The evolution of agglomeration patterns in Italian manufacturing and services

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Abstract

This paper assesses the spatial concentration of employment at plant level in Italy between 2007 and 2021. We rely on a comprehensive data set including both manufacturing and service sectors at 3-digit ATECO. Our key measure of spatial concentration is the M function, which we analyze both at the aggregate and local level. In this way, we trace how the spatial concentration of economic activities has evolved across various geographic scales, while also keeping track of which local economies have contributed to such change.

JEL codes: R10, R12, R15.

Keywords: Spatial concentration · M function · Industrial clusters · Structural change.

1 Introduction

Over the last decades, virtually all advanced economies have experienced a systematic decline in the share of manufacturing employment and a parallel rise of the service sector. This common trend has been termed in various ways, such as "tertiarization" or "deindustrialization", often depending on whether it was being interpreted as an opportunity or a threat. At any rate, some of its spatial effects have been so blatant that they entered common parlance, for instance by transforming what once was called the "Factory Belt" into the present day "Rust Belt". Aside from these abrupt instances, it is less clear whether the spatial reorganization of the economy might have occurred in more subtle, gradual ways that would require more sophisticated detection tools.

In this scenario, the Great Recession is often regarded as a historical watershed representing the definitive requiem for the manufacturing sector, at least in some regions. Southern European countries by and large were strongly hit, and Italy in particular was traditionally characterized by a relatively strong presence of manufacturing activities often organized as Marshallian industrial districts. This peculiar organization of production is broadly believed to benefit from greater flexibility in adapting to exogenous shocks, as compared to more vertically-integrated alternatives (see Becattini, 2004, Bellandi and De Propris, 2015). On the other hand, industrial district rely on local specialization, which might entail a lower diversification of risk from external shocks, as compared to places characterized by greater productive variety. How, then, has the spatial structure of production evolved in this type of scenario after the Great Recession?

Answering this question in light of the broader structural change discussed above entails a key empirical challenge. Namely, the relevant geographic transformations of the economic landscape may unfold at different spatial scales, which cannot generally be guessed in advance. As a consequence, the methods by which such transformations are investigated need to be conceived so as to potentially allow for meaningful detection "from neighbors to regions". In order to cope with this kind of measurement challenge, some of the more recent statistical methods have moved away from evaluating the spatial distribution of economic activity according to pre-defined administrative borders. Instead, they focus on distance-based measures that treat space as continuous, and are thus able to carry out measurement at any spatial scale in a fully comparable way (see Marcon and Puech, 2017, for a review of these methods).

In this paper, we contribute primarily to assessing the spatial concentration of economic activities in Italy since the Great Recession. To do so, we rely on an especially detailed and complete data set, featuring information about location, employment, and other economic variables for every single plant in Italy across a large variety of 3-digit ATECO sectors. In order to capture the behavior of interest at different spatial scales, we turn to the M function as defined by Marcon and Puech (2010). While allowing for a thorough evaluation of statistical significance, this approach also permits to decompose the aggregate measure of spatial concentration into its local components, as described by Marcon and Puech (2023). Hence, by computing the M function for 2007 and 2021, we can trace how the spatial concentration of economic activities has evolved across various geographic scales and how the different local economies have contributed to such change. In parallel, we use the M function also to provide a fine-grained measure of local productive variety, thus allowing to evaluate in detail where and how variety has evolved in Italy after the Great Recession.

The paper is organized as follows. Section 2 presents the main previous contributions on the different methods and applications of distance-based measures. Section 3 offers a summary of the M function used in this paper and of the related data for Italy in 2007 and 2021. Section 4 presents the main results of the analysis, which are then commented upon in the concluding section.

2 Literature review

Given the early importance that Marshall (1890) recognized to the spatial concentration of economic activity, several empirical methods have been developed over time to assess how industries distribute in space.

An early approach developed by Hoover (1936) relies on the location quotient, which is a ratio between the share of industry employment situated in some locality and the share that such industry detains on overall employment within some larger reference area. The quotients obtained for the various localities of interest can be ordered and cumulated, so as to form a location curve illustrating the extent to which the spatial distribution of employment in a particular industry deviates from the spatial distribution of overall employment. Since this early approach, the spatial distribution of an industry is generally evaluated against some reference distribution.

Starting from this general idea, different pathways of research have developed. Some contributions have taken a more econometric approach to characterize the spatial behavior of firms (see Bottazzi and Gragnolati, 2015, Bottazzi et al., 2017, Desmet and Fafchamps, 2005, 2006, among others). Other works, instead, stick to elaborating synthetic indexes of spatial concentration to describe the underlying geographic distribution of economic activity (see Devereux et al., 2004, Duranton and Overman, 2005, Ellison and Glaeser, 1997, Marcon and Puech, 2010, Maurel and Sédillot, 1999, among others). These various approaches are obviously concerned with ensuring direct comparability across industries, space, and time, which brings to two key considerations.

First, Ellison and Glaeser (1997) signal the importance of controlling for industrial concentration at the plant level in accounting for the spatial distribution of economic activity. To illustrate the point, consider two sectors with the same total employment size but different average plant size: in this case, the sector characterized by higher industrial concentration will necessarily have fewer plants and each plant will tend to host a larger portion of sectoral employment. When measuring spatial concentration through employment, then, one needs to ensure that the observed measurement differences between these two sectors are solely due to underlying dissimilarities in the spatial behavior of firms, rather than being a statistical consequence of different employment concentration at the plant level.

Second, Duranton and Overman (2005) discuss the importance of developing a measure that can be computed and compared across different geographic scales. For instance, firms in a sector may contemporaneously diffuse beyond the scale of a city neighborhood while increasingly concentrating in a few regions. A traditional way to test for this kind of behavior consists in adopting different types of discrete spatial units, such as municipalities and departments, that would ultimately identify the different spatial scales of interest. This reliance on administrative borders, however, gives rise to the so-called "modifiable areal unit problem" (Openshaw, 1984, Openshaw and Taylor, 1979). That is, when spatial patterns are assessed using aggregated units such as provinces or municipalities, the choice of boundaries can distort results by hiding within-unit variation or exaggerating between-unit differences.

In response to these challenges, distance-based methods have emerged as a more sophisticated approach to the measurement of spatial concentration. Basically, this methodology relies directly on the geographic coordinates of plants, thus allowing for a continuous treatment of space independent from pre-defined areal units. Specifically, Duranton and Overman (2005) pioneered this approach by introducing the $\hat{K}_d$ function, which is a kernel density estimator for pairwise distances between firms belonging to the same industry. Spatial concentration is here identified by comparing an observed geographic distribution to a counterfactual generated through Monte Carlo simulations, while also controlling for industrial concentration and test statistical significance. Yet, $\hat{K}_d$ assesses the likelihood of finding a plant *at* a specific distance, which may not provide a complete picture of the cumulative spatial effects occurring *within* that distance. In turn, this may hinder comparability.

To address these gaps, Marcon and Puech (2010) proposed the M function, a cumulative and relative distance-based measure. Unlike $\hat{K}_d$, the M function compares the local share of a target industry to its global share in the economy, in the entire space *within* a specified distance. While being able to control for industrial concentration via employment weights, the M function allows also to test for statistical significance through Monte Carlo simulations (Marcon and Puech, 2015). Despite its many desirable properties, however, the M function has seen limited empirical application mainly due to computational obstacles: its estimation requires to calculate distances not only among all plant pairs in a sector, but also between each plant and all other plants in the economy. This can make the estimation of M prohibitive for large datasets. As a result, most empirical applications have been restricted to small urban areas or selected sectors (see Jensen and Michel, 2011, Marcon and Puech, 2015, Méndez-Ortega and Arauzo-Carod, 2019, Moreno-Monroy and García Cruz, 2016). Nonetheless, Tidu et al. (2024) show that approximating plant coordinates with municipal centroids can sensibly reduce computation time while introducing only a limited distortion in the estimated value of M.

