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FULL ARTICLE

New evidence on measuring the geographical concentration of economic activities

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Abstract

Spatial interactions among regional units may influence the geographical distribution of economic activities. Many traditional measures of geographical concentration fail in capturing this aspect, being insensitive to permutations of the spatial position of regions. This paper proposes an approach to the measurement of geographical concentration of economic activities that accounts for spatial interactions among regions. The locational Gini is split into spatial and non-spatial components, so that a new interpretation of the index is presented. The measure is applied to evaluate the geographical concentration of different economic sectors for 1,323 NUTS 3 regions in the European Union over the period 2001–2018.

KEYWORDS

cluster-based measures, locational Gini index, NUTS 3 EU regions, regional specialization, spatial dependence

JEL CLASSIFICATION

C40, R12, D63

1 | INTRODUCTION

In the regional sciences, there has been a large debate around geographical concentration of industries as well as the effects that specialization has on economic growth (Caragliu et al., 2016; Dissart, 2003; Wagner, 2000). Concentration and specialization have been considered as driving forces for growth (Becattini, 1979), and some authors have more recently continued to support this idea (Porter, 2003). Conversely, others stressed the advantages of diversity in terms of innovating potential (among others, Camagni, 1991; Kemeny & Storper, 2015; Lundvall & Johnson, 1994). In the aftermath of the crisis, the discussion was extended in a business cycle perspective to also consider regional differences and economic stability (Boschma & Gianelle, 2014; Cainelli et al., 2019; Faggian et al., 2018; Martin et al., 2016).

Not surprisingly, the consideration of spatial effects represents a well-known occurrence for regional phenomena (Anselin, 1988). This happens while modelling the effect of specialization on economic growth (or other objective variables) allowing for direct and indirect impacts or considering technological externalities (LeSage & Pace, 2009).

However, statistical indices of geographical concentration have been less considered under a spatial lens (Arbia, 2001; Guillain & Le Gallo, 2010), despite geographical aspects calls for more *ad hoc* tools (Cutrini, 2010).

Common indices used to measure geographical concentration of economic activities - as locational Gini and the Herfindahl indices—do not consider spatial information. In fact, they are insensitive to spatial ordering, a feature known as anonymity (Bickenbach & Bode, 2008). This makes difficult for policy-makers to avail information embedded into the geographical structure on how regions may influence each other (Arbia, 2001). In this sense, there has been some previous attempts to consider spatial features in the analysis of geographical concentration (De Dominicis et al., 2013; Guillain & Le Gallo, 2010; Lafourcade & Mion, 2007; Sohn, 2004) and, more recently, new spatial indices of concentration have been introduced at this purpose (Ferrante et al., 2020; Guimarães et al., 2011).

In this paper, we propose to apply a spatial approach for measuring geographical concentration based on the locational Gini index. Following the same rationale of Panzera and Postiglione (2020), we isolate the spatial and non-spatial components of the index to obtain a clearer picture about the relevance of the space in the distribution of economic activities. Therefore, we show how locational Gini subsumes two different measures. On the one side, it includes a measure of concentration driven by spatial dependence and, on the other one, it subsumes an indicator driven by specific characteristics of the regions. In this sense, our proposal enriches the interpretation of the standard locational Gini.

The use of a spatial indicator of economic concentration may reveal how geographical distribution of economic activities is influenced by specific spatial patterns (Combes & Overman, 2004), and allow to define *ad hoc* local policies for different levels of territories. For instance, neighbouring effects between regions may have influence on the diversification/specialization choices. Therefore, large presence of a sector in one region may be due by the same occurrence in neigbouring regions. Applying tools that analyse spatial proximity in geographical concentration of economic activities could help policy-makers to assess these effects, and improve multi-level governance in short and long-run. Additionally, our spatial decomposition may also be used in spatial growth equations to measure what are the effects of spatial concentration on economic growth (e.g., Caragliu et al., 2016; Panzera & Postiglione, 2021).

To show the insights offered by this approach, our spatial locational Gini is applied to the employment in European NUTS 3 regions over the years 2001–2018. Differently from previous research, we consider all the 28 EU countries at a relatively fine scale and different economic sectors corresponding to the NACE Rev. 2 classification are taken into account. The choice of our application is motivated by the economic integration occurred in the European Union and its effects on the sectoral distribution (Alonso-Villar & del Río, 2013; Cutrini, 2010; Resmini, 2007). At this purpose, results add on previous literature about the relevance of the spatial component for each sector, while the statistical significance of the spatial index is tested by a randomization procedure.

The paper is organized as follows. Section 2 presents an overview about previous contributions on the measurement of geographical concentration. Section 3 presents our methodological proposal, which is empirically illustrated in Section 4. In Section 5 we discuss potential implications also in terms of policy. Final remarks are given in Section 6.

2 | SPATIAL INTERACTIONS AND THE GEOGRAPHICAL CONCENTRATION OF ECONOMIC ACTIVITIES

Popular measures of geographical concentration of economic activities derive their properties from the literature on income inequality and segregation (Alonso-Villar, 2011; Alonso-Villar & del Río, 2013; Hutchens, 1991, 2004; Massey & Denton, 1988). Concentration measures that have been derived from the income inequality measures, such as the Gini index and generalized entropy measures, satisfy basic requirements corresponding to symmetry in location, movement between locations, scale invariance, and insensitivity to proportional subdivisions of locations (Alonso-Villar, 2011).

