the clustering structure varies with the level of aggregation imposed by the choice of K (Chavent et al., 2018). The results reveal a hierarchical territorial organization of the Italian economy.

For $K = 3$, the algorithm identifies a coarse partition that separates Northern Italy from the rest of the country, effectively capturing the well-known North–South divide that has historically shaped the Italian regional development (Felice, 2011; Mussida and Parisi, 2020). In this configuration, one large cluster encompasses most of the Center–South, while the North forms a distinct economic macro-area.

When the number of clusters increases to $K = 8$, the segmentation closely mirrors the traditional macro-regional structure (Northwest, Northeast, Center and South–Islands), while also revealing internal differentiation within the North, where multiple production

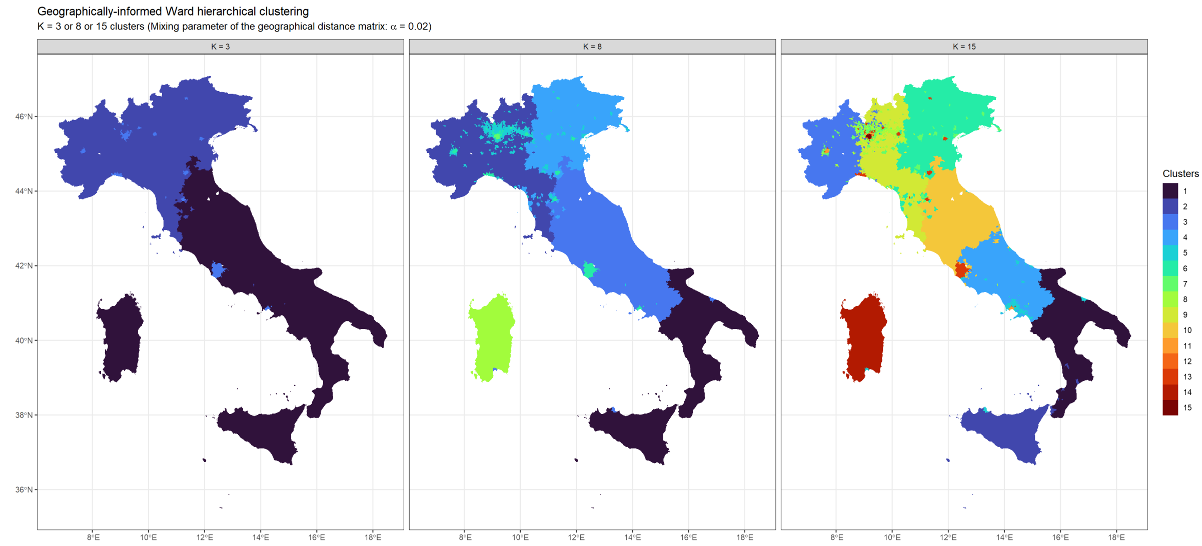

Figure 8: Clusters obtained from hierarchical clustering with spatial information ($\alpha = 0.02$), for $K = 3, 8, 15$.

systems coexist. This intermediate level highlights how national territorial divides are made up of sub-regional economic systems with distinct specialization patterns.

For $K = 15$, clustering uncovers a more granular spatial organization in which macro-regional patterns persist but are complemented by localized clusters corresponding to specific regional production structures, metropolitan areas, and peripheral territories. This progression from broad macro-areas to finer territorial systems suggests that the Italian economic geography exhibits a nested and hierarchical structure, in which local production systems are embedded within larger regional frameworks (Maranzano et al., 2025; Monturano et al., 2025a).

In general, the national-level results show that integrating spatial information is essential to uncover economically homogeneous and geographically coherent clusters. The emergence of partitions that progressively reproduce Italy's macro-regional structure as the number of clusters increases indicates that sectoral exposure to COVID-19 restrictions is deeply intertwined with long-standing territorial configurations.

Rather than creating entirely new spatial patterns, the pandemic shock appears to have interacted with pre-existing regional inequalities and production structures, reinforcing the importance of spatially constrained approaches for understanding nationwide economic shocks and their territorially differentiated impacts.