At any rate, the growing relevance of distance-based methods has prompted deeper theoretical and methodological explorations. For example, Kopczewska (2018) offers a systematic critique of various agglomeration metrics, highlighting their sensitivity to spatial configuration and proposing alternative cluster-based indices. Such sensitivity is especially critical because economic activities are constrained by the physical and regulatory landscape: as argued by Sweeney and Feser (1998), factors such as rivers, mountains, and land-use policies shape firm location choices in ways that homogeneous-space assumptions fail to capture. Kopczewska et al. (2019) introduce the SPAG index, emphasizing the need for spatially explicit and computationally feasible tools that can work with disaggregated data. Importantly, they stress that reliable spatial concentration measures must not only reflect local intensity but also adjust for structural economic conditions and sectoral scale: indeed, these are all criteria that are met by the M function thanks to its relative and weighted formulation. Similarly, Fratesi (2008) provides a critical evaluation of localization measures, noting the pitfalls of using administrative units in empirical analysis. He underscores the importance of identifying appropriate spatial scales for evaluating agglomeration, arguing that the effects of proximity often vary depending on the type of industry and regional context. He also highlights the trade-off between interpretability and complexity in spatial metrics: a dilemma that the M function addresses through its balance of statistical rigor and intuitive meaning.

Beyond methodological concerns, the application of these tools has typically focused on manufacturing. One reason for doing so is that data on services have been traditionally scarcer and less reliable. However, as economies undergo tertiarization, it becomes increasingly important to assess whether services replicate or diverge from the spatial patterns observed in manufacturing. In this respect, De Dominicis et al. (2013) argue that manufacturing is dispersing while services cluster, whereas several other studies point to more mixed results. For instance, Boschma and Frenken (2011) emphasize sectoral heterogeneity across services, with knowledge-intensive and creative industries often displaying strong localization. Nakajima et al. (2012) show that while many Japanese manufacturing sectors are localized, services tend to be more spatially diffused. Barlet et al. (2013) and Koh and Riedel (2014) find varying degrees of localization across services and manufacturing in France and Germany. More broadly, studies from Canada, Brazil, and Russia have found that agglomeration persists in manufacturing but shows mixed patterns in services (Aleksandrova et al., 2020, Behrens and Bougna, 2015, de Almeida et al., 2022). In contrast, Cainelli et al. (2020) suggest that the Great Recession triggered a general dispersion of manufacturing in Italy, particularly over short time frames and spatial distances.

Nonetheless, most regional studies on the Great Recession and its aftermath focus mainly on resilience, broadly defined as the capacity of regions to withstand, recover from, and adapt to external shocks (see Boschma, 2015). This issue has been explored from various perspectives. Some contributions highlight the role of specific factors in favoring local resilience: specifically, Rios and Gianmoena (2020) look at the role of institutions, Filippetti et al. (2020) consider the effect of innovativeness, and Antonietti and Boschma (2021) evaluate the contribution of social capital. Other studies, instead, focus more broadly on how the pre-existing economic and industrial structure of regions affect their capacity to withstand an adverse exogenous shock. For instance, Martin et al. (2016) analyze how different UK regions responded to multiple recessions finding that regional specificities and competitiveness significantly influence resilience. For the case of Italy, instead, Di Caro (2015) points to the importance of manufacturing for the long-term resilience of local economies, while Martini and Platania (2019) analyze the impact of specialization, geographical localization and spillovers on the resilience of commuting zones.

In the debate about regional resilience, however, an especially prominent position is occupied by the notion of variety. In the qualitative account of Jacobs (1969), the addition of "new work" to the local economy is the quintessential ingredient for the development of cities, which are regarded as being better able to resist external shocks the more their productive fabric is diversified. As reviewed by Beaudry and Schiffauerova (2009), the literature has since kept on testing this conjecture, particularly by contrasting the role of variety against the advantages from specialization described by Marshall (1890). In this context, Boschma and Iammarino (2009) have further qualified the role of variety according to the degree of complementarity displayed by the different industries that compose the local productive fabric. Following this broad interpretative framework, a number of contributions have then discussed the role of variety for regional resilience. Notably, Xiao et al. (2018a) present an evolutionary approach, indicating that regions with high industrial relatedness, industrial diversity, and knowledge-intensive industries exhibit higher resilience post-crisis. Relatedly, Xiao et al. (2018b) highlight the positive effect of local variety on the probability for European regions to develop new industrial specializations after the Great Recession. In parallel, Cainelli et al. (2019b) emphasize the different roles of technological and vertical relatedness in shaping regional resilience. Then, Brakman et al. (2015) and Capello et al. (2015) further emphasize the role of urbanization and industrial specialization. The former finds that urbanized regions with diversified industry profiles and advanced manufacturing tend to be more resilient, whereas the latter underscores city infrastructure quality and external linkages as vital sources of resilience. For the case of

Italy, Sedita et al. (2017) and Cainelli et al. (2019a) assess the relation between related variety and regional resilience at the level of local labor market areas, finding a generally positive association. Overall, these studies suggest that spatial heterogeneity and industry composition critically shape how regions withstand economic shocks.

This paper contributes to this growing body of literature in multiple ways. First, we apply the M function to the entire Italian economy, covering both manufacturing and services at the plant level for 2007 and 2021. Second, we discuss how the evolution of agglomeration patterns can be tracked across time and across sectors using a consistent and interpretable metric. Third, we extend the use of the M function to obtain a fine-grained measure of local productive variety. Finally, we illustrate the practical feasibility of conducting granular, national-scale spatial analysis using micro-geographic data.

3 Data and methods

The present paper assesses the spatial concentration of economic activity in Italy by means of a distance-based measure known as the M function. The related computations involve information about the position, employment size, and sectoral classification of plants. This section describes the data as well as the measure on which the subsequent analysis is based. In general, our quantitative approach follows Duranton and Overman (2005) in adopting a sectoral measure of spatial concentration that *(i)* is comparable across sectors; *(ii)* controls for employment concentration at the plant level; *(iii)* controls for the underlying spatial distribution of the economy; *(iv)* is comparable across geographic scales; and *(v)* allows to test for its statistical significance.

3.1 Data and summary statistics

The methodology adopted in this paper employs plant-level data at 3-digit ATECO sectoral classification. In particular, we use the ASIA data set for year 2007 and the Frame SBS-Territoriale for year 2021, relying on the fact that these two distinct sources can be fully harmonized and compared. The main advantage of these data sets is the vast coverage they ensure: each year includes 235 sectors at 3-digit ATECO, which in 2021 amount overall to nearly 5 million plants and 17 million employees (about 75% of the Italian labor force). Essentially, the sectors that are not included in our analysis are in agriculture, forestry, fishing, finance, insurance services, and some parts of the public sector. Tables 1 provide an overview of the number of plants and employees across the largest manufacturing and service sectors in year 2021.

In order to use a distance-based approach to the measurement of spatial concentration, plants need to be associated with individual geographic coordinates. In this respect, Tidu et al. (2024) show that grouping nearby observations within relatively small distance thresholds produces nearly indistinguishable results relative to the case in which actual plant coordinates are used, in line with the intuition that "cumulative functions are insensitive to errors at smaller scales than the distance they consider" (Marcon and Puech, 2017, p. 66). In light of

Table 1: Largest manufacturing and service sectors in year 2021.