The symmetry in location, also known as anonymity (Bickenbach & Bode, 2008), implies that concentration measures are insensitive to the spatial position of data. The movement between locations corresponds to the Pigou–Dalton principle of transfers of income inequality measures and implies that when a location, with a lower level of employment in a sector with respect to another location, loses employment in this sector in favour of the other location, concentration should increase. Scale invariance implies that the share of employment, rather than the level of employment, matters in measuring concentration. The fourth property, borrowed from occupational segregation indices (Hutchens, 2004), is respected when subdividing a location into several units, with the same aggregate level of employment and the same level of employment in the sector under consideration, does not impact on the geographical concentration of the sector.

Additional properties of geographical concentration measures have been identified by Duranton and Overman (2005) related to the comparability of the measures across sectors, the unbiasedness with respect to scale and aggregation, and the possibility to report the statistical significance of the results. Trying to address those issues, the authors defined a measure that satisfies these properties for the special case of measuring localization of plants. This approach focuses on the selection of relevant establishments and on the estimation of the density of the Euclidean distances between any pairs of establishments.

The anonymity condition has been considered as a limitation of concentration measures. In fact, this property implies that these measures consider information within each regional unit, while they completely neglect the position of regions in space. Discarding this aspect leads to consider regions as independent in analysing geographical concentration, while, as it is well known, spatial independence is patently violated in all territorial studies.

The position of regions as well as relations among neighbour units could play a role in determining a specific geographical distribution of economic activities. Geographical proximity could determine similarity of values in space, yielding to neighbour regions with similar level of sectoral specialization. Hence, measures of geographical concentration of economic activities should account for the role of space (Arbia, 2001).

Some previous contributions tried to address the insensitivity of cluster-based measures to the spatial arrangement of data. Arbia (2001) introduced the distinction between a-spatial concentration, invariant to spatial permutations, and polarization, that refers to the geographical position of data. While the first aspect can be captured by traditional measures of geographical concentration, the second one could be measured by using indicators of global and local spatial association. Sohn (2004) examined the concordance of economic linkages between sectors and the spatial proximity relationships. Hence, the correlations between input–output table coefficients and measures of geographical concentration and spatial association have been investigated. Lafourcade and Mion (2007) proposed analysing concentration of industries and spatial dependence using conventional indices and assessing the influence of plant size on both these features. Guillain and Le Gallo (2010) focused on several manufacturing and service sectors in Paris and the surrounding area. In this study, the authors assessed concentration of economic activities and location patterns by combining traditional concentration measures and Exploratory Spatial Data Analysis (ESDA). De Dominicis et al. (2013) extended the approach proposed by Guillain and Le Gallo (2010) by adding firm size in the analysis.

While the aforementioned studies have been mainly focused on combining conventional indices of concentration and spatial association, other contributions proposed new measures that account for spatial interactions.

Guimarães et al. (2011) proposed an approach to account for spatial proximity and neighbouring effects in popular measures of geographical concentration of industries. The authors focused on the Herfindahl and the Ellison and Glaeser (EG) indices (Ellison & Glaeser, 1997) introducing their spatially weighted versions, that merge information from the conventional indices with that of Moran's I.

Denoted by $\mathbf{y}$ the n-dimensional column vector containing the regional shares, y_i, of a measure of interest (e.g., the share of industry's employment) the Herfindahl index H can be defined as (Ellison & Glaeser, 1997):

$$H = \mathbf{y}'\mathbf{y} = \sum_{i=1}^{n} y_i^2. \tag{1}$$

While the index in 1 is an absolute measure of concentration, a relative measure, that involves comparisons with a reference distribution, is represented by the raw geographic concentration index G_{EG} (Ellison & Glaeser, 1997). Denoted by $\mathbf{z}$ the vector containing the elements z_i, $i = 1, 2, \ldots, n$, of the reference distribution, this measure can be defined as (see also Guimarães et al., 2011):

$$G_{EG} = (\mathbf{y} - \mathbf{z})'(\mathbf{y} - \mathbf{z}) = \sum_{i=1}^{n} (y_i - z_i).^2 \tag{2}$$

Based on the indices in Equations 1 and 2 the Ellison and Glaeser index γ_{EG} (Ellison & Glaeser, 1997) can be defined as:

$$\gamma_{EG} = \frac{G_{EG} - H}{1 - H}. \tag{3}$$

As mentioned, all these indices are insensitive to the geographical position of data that, which does not have an impact on the results.

The definition of the spatially weighted Herfindahl index, H_s, introduced by Guimarães et al. (2011), only requires defining the spatial weight matrix $\mathbf{W}$, that summarizes the proximity relationship between geographical units. This index accounts for neighbourhood effects and is specified as:

$$H_s = H + \mathbf{y}'\mathbf{W}\mathbf{y}. \tag{4}$$

Similarly, a spatial version of the raw concentration measure in 2 can be specified as:

$$G_{EGs} = G_{EG} + (\mathbf{y} - \mathbf{z})'\mathbf{W}(\mathbf{y} - \mathbf{z}), \tag{5}$$

and, using the spatially weighted measures defined in Equations 4 and 5 as starting points, a spatial version of γ_{EG} can be derived (for further details see Guimarães et al., 2011).