7 Conclusion and policy implications

This study aims to identify territorially fragile subareas within Lombardy using detailed municipal-level socio-economic information on the suspension of economic activities during the COVID-19 pandemic. Using data on suspended and active firms, workers and value added in industry and services, the analysis uncovered systematic spatial patterns in the exposure of local economies to lockdown measures, and more in general to the underlying economic fragility of the territories.

We implemented a Ward-like hierarchical clustering approach under spatial constraints that combined a set of fragility indicators with geographical proximity. This framework makes it possible to identify groups of municipalities that are similar not only in their economic structure and exposure to restrictions, but also geographically coherent. By explicitly incorporating spatial information, the analysis moves beyond purely spatial-agnostic classifications and provides a territorially grounded representation of regional heterogeneity.

The comparison between non-spatial and spatial clustering results highlights the importance of geography in shaping territorial vulnerability. When spatial information is excluded, the clustering procedure reflects mainly differences in economic scale, isolating large urban centers from smaller municipalities. However, this approach does not capture broader territorial structures, such as the distinction between Alpine areas, industrial plains, and metropolitan systems. In contrast, spatially informed clustering produces partitions that are both economically interpretable and geographically consistent, revealing coherent territorial systems that correspond to recognizable regional configurations.

At the Lombardy level, the results indicate that urban service-oriented municipalities were generally less exposed to the economic consequences of shutdown measures, while rural and suburban areas with stronger industrial specialization experienced more severe disruptions in terms of suspended firms, workers, and value added. These findings are particularly evident in manufacturing-intensive zones, such as parts of southern Brescia and Mantova, where production structures are less adaptable to activity restrictions.

Extending the analysis to the national scale confirms that these patterns are not specific to Lombardy. The spatial clustering of Italian municipalities reveals a hierarchical territorial organization in which broad macro-regional divides coexist with finer local production systems. As the number of clusters increases, the resulting partitions progressively reproduce Italy's well-known economic geography, from the North–South divide to intermediate macro-areas and localized economic systems. This evidence suggests that the impact of the pandemic interacted with pre-existing spatial inequalities rather than generating entirely new territorial patterns.

From a policy perspective, these findings underline the importance of territorially differentiated approaches to crisis management and recovery strategies. Uniform policy interventions risk overlooking substantial heterogeneity in economic exposure and adaptive capacity across municipalities. Spatially targeted measures, accounting for local production structures and sectoral specialization, may improve both the effectiveness of emergency containment policies and the allocation of recovery resources. In particular, manufacturing-intensive territories with limited operational flexibility may require stronger support during activity restrictions, while urban service economies may benefit more from policies aimed at sustaining demand and employment stability.

Several extensions of this work can be envisaged. First, the results of the clustering could be integrated with composite indicators of socio-economic fragility, allowing the territories to be ranked according to their vulnerability to future shocks. Second, incorporating additional variables related to labor markets, institutional capacity, infrastructure, and social protection would enable a broader assessment of structural resilience beyond short-run lockdown exposure. Finally, future research could combine spatial clustering with econometric modeling to formally test how territorial characteristics influence economic performance during systemic crises.

In general, this study provides both methodological and empirical evidence that the economic impact of pandemic restrictions is deeply embedded in the spatial organization of production systems. Understanding this territorial dimension is essential for designing policies capable of addressing not only aggregate downturns, but also the geographically uneven distribution of economic vulnerability.

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Declaration

The manuscript reflects only the authors' views and opinions, and neither the Ministry of University and Research can be considered responsible for them.

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Data Availability statement

The data used in the study are drawn entirely from by ISTAT (2020), and are publicly accessible (available at link: https://www.istat.it/it/archivio/241341, accessed on March 2nd, 2026). The database construction process described in the article is therefore entirely replicable, relying on open, freely accessible, and downloadable data sources. More details on the processing or direct links to data publishing platforms can be provided by the authors upon request. The main code used for the estimates is made public on GitHub at the following link: https://github.com/-------.