ATECO	Description	Plants	Employees
	Manufacturing		
256	Treatment and coating of metals; machining	24 200	192 462
282	Manufacture of other general-purpose machinery	9142	177 916
107	Manufacture of bakery products	32 181	164 021
141	Manufacture of wearing apparel, except fur apparel	27 221	162 805
251	Manufacture of structural metal products	29 798	161 058
222	Manufacture of plastics products	8765	142 236
310	Manufacture of furniture	16 829	126 031
289	Manufacture of other special-purpose machinery	7168	120 824
331	Repair of fabricated metal products, machinery and equipment	30 784	116 852
259	Manufacture of other fabricated metal products n.e.c.	15 111	114 558
	Services		
561	Restaurants and mobile food service activities	173 877	757 174
477	Retail sale of other goods in specialized stores	208 988	587 436
471	Retail sale in non-specialized stores	60 154	505 546
432	Electrical, plumbing and other construction installation activities	153 900	500 183
812	Cleaning activities	61 715	453 142
433	Building completion and finishing	242 251	431 425
960	Other personal service activities	193 731	426 216
782	Temporary employment agency activities	29 818	420 462
494	Freight transport by road	64 923	371 452
522	Support activities for transportation	26 182	351 466

Note: Agriculture, forestry and fishing sectors are not part of the data used in this work. Some sectors are kept separate from manufacturing and services and are not reported in the table; specifically, this occurs for sectors belonging to: mining and other extractive activities; energy production and distribution; utilities; construction.

this evidence, here we approximate the position of a plant with the coordinate of the main center in the municipality where the plant is located. Such coordinates are provided by the Italian statistical office (Istat, 2025a). The exact definition of these coordinates can slightly change over time, due to underlying variations in the definition of municipalities. Hence, to ensure consistency across years, we associate the coordinates of the main municipal centers in 2007 to their nearest municipal centers in 2021.

Clearly, the Italian economy has undergone some structural changes between 2007 and 2021. In particular, here we point out the general tendency for services to grow while manufacturing shrinks. Figure 1 illustrates this pattern by plotting the growth rate of total employment by sector against the corresponding growth rate in the number of plants. Indeed, services a more present in the upper-right quadrant, while manufacturing sectors show up more densely in the lower-left quadrant. As a result, median growth rates are positive for services and negative for manufacturing. Figure 1 also highlights four illustrative sectors that will be used to discuss the results presented in Section 4.2. Both for manufacturing and services, we pick one sector that is close to the group median and another sector that is instead more anomalous within its group.

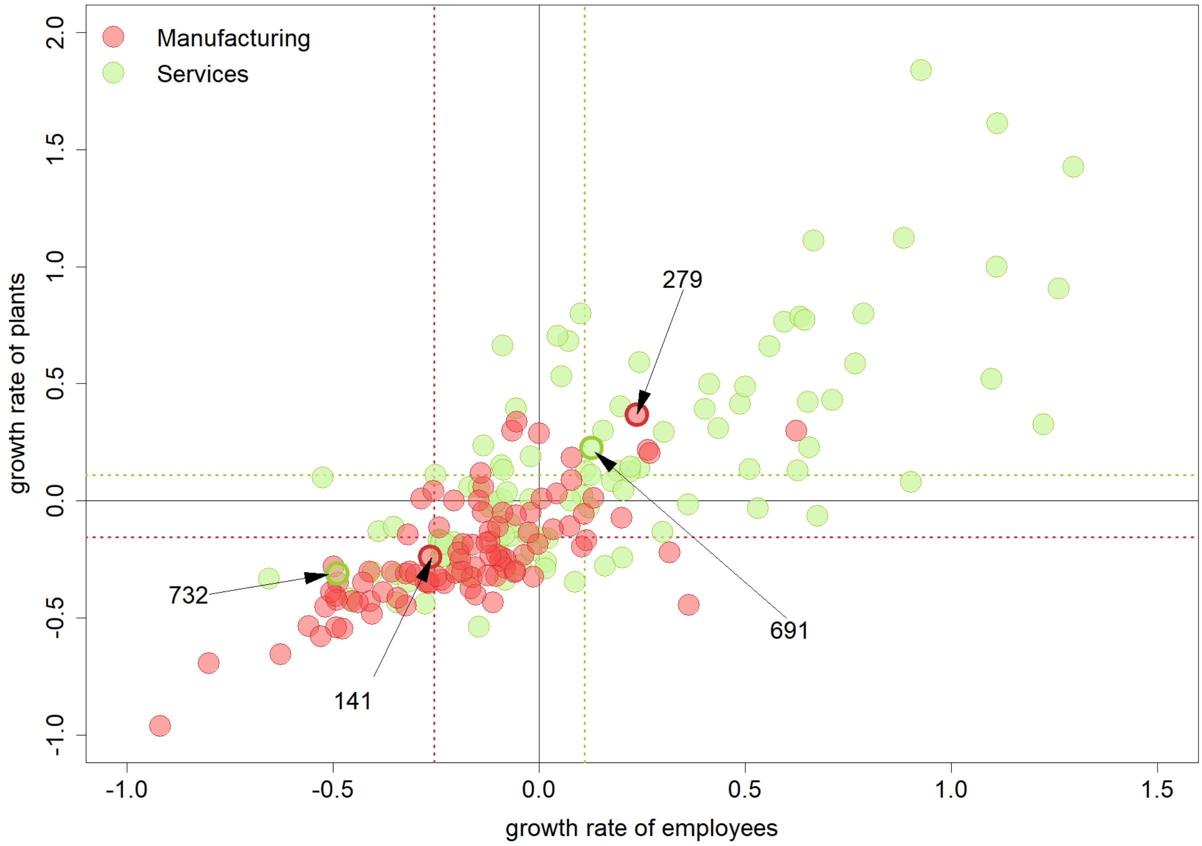


Figure 1: Growth rate of plants and employees between 2007 and 2021.

Note: Dotted lines indicate median values for manufacturing (red) and services (green). The four highlighted sectors are: 141-Manufacture of wearing apparel, except fur apparel; 279-Manufacture of other electrical equipment; 691-Legal activities; 732-Market research and public opinion polling.

3.2 M function

The empirical analysis presented in this paper relies on the M function, as defined by Marcon and Puech (2010). In loose terms, this function compares the *local* relative frequency for some units of interest against the *global* relative frequency that such units have in the entire area under study, provided that the various units are properly weighted. In what follows, our unit of interest is a plant belonging to some sector s, with w as its weight in terms of employment. For each plant i in sector s, the intra-sectoral M function performs a weighted count of the plants belonging to the same sector that are located within a radius of length r from i. This weighted count of intra-sectoral neighbors is expressed as a ratio to the weighted count of generic neighbors, and it is then compared to the global relative frequency of sector s in the economy as a whole. Formally, when looking at sector s, one has

$$\hat{M}(r) = \frac{\sum_i \left\{ \frac{\sum_{j \neq i} \mathbb{1}\left(\|x_i^s - x_j^s\| \leq r\right) w(x_j^s)}{\sum_{j \neq i} \mathbb{1}\left(\|x_i^s - x_j\| \leq r\right) w(x_j)} \right\}}{\sum_i \frac{W^s - w(x_i^s)}{W - w(x_i^s)}}, \tag{1}$$

where x_i^s is the position of some plant i belonging to sector s, x_j^s is the position of a neighboring plant belonging to same sector s, and x_j is the position of a neighboring plant belonging to any sector in the economy, while W^s is total employment in sector s and W is overall employment in the economy. The indicator function $\mathbb{1}(\cdot)$ is equal to 1 if the distance in its argument does not exceed r, and 0 otherwise.