An absolute measure of spatial concentration has been also proposed by Ferrante et al. (2020). This measure is derived as the solution of a transportation problem (Lo Magno et al., 2017). The authors considered the problem of transferring the amount of a phenomenon of interest among regions to eliminate any imbalance in the distribution of this phenomenon. The transportation problem can be defined by identifying two sets of regions, $\mathcal{A}$ and $\mathcal{B}$, which contain the regional units that have an amount of a quantity of interest, y_i, above the average μ_y, and below the average, respectively. Denote by t_{ij} the transfers between regions, with $i, j = 1, 2, \ldots, n$, and by c_{ij} the relative costs, that can be summarized in the $n \times n$ matrix $\mathbf{C}$. The optimal solution to this transportation problem is given by the values t_{ij}^* and the corresponding minimum costs $\mathbf{c}^*$. This optimal solution defines the absolute measure of spatial concentration, $S_A(\mathbf{y}, \mathbf{C})$, introduced by Ferrante et al. (2020), which is a function of the vector $\mathbf{y}$ and the matrix $\mathbf{C}$ as:

$$S_A(\mathbf{y},\mathbf{C}) = \mathbf{c}^* = \sum_{i \in \mathcal{A}} \sum_{j \in \mathcal{B}} t_{ij}^* c_{ij}, \quad (6)$$

where all the quantities are defined as above. Starting from the absolute concentration measure, a relative concentration index can be derived by dividing the latter by its maximum value. This index specifically allows comparisons between situations characterized by a different total amount of the phenomenon under investigation.

As spatial position and neighbourhood effects are considered as pivotal in the paper, we address geographical concentration of economic activities accounting for these aspects. Specifically, we extend the spatial decomposition introduced by Panzera and Postiglione (2020) for the general case of the Gini inequality index to the locational Gini index, obtaining a spatial version of the measure. This spatial measure allows to analyse the geographical concentration of economic activities while addresses the anonymity condition. The rationale of Panzera and Postiglione (2020) is thus applied to a different field of study, and the existing literature is enriched by assessing the statistical significance of the spatial index. This contribution is presented in the following section.

3 | METHODOLOGY

A common cluster-based measure of geographical concentration of economic activities is represented by the locational Gini index (Krugman, 1991; Suedekum, 2006). The large success of this index in empirical applications is due to easy calculation and to the limited amount of data required (Guillain & Le Gallo, 2010). Formally, the locational Gini index for a given economic sector m is specified as:

$$G_m = \frac{\frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j|}{4\mu_x}, \quad (7)$$

where n is the number of regions, $\mu_x = \frac{\sum_{i=1}^{n} x_i}{n}$, and $x_{i(j)}$ expresses the location quotient that is computed for region $i(j)$ as:

$$x_{i(j)} = LQ_{i(j)} = \frac{E_{m,i(j)}/E_{i(j)}}{E_{m,C}/E_C}, \quad (8)$$

where $E_{m,i(j)}$ is the employment intensity in the economic sector m in region $i(j)$, $E_{i(j)}$ is the total employment intensity in region $i(j)$, $E_{m,C}$ is the employment intensity in the economic sector m in the whole country, and E_C is the total employment intensity in the whole country.

Location quotients (LQ s) express the relative concentration of an economic sector in a region in comparison to the whole country. Different cut-off values for LQ s have been considered in the literature to identify regional specialization in a particular economic sector (among others, O' Donoghue & Gleave, 2004). Generally, a region is considered as specialized when it has a $LQ > 1$ (Carroll et al., 2008), while other contributions proposed cut-off values higher than one (Malmberg & Maskell, 2002).

The index in 7 measures the relative concentration of a given economic sector in a region compared to the same economic sector in other regions. If, for a given sector, the economic activities are uniformly distributed across regions (i.e., the employment shares of a given sector in all regions is equal to the total employment share), $G_m = 0$. When the sector employment is totally concentrated in one region, the index reaches its maximum value $G_m = 0.5$.

The locational Gini meets the four properties of concentration measures which are described by Alonso-Villar (2011) and mentioned in the previous section. However, the anonymity property, which characterizes this index, could be viewed as a drawback of the measure (Sohn, 2004).

With respect to the properties highlighted by Duranton and Overman (2005), the standard locational Gini only satisfies the first one, sharing this feature with other well-known measures of geographical concentration. In fact, the locational Gini index is comparable across different economic sectors, but conceptually differs from the measure by Duranton and Overman (2005). In fact, while the latter is a distance-based measure, using data on point geo-localizations of firms (Kopczewska, 2018; Kopczewska et al., 2019), the locational Gini index is a cluster-based measure that focuses on aggregated data.

The insensitivity of the locational Gini index to the spatial position of regions highlights the need for a measure which accounts for spatial interactions among neighbour observations.

To address this issue, we extend the spatial decomposition approach introduced by Panzera and Postiglione (2020) to the locational Gini index defining a measure of geographical concentration which embeds spatial information.

Using little algebra and following Lerman and Yitzhaki (1984) and Schechtman and Yitzhaki (1987), the locational Gini in 7 can be alternatively written as:

$$G_m = \frac{n}{n-1} \frac{Cov(x,\ R_X/n)}{\mu_x}, \tag{9}$$

where R_X is the rank of the variable X (i.e., the LQ for a given sector), such that the lower value of X is ranked 1 and the highest value of X is ranked n, with n the number of observations.

Considering Equation 9, we define a *spatial locational Gini* as:

$$G_{sm} = \frac{n}{n-1} \frac{Cov(x,\ R_{WX}/n)}{\mu_x}, \tag{10}$$

where R_{WX} is the rank of the variable WX, that expresses the spatial lag of the variable X, defined through the spatial weight matrix $\mathbf{W}$. This spatially lagged variable expresses a weighted average of the values of X observed on neighbouring regions (Panzera & Postiglione, 2020).