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Appendix

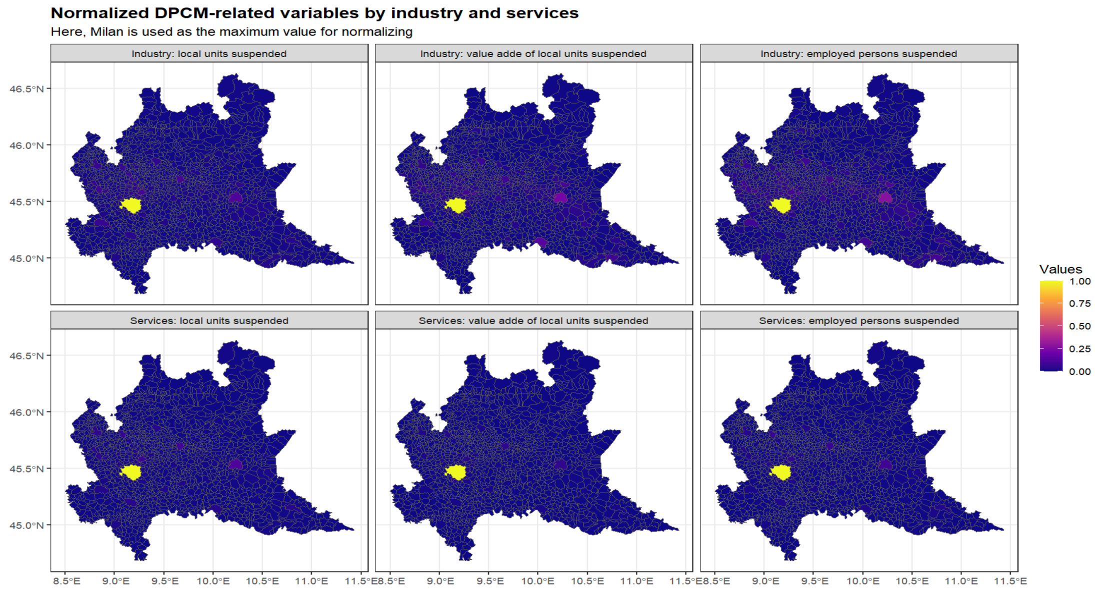

Figure A1: Normalized w.r.t. the maximum observed value (Milano).