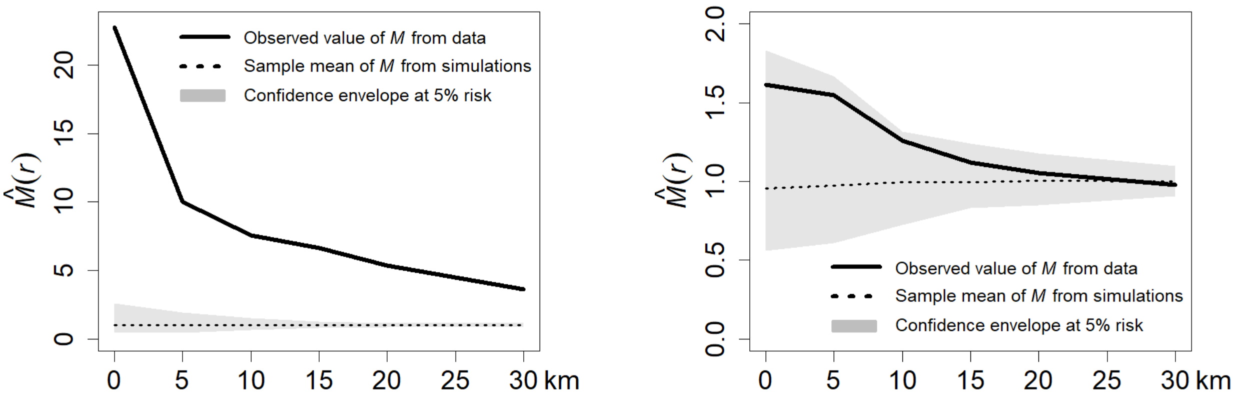
According to equation (1), $M(r)$ compares a local relative frequency at the numerator against a global relative frequency at the denominator. Therefore, values of $\hat{M}(r) > 1$ indicate that employment in sector s is proportionately more represented locally than it is globally, in this sense being spatially concentrated within distance r from the plants. Vice versa, values of $\hat{M}(r) < 1$ indicate that there is proportionally less employment in sector s within distance r from the plants, as compared to the overall share of sector s in the economy. Besides having a clear economic interpretation, the metric provided by the M function is also readily comparable. For instance, if sector a is associated to the value $\hat{M}_a(r) = 2\hat{M}_b(r)$, this can be directly read as sector a being twice as spatially concentrated as sector b within radius r, regardless of the underlying differences that the two sectors might display in terms of plant numerosity or plant size.

Nonetheless, especially for sectors composed by a small number of plants, it is necessary to test whether the observed divergence of $\hat{M}$ from 1 might be due to sheer chance or not. To this end, statistical significance can be evaluated via Monte Carlo simulations, that is by comparing $\hat{M}$ with the simulations of a null model in which plants are randomly redistributed across the observed locations (see the R **dbmss** package introduced by Marcon et al., 2015, for further details).

Another key feature of $\hat{M}(r)$ is that it can be mapped into its individual components, thus defining the local M function. Specifically, equation (1) is an average of the individual values calculated for every plant i, so that one can actually map these individual values and interpolate them spatially as discussed by (see Marcon and Puech, 2023). This kind of application allows to identify, within the sector of interest, *where* spatial concentration actually occurs according to the M function. Generally, this local measure will *not* correspond to the sheer density of sector s in an area, precisely because the M function measures the spatial concentration of a sector *relative* to the local presence of employment in all other sectors. For instance, a big city might host a comparatively large share of all restaurants in the national economy; but if the same city also hosts similarly large shares of all other sectors in the economy, then restaurants will not turn out to be highly concentrated in the city according to the M function. By converse, concentration may be higher if comparatively few restaurants are located in an area that is otherwise void of most other sectors in the economy.

4 Results

We present here two different types of intertwined results. First, we discuss how the M function behaves across manufacturing and service sectors of the Italian economy. Second, we map the individual values of the M function is some key sectors, thus showing the local behavior of spatial concentration. In particular, we run these applications for 2007 and 2021, ultimately



(a) Manufacture of pulp, paper, and paperboard.

(b) Passenger rail transport, interurban.

Figure 2: Values of $\hat{M}$ and confidence envelopes for two illustrative sectors, year 2021.

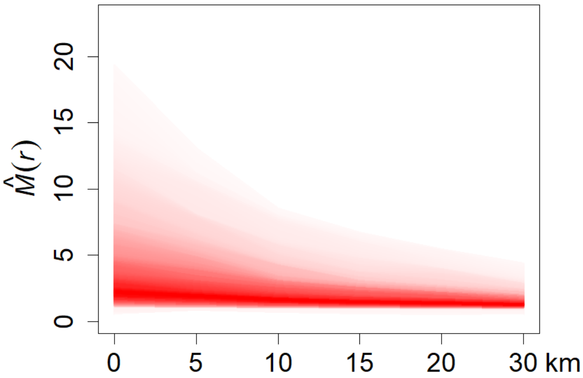
discussing how spatial concentration has evolved over the last decades in a country that has been hit particularly strongly by the Great Recession in 2008–09 and by the ensuing double dip in 2011–13.

4.1 Spatial concentration at the aggregate level

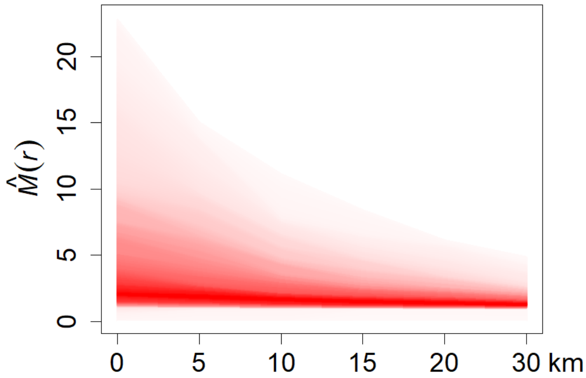
This section discusses the results obtained from applying the M function defined in equation (1) to 3-digit ATECO sectors in Italy, for year 2007 and 2021. The main outcome of this application is twofold. On the one hand, it allows to show how spatial concentration behaves across different geographic scales, which correspond to the different values of r for which $\hat{M}(r)$ is computed. On the other hand, this application allows to trace how spatial concentration has evolved in the aggregate between 2007 and 2021.

As a first step, let us clarify the nature of our results by discussing two illustrative sectors shown in Figure 2, where the values of $\hat{M}(r)$ are displayed together with the corresponding assessment of statistical significance. In both cases the results refer to year 2021 and the distance range expressed in kilometers spans $r = \{0, 5, 10, 15, 20, 30\}$, while the confidence envelope is computed on 100 simulations under the null hypothesis of random location with a 5% risk level. Under this common setting, the two particular cases illustrated in Figure 2 are very different in terms of their spatial behavior. On the one hand, sector "Manufacture of pulp, paper, and paperboard" in Figure 2a is characterized by values of $\hat{M}(r)$ that are largely above 1 across the entire distance range. Moreover, these values lie well outside of the confidence envelope, thus rejecting the null hypothesis $\hat{M}(r) = 1$. It is then possible to conclude that plants in the paper sector are far from following a random pattern of location, while being instead strongly concentrated in space. On the other hand, sector "Passenger rail transport, interurban" in Figure 2b is characterized by values of $\hat{M}(r)$ that are rather close to 1 and fall systematically within the confidence envelope. In this case, then, the null hypothesis $\hat{M}(r) = 1$ is never rejected over the distance range of interest. Therefore, establishments providing interurban rail transport services are not concentrated, in the sense that they distribute in space somewhat similarly to other economic activities.

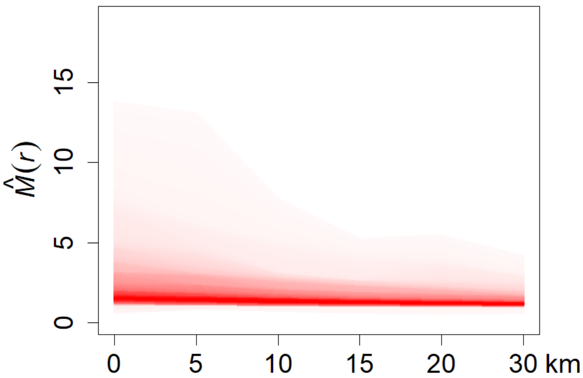
If Figure 2 serves a merely illustrative purpose, it is useful to understand which aspects of



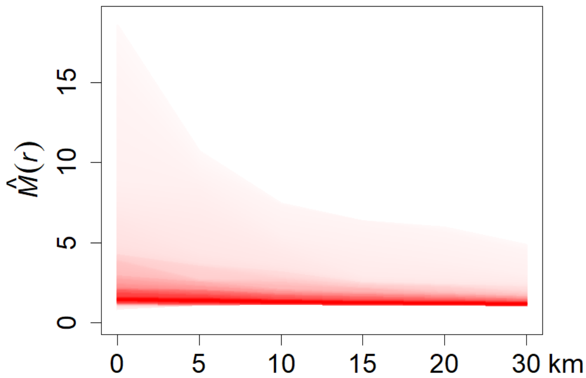
(a) All sectors, year 2007.