The index in 10 thus defines the correlation between the LQ values that, for a given sector, are observed on a set of geographical units with a rank of these units that is based on the average value of LQs observed for the same sector on neighbour regions. In this sense, the measure in (10) captures the spatial interactions among neighbour regional units and represents a spatial measure of concentration.

Since it focuses on the correlation between the LQ of an industry in a particular region and the rank associated to the LQs in neighbour regions, the measure in Equation 10 considers the information related to either the region or its neighbours. Neighbour regions can be identified according to different criteria that can capture distance decay effects (Duranton & Overman, 2005). Focusing on the interactions among a particular region and a small number of neighbours could be useful in regional analysis to capture the influence among spatial units belonging to the same country.

It is worth noting that our spatial locational Gini index in 10 is obtained by reranking the observations, and for this reason, the same rationale of Dawkins (2004) can be applied. So, in this case $-G_m \leq G_{sm} \leq G_m$ and the following decomposition is verified:

$$G_m = G_{sm} + G_{nsm}, \tag{11}$$

where $0 \leq G_{nsm} \leq 2G_m$ represents the non-spatial component of G_m, that is the part of geographical concentration that is linked to specific regional characteristics and is not influenced by a specified pattern of spatial dependence. Equation 11 thus introduces the decomposition of the locational Gini index in its spatial and non-spatial components.

To assess the impact of spatial interactions on a given pattern of geographical concentration of a particular economic sector, we can introduce a novel measure defined as the ratio between the spatial locational Gini index in 10 and the global locational Gini index in 9 as:

$$\gamma_m(x, Wx) = \frac{G_{sm}}{G_m} = \frac{Cov(x, R_{WX}/n)}{Cov(x, R_X/n)}. \tag{12}$$

The numerator in 12 corresponds to the Gini covariance between *X* and *WX*, and provides a measure of spatial autocorrelation. The denominator in 12 expresses the variability in *LQ*s for a given sector. In fact, as shown by Schechtman and Yitzhaki (1987), it corresponds to one quarter of the Gini's mean difference, which is a measure of dispersion. The resulting measure, $\gamma_m(x, Wx)$, can be thus used to assess the relative contribution of a pattern of spatial autocorrelation to a given pattern of geographical concentration.

The measure in 12 shares the same properties of the Gini correlation measure[1] and ranges between -1 and 1 (Schechtman & Yitzhaki, 1999). Specifically, when the ranking of *WX* is identical to the original ranking of *X*, $G_{sm} = G_m$, $G_{nsm} = 0$ and $\gamma_m(x, Wx) = 1$, indicating that the overall geographical concentration of the sector is completely explained by the given pattern of spatial dependence.

As the ranking of *LQ*s becomes more dissimilar to the ranking of average *LQ*s in neighbour regions (i.e., *WX*), the spatial component of the geographical concentration of the sector under consideration becomes smaller and approaches its minimum value of $-G_m$ when the average *LQ*s in neighbour regions are ranked as the opposite with respect to the original order of regional *LQ*s. In this case, the non-spatial component of sectoral concentration reaches its maximum value of $2G_m$ and $\gamma_m(x, Wx) = -1$.

When *X* and *WX* are uncorrelated, we have that $G_{ms} = 0$, and, thus, $G_m = G_{nsm}$ and $\gamma_m(x, Wx) = 0$, indicating that the overall inequality is completely explained by its non-spatial component (see also Panzera & Postiglione, 2020, for the case of general Gini index).

Note that the replacement of data by their rank in expressing the spatially lagged variable could mask variations in the values observed for the neighbour units. This implies that changes in the variate values could not impact on their rank. However, the rank transformation is able to capture the relative position of data and our measure, that is based on the rank transformation, is always applicable when one variable can be expressed as the weighted or the unweighted sum of several components (Schechtman & Yitzhaki, 1987).

The methodology proposed in the current study reveals that, when decomposing the overall locational Gini index in its spatial and non-spatial components, this measure gives further evidence with respect to its traditional interpretation. In fact, our approach allows the identification of new features of the standard locational Gini, that subsumes two different dimensions of concentration, such as the idiosyncratic component, related to specific characteristics of the region, and the spatial component, expressing the component of geographical concentration driven by proximity relationships between regional units. Hence, using a decomposition that follows the rationale proposed by Panzera and Postiglione (2020), we offer a new interpretation of the locational Gini index. The spatial component allows measuring the neighbourhood effect, while the non-spatial part of the index provides information on the component of geographical concentration not influenced by the spatial interactions.

Besides, the spatial component relies on the definition of proximity relationships between the units under consideration summarized through the weight matrix **W**. However, the opportunity of using several different specifications for the matrix **W**, based on either physical distances or economic and social similarities (Conley & Topa, 2002) provides a certain flexibility to our proposed measure.

Also Rey and Smith (2013) proposed a decomposition of the Gini index into a spatial and non- spatial component. The differences between these two measures lies in the derivation of the spatial expansion and in the interpretation. The spatial term calculated by Rey and Smith (2013) is a spatial expansion due to positive (or negative) spatial autocorrelation directly addressed in the lag of the variable *Y*. Rey and Smith (2013) considered the Gini index expressed in relative mean difference form. They rewrote the sum of all pairwise differences as the sum of absolute differences between pairs of neighbour observations and absolute differences between pairs of non-neighbour observations. Hence, in Rey and Smith (2013), the spatial component is derived by addressing spatial autocorrelation focusing on the lag of the variable under consideration. In our approach the spatial part is obtained by reformulating the Gini coefficient as a correlation between the variable and the rank of the spatially lagged variable following Panzera and Postiglione (2020).