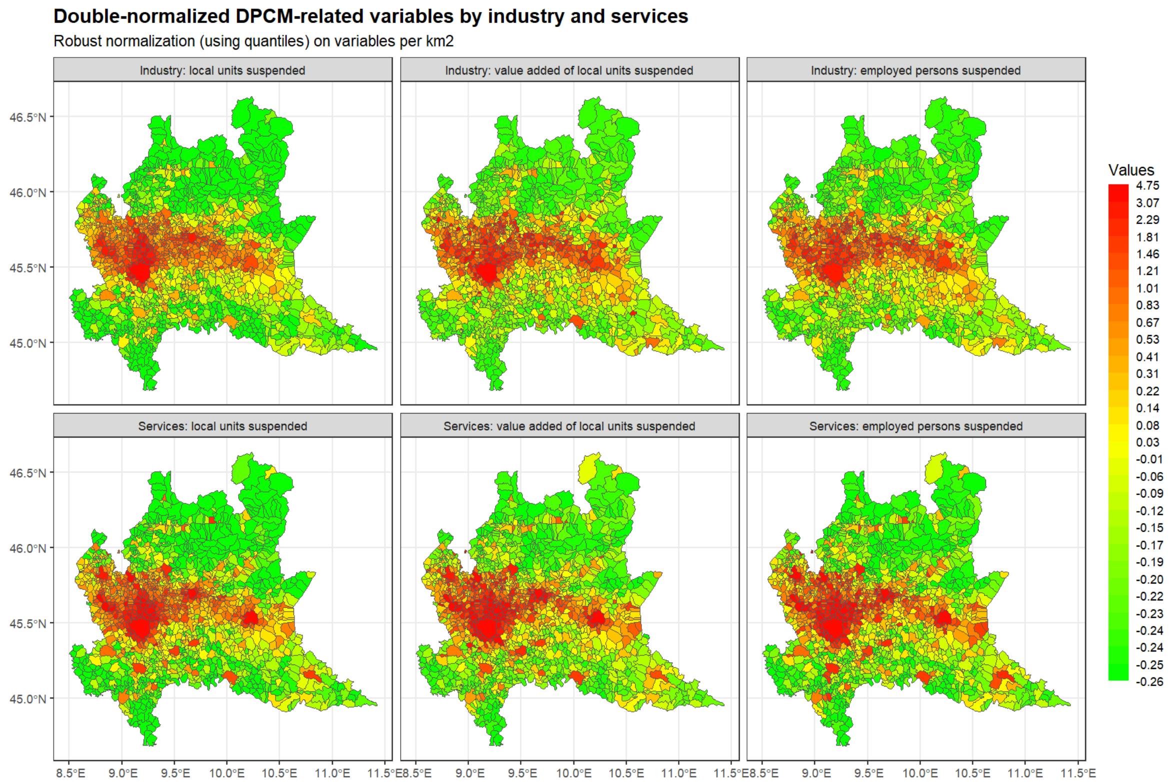

Figure A2: Spatial distribution of normalized socio-economic indicators related to the suspension of economic activities across Lombardy.

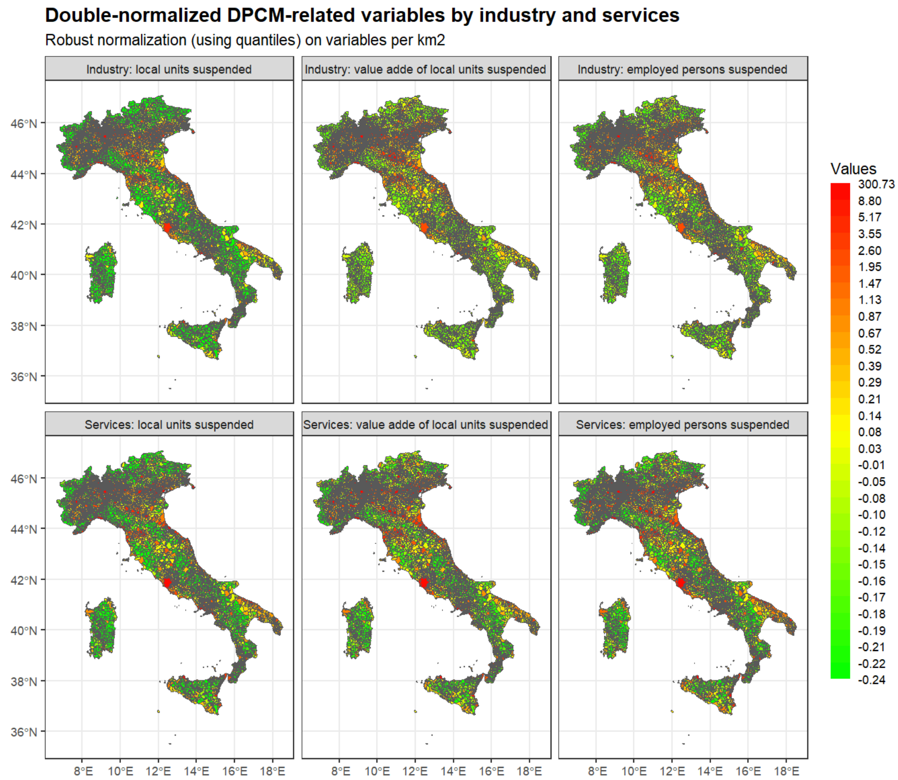

Figure A3: Spatial distribution of normalized socio-economic indicators related to the suspension of economic activities across Italian municipalities.