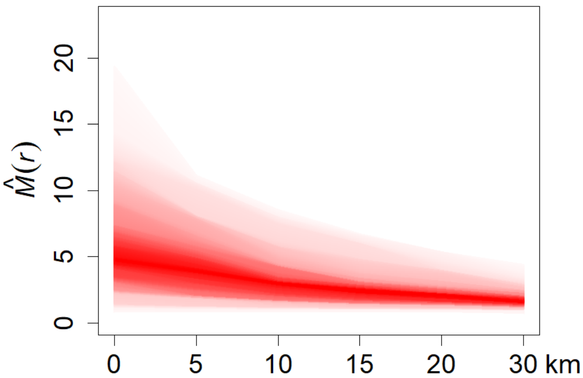
(b) All sectors, year 2021.



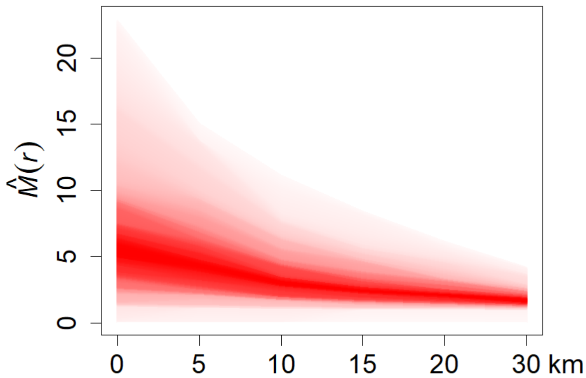
(c) Service sectors, year 2007.



(d) Service sectors, year 2021.



(e) Manufacturing sectors, year 2007.



(f) Manufacturing sectors, year 2021.

Figure 3: Values of $\hat{M}$ in 2007 and 2021.

Note: A darker shade indicates a higher density of $\hat{M}(r)$ values. To favor readability, the plots omit outliers and non statistically significant values at 5% risk level: this selection reduces the total number of sectors from 235 to 196.

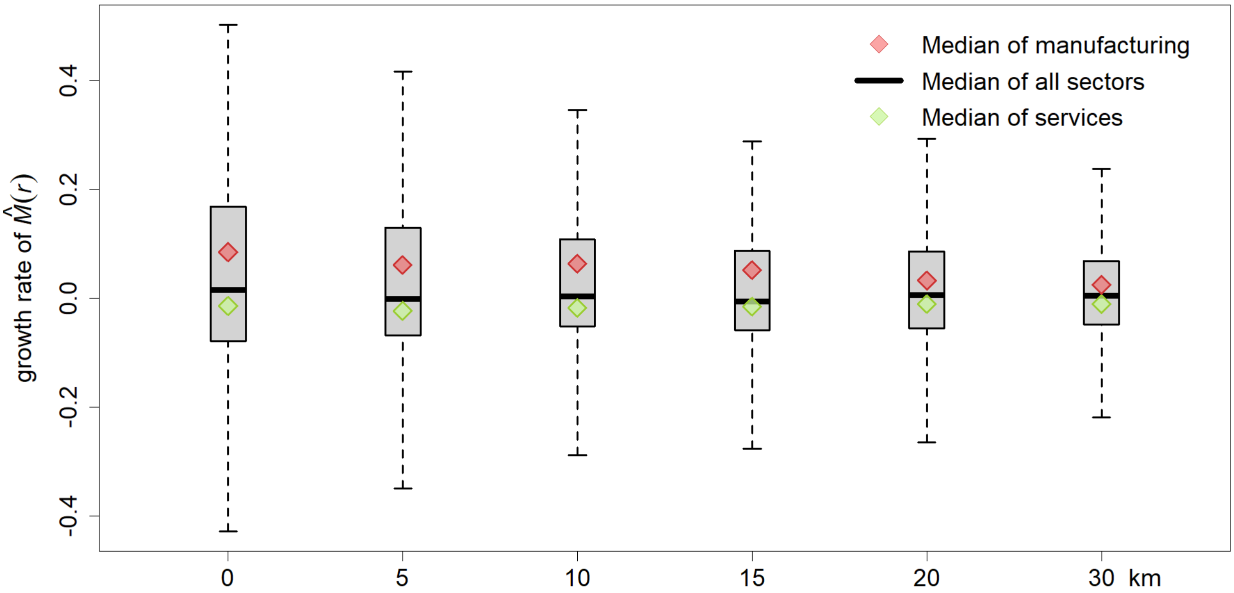


Figure 4: Box plot of the growth rate of $\hat{M}(r)$.

Note: For each distance, the following statistics are represented: minimum (excluding outliers), 25th percentile (lower part of the box) ; median (black line); 75h percentile (upper part of the box); maximum (excluding outliers).

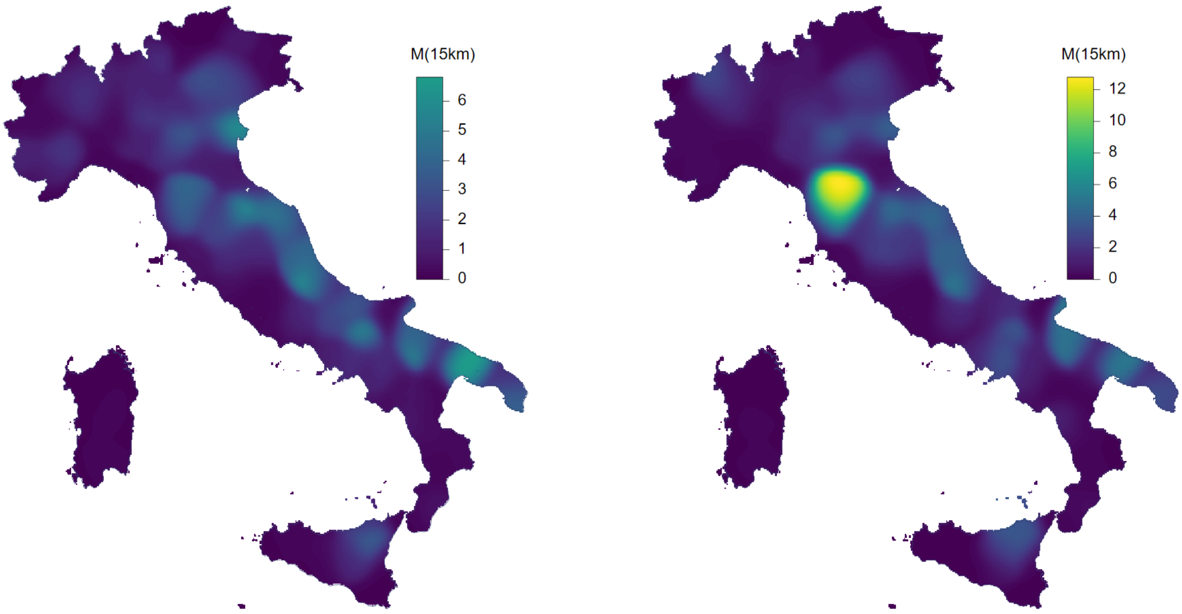
these particular results bear a more general message and which, instead, do not. As discussed at greater length below, it is indeed often the case that manufacturing sectors are characterized by a stronger spatial concentration as compared to services. By contrast, it is very rare to find sectors for which the values of $\hat{M}(r)$ are never statistically significant at 5% risk level for any r, as in Figure 2b. For instance, in 2021 there are only 6 out of 235 sectors that meet this condition, and 4 of these are sectors with less than 15 plants. More generally, it is rare that $\hat{M}$ is not statistically significant even just for some value of r within the range under study. In this sense, results like those shown in Figure 2b are an exception rather than the rule. Given this evidence, while statistical significance is always computed in the various cases discussed below, we will not discuss it any further. Typically, the few sectors that do not display statistically significant values of $\hat{M}(r)$ are simply dropped from the analysis.