Our method presents some advantages with respect to other approaches in the previous literature. Unlike Guimarães et al. (2011), we do not modify a traditional measure of geographical concentration adding a spatial part. In our case, the spatial component is contained in the locational Gini index and obtained through its decomposition. This offers a new interpretation of the index. Furthermore, additional data, related to the employment at the firm level, are required in Guimarães et al. (2011) to calculate the Herfindahl indices and also in Ferrante et al. (2020), which implies identifying above average and below average regions and transportation costs. Conversely, our decomposition only requires data on employment, aggregated by industry and region, and the definition of proximity relations among regional units through a **W** matrix.

In this paper, the inference on the spatial locational Gini G_{sm} is implemented following the same procedure introduced by Rey (2004) and applied by Harris et al. (2015). At this purpose, 9,999 values of the G_{sm} are simulated by spatial random permutations. Particularly, this sampling distribution is obtained by randomly reassign the observed values of *LQ*s to different spatial units, under the null hypothesis that each pattern is equally likely. Also, the G_{sm} indicator is calculated by assuming the same underlying topology (i.e., the same **W** matrix) at each iteration. The true value obtained for the G_{sm} is then added to the computationally based distribution and the statistical significance of the G_{sm} is evaluated by the position assumed into this ranked distribution. As remarked by Rey and Smith (2013), the spatial permutation approach consents for inference only on the spatial component G_{sm}, and not on the value of the global locational Gini coefficient.

4 | GEOGRAPHICAL CONCENTRATION OF ECONOMIC ACTIVITIES AND SPATIAL INTERACTIONS AMONG NUTS 3 EU REGIONS

In the empirical application, we focus on different sectors in the period 2001–2018. Data on 1,323 NUTS 3 regions belonging to 28 EU countries[2] for different classification of economic activities NACE Rev. 2 are collected from the ARDECO database. The following sectors are considered: agriculture, forestry, and fishing (A); industry (except construction, B–E); construction (F); wholesale and retail trade, transport, accommodation and food service, information and communication (G–J); financial and business services (K–N); non-market services (O-U).

The choice of focusing on sectors different from the only industry origins in the growing importance proportion that services and trade has in regional economics, especially in more developed regions. A further reason is represented by the possibility to observe together the geographical concentration and spatial dependence for different sectors in the EU (Guillain & Le Gallo, 2010). Particularly, the EU enlargement has caused relocation of resources so that it is interesting to assess if geographical proximity plays a role in geographical concentration of economic sectors (Resmini, 2007).

The geographical distributions of the *LQ*s are presented for 2018 in the following figures, besides the value of the locational Gini index and of the Moran's *I*.[3] Figure 1 displays in (a) the geographical distribution of *LQ*s for agriculture, forestry, and fishing and in (b) the geographical distribution of *LQ*s for industry (except construction). Darker colours indicate higher values of *LQ*, light colours denote lower values of *LQ*. For agriculture, about 60% of the regions have a value of *LQ* that is not greater than 1, which implies that many regions show low incidence of this sector. Conversely, higher values of *LQ*s for the agricultural sector are reported for regions located in Portugal, for the South-West of Spain, and for Eastern Europe regions.

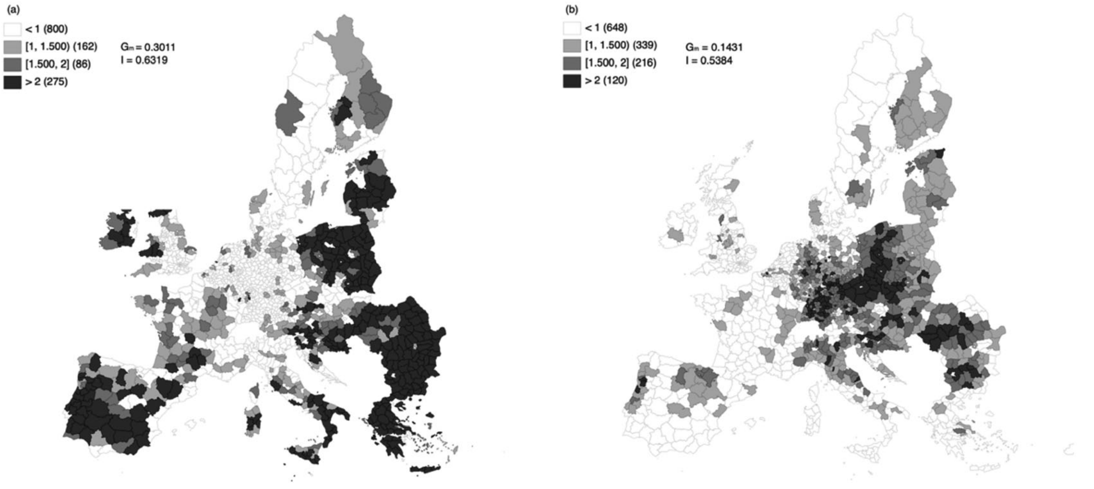

FIGURE 1 *LQ*s for (a) agriculture, forestry, and fishing and (b) industry (except construction) in 1,323 NUTS 3 EU regions, 2018