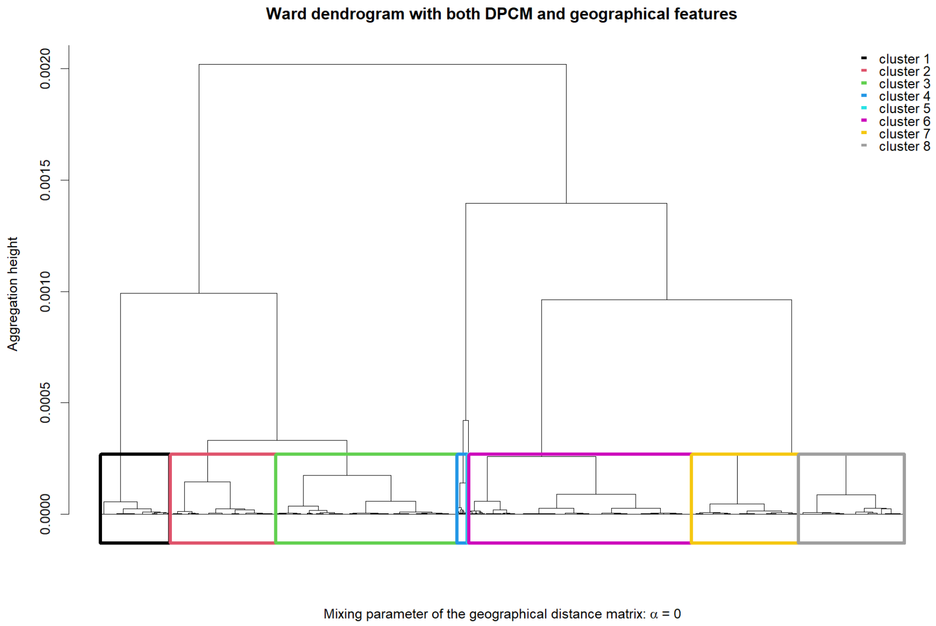

Figure A4: Dendrogram associated with the hierarchical clustering procedure incorporating spatial information, with mixing parameter $\alpha = 0.10$.

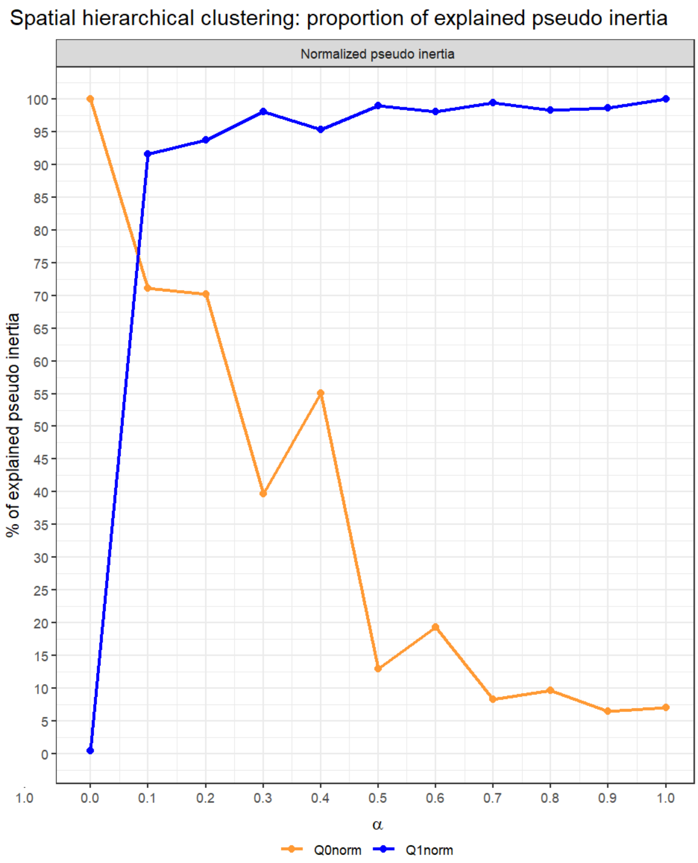

Figure A5: Proportion of pseudo-inertia explained by $K = 8$ clusters and normalized proportion of explained pseudo-inertia as a function of the mixing parameter α.

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