Let us then turn to a more general analysis of the results. A first visual summary is shown in Figure 3, which plots the values of $\hat{M}(r)$ in 2007 and 2021 for different groups of sectors. Here darker shades of color indicate a greater density of $\hat{M}(r)$ values. When all sectors are pooled as in Figures 3a–3b, the overall behavior of $\hat{M}(r)$ appears to be fairly stable between 2007 and 2021, apart for the more extreme values. Yet, grouping sectors in services and manufacturing uncovers some underlying heterogeneity. Namely, the darker shades of the plots lay around lower values of $\hat{M}(r)$ in Figures 3c–3d as compared to Figures 3e–3f. Hence, manufacturing sectors are generally characterized by a stronger spatial concentration relative to services, especially in the distance range 0–15 km.

Furthermore, spatial concentration has typically grown more in manufacturing sectors than in services between 2007 and 2021. Figure 4 illustrates this point with a box plot of the growth rates of $\hat{M}(r)$ between 2007 and 2021. In fact, the median growth rate across all sectors is nearly 0 for all distance ranges, generally with greater variability across positive growth rates. Yet, the growth rate of $\hat{M}(r)$ is typically positive for manufacturing and negative for services. So, although Italy went down a path of deindustrialization as shown in Figure 1, this did not generally attenuate spatial concentration in manufacturing, whereas services became typically more disperse in space.

4.2 Spatial concentration at the local level

Having looked at the aggregate behavior of $\hat{M}(r)$ across sectors and over time, we now turn to a local analysis of spatial concentration. In particular, as already anticipated when discussing Figure 1 in Section 3.1, here we map the individual values of $\hat{M}(r)$ for a few illustrative sectors in manufacturing and services. For each group, we pick both a typical and an anomalous sector in terms of its industrial dynamics, so as to facilitate the discussion of some more general findings. The results are mapped in Figures 5–8 for the distance $r = 15$ km, which captures spatial concentration at an intermediate geographic scale. As a possibly useful reminder, these maps do not generally correspond to the sheer absolute local density of plants in a sector: in fact, the M function measures the local frequency of a sector *relative* to the local frequency of all other sectors in the economy, as defined in equation (1).

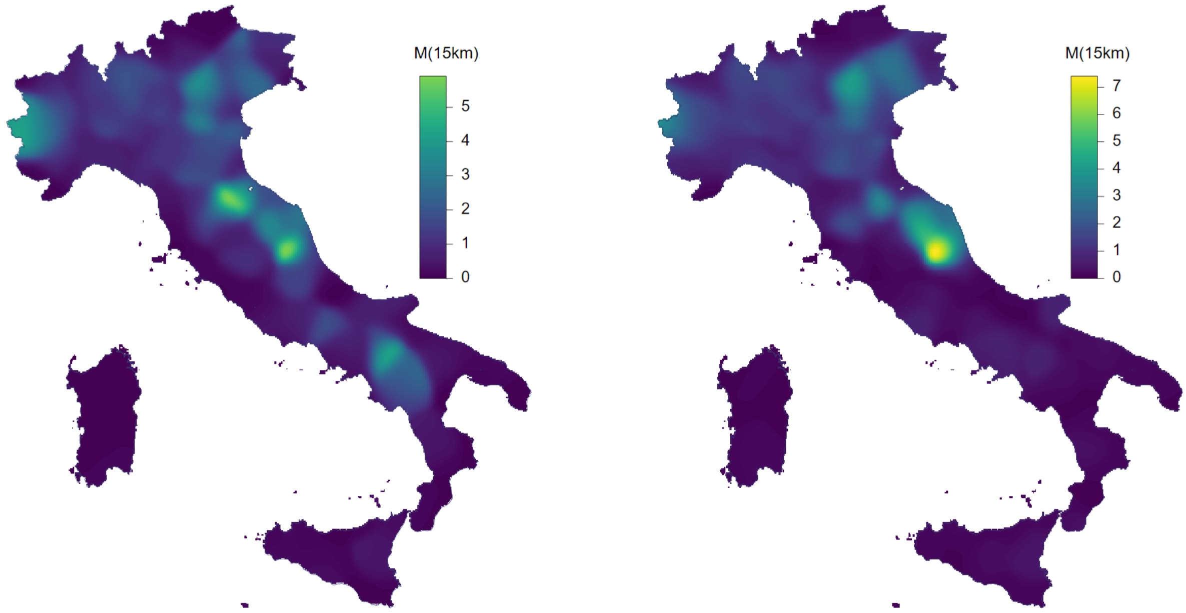


(a) Year 2007.

(b) Year 2021.

Figure 5: Local values of $\hat{M}(15 \text{ km})$ for ATECO 141-Manufacture of wearing apparel, except fur apparel, years 2007 and 2021.

For what concerns manufacturing, "141-Manufacture of wearing apparel, except fur apparel" is representative of the general tendency for manufacturing activities to lose both plants and employees over time (see Figure 1). Yet, the shrinking of this sector has translated into stronger spatial concentration: namely, $\hat{M}(15 \text{ km})$ has increased from 2.16 in 2007 to 3.79 in 2021. In parallel, the local values of $\hat{M}(15 \text{ km})$ in Figures 5 show where and how such an increase in spatial concentration materialized. In 2007, the sector was composed by multiple hotspots

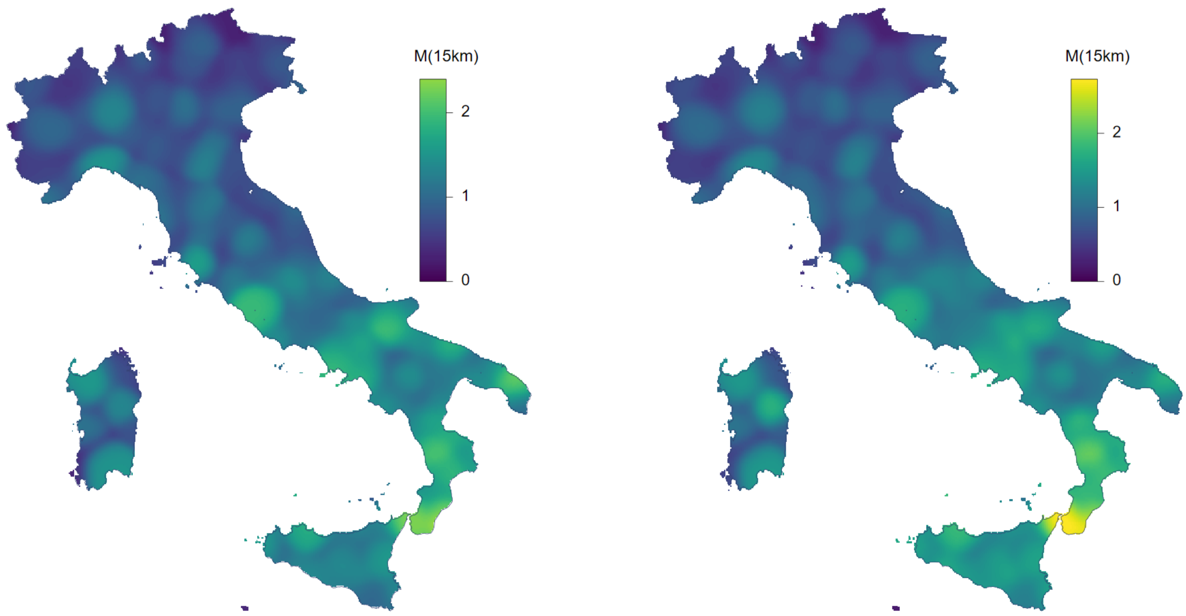


(a) Year 2007.