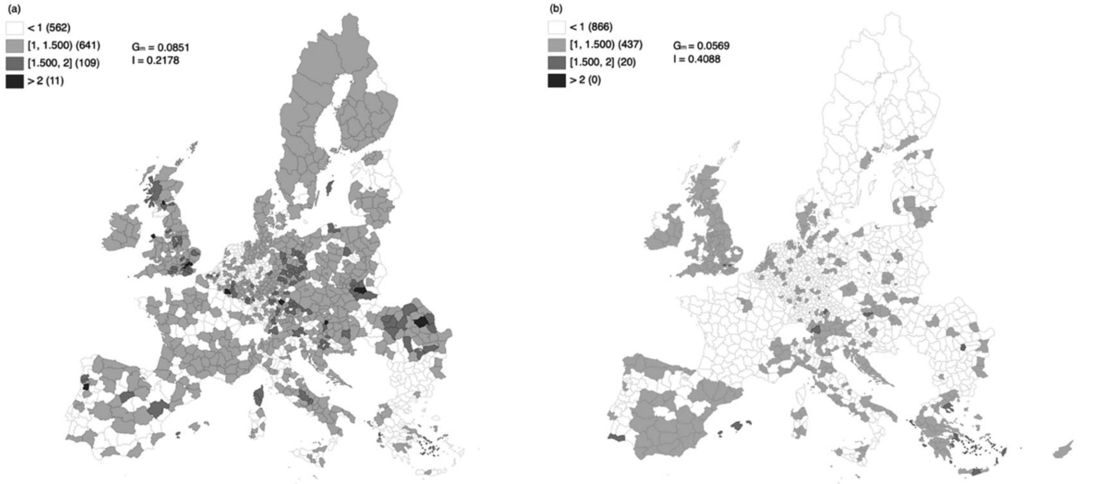

FIGURE 2 *LQ*s for (a) construction and (b) wholesale and retail trade, transport, accommodation and food service, information and communication in 1,323 NUTS 3 EU regions, 2018

With respect to the distribution in (a) the distribution in (b) appears more scattered, as confirmed by the lower value of the Moran's *I*. For industry, about the 49% of regions has a *LQ* that is not greater than 1. Higher industrial specialization is observed in some regions in the North-East of Italy, Germany, and in the East of Europe.

The higher geographical concentration of agriculture, forestry, and fishing corresponds to a higher level of spatial autocorrelation, which also suggests how spatial autocorrelation may be at the basis of progressive regional specialization.

Figure 2 displays in (a) the geographical distribution of *LQ*s for construction and in (b) the geographical distribution of *LQ*s for wholesale and retail trade, transport, accommodation and food service, information, and communication.

For the construction sector, about the 42% of regions has a *LQ* value that is not greater than 1. For trade and services, the percentage of regions with a *LQ* value not greater than 1 is about 65%. Higher level of specialization in construction are reported in some regions of the United Kingdom. Regions more specialized in trade and services are mainly located in Ireland, United Kingdom, and South and North of Spain. Lower *LQ*s for this sector are in Sweden and Finland. These economic sectors also show different behaviours, since to the higher spatial dependence observed for trade and services does not correspond a higher concentration.

Figure 3 shows *LQ*s for financial and business services in (a) and for non-market services in (b). Both distributions appear clustered as evidenced by the magnitude of Moran's *I*. For financial and business services the percentage of regions with a *LQ* value that is not greater than 1 is about 74%. Groups of regions with lower value of *LQ* are mainly located in the East of Europe.

Non-market services that include, among others, public administration, defence, education, human health, and social work activities, present higher *LQ*s for regions located in Sweden and Finland as well as for groups of regions in France. Conversely, the percentage of regions with a *LQ* value not greater than 1 is about 49%. With respect to the financial and business services, this sector is characterized by lower spatial autocorrelation of *LQ*s and lower concentration.

Combining the information from the locational Gini index with measures of spatial autocorrelation is the approach followed in some previous studies to assess the location patterns of economic sectors (Arbia, 2001; Guillain & Le Gallo, 2010). However, this brings to separately measure spatial dependence and geographical concentration.

In this paper, we try to move a step ahead, by identifying a measure that expresses the spatial component of geographical concentration of the locational Gini index. In Table 1, the values of the overall locational Gini index, its spatial and non-spatial components, and the index γ_m are presented for all the economic sectors for 2018.

As displayed in Table 1, the G_{sm} is a spatial measure which preserves comparability with the standard locational Gini, as reported by the indicator γ_m. Moreover, the remaining part obtained by difference may be easily conceived as the non-spatial component. The G_{sm} of concentration is generally higher than the non-spatial part for all the economic activities under consideration, with the only exception of the construction where $G_{nsm} > G_{sm}$. The agricultural sector appears to be the most concentrated as well as the most influenced by spatial dependence.