(b) Year 2021.

Figure 6: Local values of $\hat{M}(15 \text{ km})$ for ATECO 279-Manufacture of other electrical equipment, years 2007 and 2021.

associated with values of $\hat{M}(15 \text{ km})$ in the approximate range 5.5–6.5 (see Figure 5a). Over the years, the situation changed: some of the early hotspots lost some of their prominence and sectoral employment became much more heavily concentrate around Prato (see Figure 5b). In this setting, then, deindustrialization brought to a greater spatial selection, which ended up creating a larger gap between the main cluster in the sector and secondary ones.

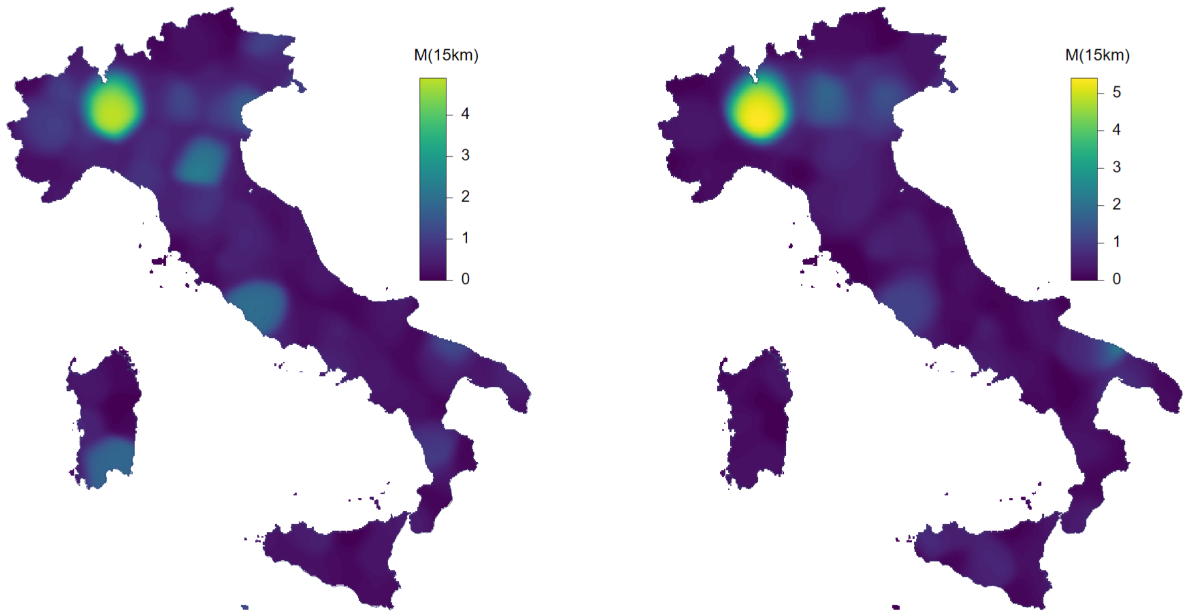


(a) Year 2007.

(b) Year 2021.

Figure 7: Local values of $\hat{M}(15 \text{ km})$ for ATECO 691-Legal activities, years 2007 and 2021.

A different scenario emerges when looking at an anomalous manufacturing sector like "279-Manufacture of other electrical equipment". The industrial dynamics that have characterized



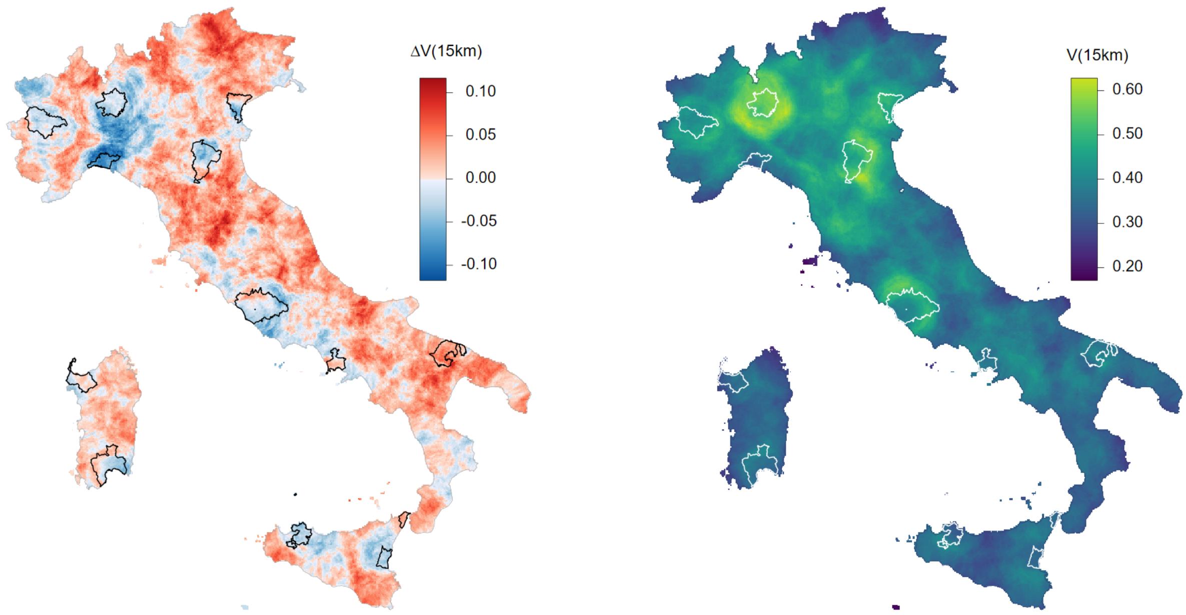
(a) Year 2007.   **(b)** Year 2021.

Figure 8: Local values of $\hat{M}(15\text{ km})$ for ATECO 732-Market research and public opinion polling, years 2007 and 2021.

this sector are not generally representative of manufacturing, as both plants and employment have grown remarkably over time (see Figure 1). Such growth, however, has entailed limited consequences in space. Indeed, $\hat{M}(15\text{ km})$ has sightly decreased from 1.52 in 2007 to 1.46 in 2021, and the corresponding local values shown in Figure 6 have kept relatively stable in space. In this perspective, then, the growth of a sector does not mechanically entail a strong tightening of geographic selection in the long term.

The spatial organization of economic activity changes quite sensibly when turning to services. For instance, Figure 7 illustrates the geographic evolution of a typical service sector such as "691-Legal activities", which has grown over time both in terms of employees and plants (see Figure 1). Between 2007 and 2021, the value of $\hat{M}(15\text{ km})$ in this sector has slightly decreased from 1.32 to 1.27, and the overall spatial organization of the sector has remained stable. In particular, lawyers and notaries public tend to follow proportionately other economic activities, although they have a clear spatial bias in favor of urban areas: as shown in Figures 7a–7b, this sector stably displays values $\hat{M}(15\text{ km}) > 1$ in correspondence of the main Italian cities. Also in this case, though, the underlying dynamic of sectoral growth does not bear any automatic implication on spatial concentration.

At any rate, the spatial concentration of services can be even more selective toward urban areas. This point is illustrated through sector "732-Market research and public opinion polling", which represents one of the relatively few service sectors that have shrunk over time both in terms of employees and plants (see Figure 1). In parallel with this contraction, also $\hat{M}(15\text{ km})$ has slightly decreased from 1.83 in 2007 to 1.74 in 2021. This is reflected in Figures 8a–8b by the weakening of spatial concentration in the urban areas around Rome, Bologna and Cagliari, to ultimately leave only Milan as a nearly untouched hotspot for market research activities and opinion polling.



(a) Variation of local variety between 2007–2021. **(b)** Level of local variety in 2021.

Figure 9: Local variety.

Note: The maps highlight local labor market areas of metropolitan cities.