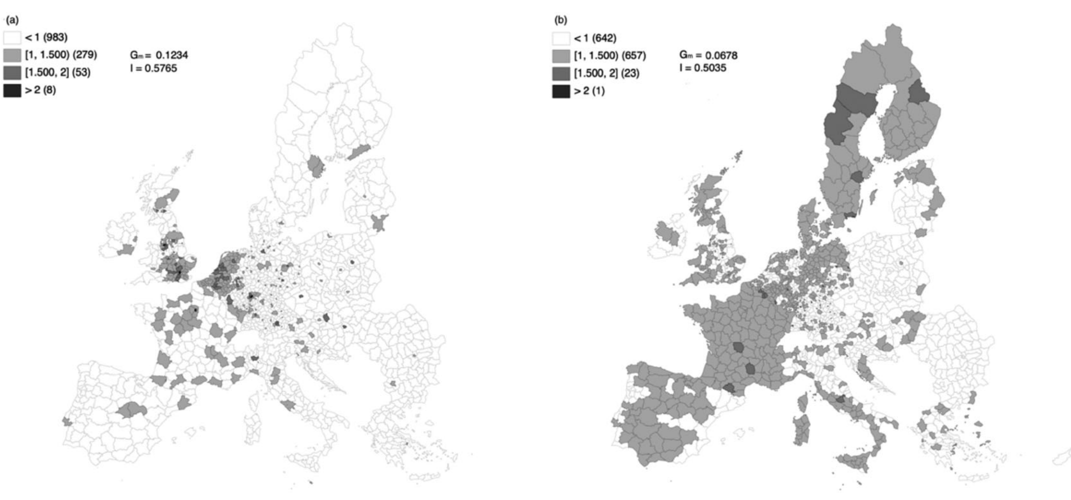

FIGURE 3 *LQ*s for (a) financial and business services and (b) non-market services in 1,323 NUTS 3 EU regions, 2018

TABLE 1 Locational Gini and its spatial and non-spatial components for different economic sectors for 1,323 EU NUTS 3 regions, 2018

Economic sector	G_m	G_{nsm}	G_{sm}	γ_m
Agriculture, forestry and fishing (A)	0.3011	0.0501	0.2510	0.8336
Industry (except construction, B-E)	0.1431	0.0363	0.1068	0.7463
Construction (F)	0.0851	0.0515	0.0336	0.3948
Wholesale and retail trade, transport, accommodation and food service, information and communication (G-J)	0.0569	0.0218	0.0351	0.6169
Financial and business services (K-N)	0.1234	0.0342	0.0892	0.7229
Non-market services (O-U)	0.0678	0.0216	0.0462	0.6814

TABLE 2 Spatial Gini and Moran's *I* for different economic sectors in 1,323 EU NUTS 3 regions, 2018. P-values in brackets

Economic sector	G_{sm}	I
Agriculture, forestry and fishing (A)	0.2510 (0.000)	0.6319 (0.000)
Industry (except construction, B – E)	0.1068 (0.000)	0.5384 (0.000)
Construction (F)	0.0336 (0.000)	0.2178 (0.000)
Wholesale and retail trade, transport, accommodation and food service, information and communication (G – J)	0.0351 (0.000)	0.4088 (0.000)
Financial and business service (K – N)	0.0892 (0.000)	0.5765 (0.000)
Non-market services (O – U)	0.0462 (0.000)	0.5035 (0.000)

As the G_{sm} represents the main focus of the paper, we also verify the significance of this component through the randomization test introduced in Section 3. The significance for the G_{sm} is reported in Table 2, where 9,999 randomizations are considered to evaluate if the level of the spatial concentration is significantly different from the ones obtained through random permutations. In Table 2, the values of the G_{sm} for the sectors are also reported together with the level of the Moran's I for 2018, while significance of these indicators is reported in the Appendix Tables A1 and A2 for all the years under analysis. A k-nearest neighbour contiguity matrix, with $k = 10$, is adopted for both indices.

The significance of the G_{sm} is confirmed in all cases. As previously mentioned, the sector characterised by the higher value of the locational Gini index is agriculture, forestry and fishing which also shows the highest value for the Moran's I. By looking at the level of spatial concentration indicators, we observe how industry ranks as second in terms of spatial component, despite its level of the Moran's I is lower of the one of finance and business services. Therefore, by jointly considering geographical concentration and spatial information, we observe how concentration in industry is more influenced by spatial dependence than the financial sectors. This means that the level of specialization in neighbouring regions has a deeper effect in industry than in the finance and business. This may be linked to the fact that firms included into B–E are more influenced by natural endowments (see, for the case of Belgium, Bertinelli & Decrop, 2005).

The geographic concentration is also considered in relations with the productivity of each sector. In Table 3 the share of total gross value added (GVA) and GVA per worker relative to each economic sector are shown.

A low value of GVA per worker characterises agriculture, which also has the lowest contribution to the total GVA at the European level. However, spatial dependence appears to have a significant effect in shaping the geographical distribution of LQs as values tend to cluster together in space. Moreover, slightly lower spatial dependence

TABLE 3 Shares of total GVA and GVA per worker for different economic sectors for 1,323 NUTS 3 EU regions, 2018

Economic sector	Share of Total GVA	GVA per worker (in PPS)
Agriculture, forestry and fishing (A)	1.67%	23029.2270
Industry (except construction, B-E)	19.88%	76558.3922
Construction (F)	5.44%	50604.2519
Wholesale and retail trade, transport, accommodation and food service, information and communication (G-J)	24.54%	52084.4228
Financial and business services (K-N)	26.81%	94683.2158
Non-market services (O-U)	21.66%	43393.4649