4.3 Local variety

The M function can be further exploited to have a fine-grained measure of local productive variety. To have an intuitive understanding of this measure, consider the local values of M shown in Figures 5–8 as taking place on grids with an identical resolution. Let us label a generic cell of one such grids as c, so that $\hat{M}_s(c,r)$ indicates the local value of the M function for sector s, at distance r, in cell c. Local variety can then be defined as the frequency of over-localized sectors in a given cell, that is

$$V(c,r) = \frac{1}{S}\sum_{s=1}^{S} \mathbb{1}\left(\hat{M}_s(c,r) > 1\right) . \tag{2}$$

Clearly, $V(c,r)$ can range between 0 and 1, with higher values indicating that cell c is characterized by greater productive variety. Given the definition in equation (2), one can then map both levels and variations of $V(c,r)$, as shown in Figure 9 for $r = 15$ km.

This exercise uncovers some basic facts about the geography of productive variety in Italy after the Great Recession. First, some specific areas of the country have lost a remarkable amount of industrial variety over time. In particular, Figure 9a shows an especially significant decrease of V in the area of Genoa and its surroundings, reaching further north toward Lombardy. No other area in the country has experienced a comparable loss of variety after 2007. Second, variety is especially high toward the fringe of some metropolitan areas such as Milan, Bologna, and Rome. By contrast, the inner parts of these metropolitan areas display a comparatively lower level of variety, while also having lost some between 2007–2021. Third, metropolitan areas in the Mezzogiorno are typically characterized by lower levels of variety,

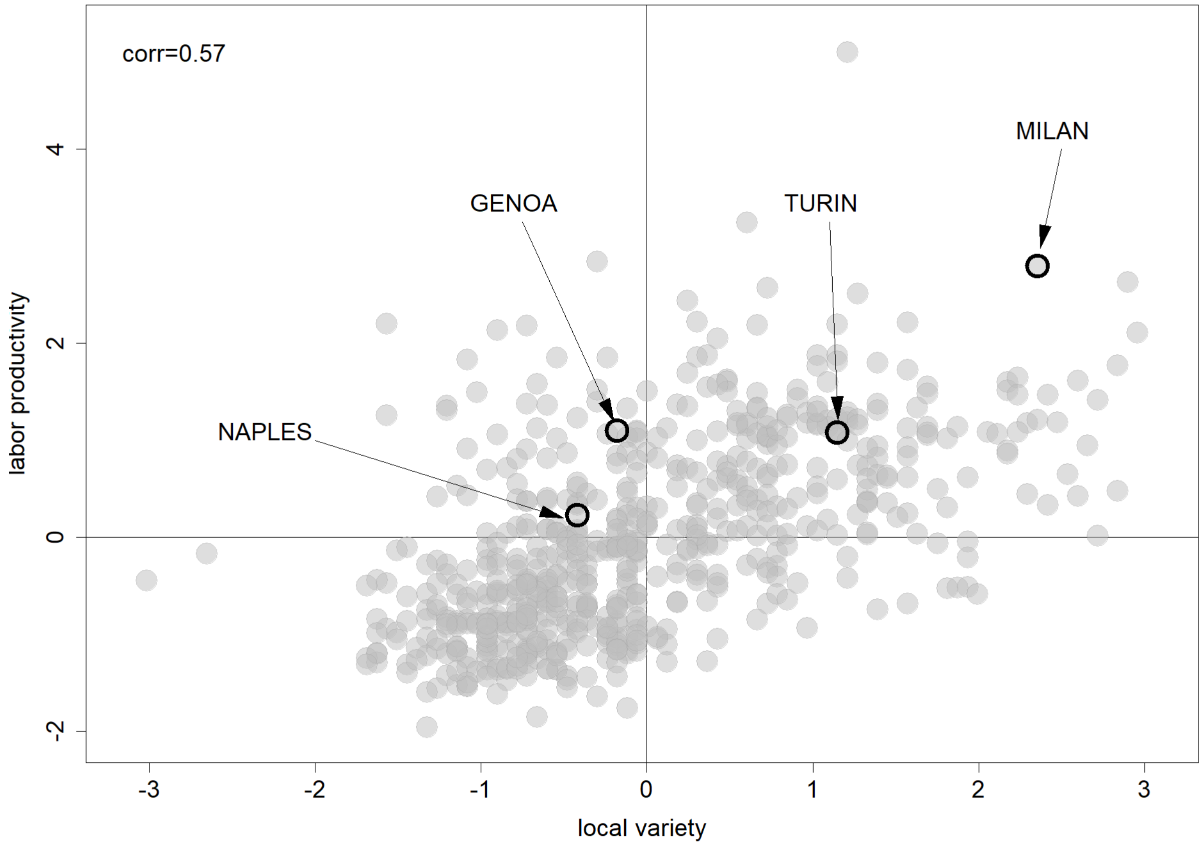


Figure 10: Variety vs Labor productivity in 2021.

Note: Both variables in the graph are standardized, so that the axes are expressed in standard deviations. Labor productivity is at the level of local labor market areas, so that also local variety was aggregated following the same spatial units.

although Naples has grown under this dimension.

To what extent, though, are these geographic facts relevant in economic terms? A look at labor productivity suggests that local variety as measured with equation (2) is indeed likely to contain key economic information. To illustrate this point we look at the correlation between variety and productivity at the scale of labor market areas. In particular, statistics on labor productivity at this level of spatial disaggregation are provided by Istat (2025b). Such data can then be correlated with the corresponding spatial aggregation of $V(15\text{ km})$, so as to gauge whether any link exists between local productive variety and labor productivity. As shown, in Figure 10, these two variables are indeed positively associated with a correlation of 0.57, thus suggesting that variety might indeed have a key role for economic development.

5 Conclusion

This paper has documented the sectoral evolution of spatial concentration in Italy between 2007 and 2021 by means of the M function, which has also be used to produce a fine-grained measure of local productive variety. The results presented here may be seen as an initial step to show how this metric can be applied on large data sets, allowing for sectoral analysis both at the aggregate and local level. By contrast, most applications appeared in the economic literature thus far were limited to rather small samples and did not exploit the local dimension.

Our analysis focused both on manufacturing and service sectors by comparing their spatial concentration before the Great Recession and well after the double dip that hit in particular southern European economies. In 2007, spatial concentration was remarkably higher for manufacturing relative to services, especially within a 15 km distance from plants. After the Great Recession, manufacturing sectors typically experienced a considerable absolute contraction both in employment and plants, whereas services typically expanded under both dimensions. The resulting spatial reorganization, however, has increased the gap between manufacturing and services in terms of spatial concentration. On average, by 2021 spatial concentration had further increased for manufacturing sectors, while slightly decreasing for services. In this sense, the contraction of a sector seems to tighten spatial selection, by reducing the number of places where the sector concentrates geographically. Although here it was applied only to a few paradigmatic sectors, our local analysis of M further shows which particular places have been selected in this sectoral process of spatial reorganization. In a similar spirit, our analysis has also shown how productive variety has evolved in space between 2007–2021, thus highlighting the specific areas that were most affected by this form of spatial reorganization.

If our present contribution represents an initial step toward the widespread empirical application of the M function, much still remains to be done along these directions. In particular, two main further applications seem relevant. First, the analysis of spatial concentration via the M function can be extended at the inter-sectoral level. That is, instead of measuring how many other plants in the *same* sector are proportionately present within some distance from an establishment, one may want to focus on plants in *other* sectors from the one in which the establishment operates. The resulting measure would then allow to evaluate the co-location of industries, as described by Marcon and Puech (2010, pp. 751–52). When evaluated at the local level, this application would allow to identify the locus of spatial interaction for any two sectors. Second, the local values of M can be further exploited for econometric analysis in the context of data sets with plant-level data. Specifically, each plant can be associated to its local value of M, ultimately allowing to test how observed spatial concentration may affect the economic performance of plants. This type of study may help to further uncover how and where geography matters to economics.

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