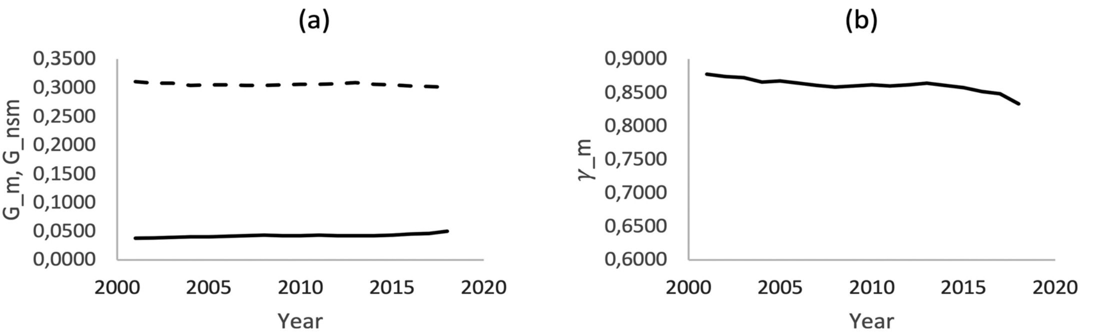

FIGURE 4 Geographical concentration of agriculture, forestry, and fishing in 1,323 NUTS 3 EU regions, 2001–2018: (a) locational Gini index (dot line) and its non-spatial component (full line); (b) relative contribution of the spatial component to the overall geographical concentration

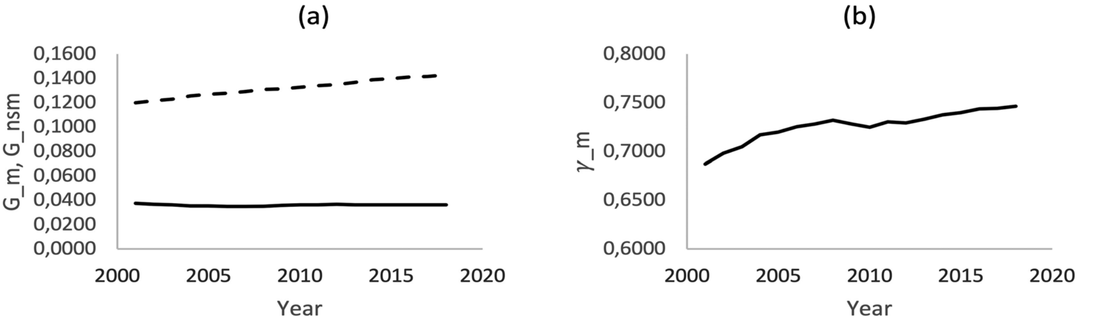

FIGURE 5 Geographical concentration of industry (except construction) in 1,323 NUTS 3 EU regions, 2001–2018: (a) locational Gini index (dot line) and its non-spatial component (full line); (b) relative contribution of the spatial component to the overall geographical concentration

effects are reported for high productivity sectors as financial and business services and industry (see Table 1). These results point out how spatial dependence operate in both very high and low productivity sectors.

Another relevant aspect concerns the dynamics of concentration across time. To analyse this aspect, we consider the evolution of concentration and its components across the period 2001–2018. Figures 4–9 show, for each

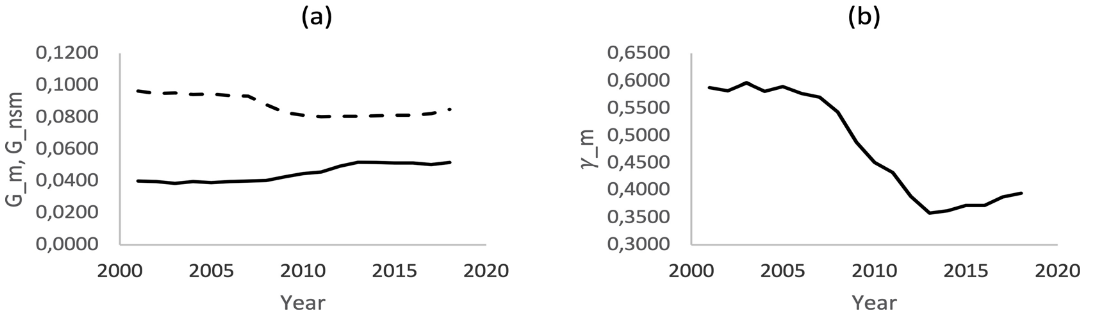

FIGURE 6 Geographical concentration of construction in 1,323 NUTS 3 EU regions, 2001–2018: (a) locational Gini index (dot line) and its non-spatial component (full line); (b) relative contribution of the spatial component to the overall geographical concentration

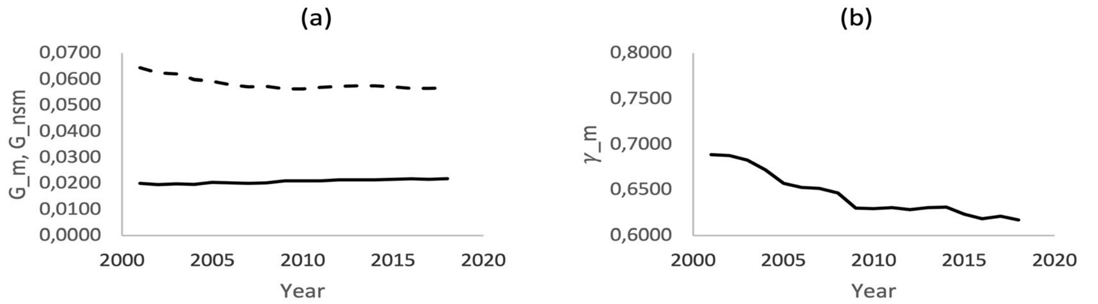

FIGURE 7 Geographical concentration of wholesale and retail trade, transport, accommodation and food service, information and communication in 1,323 NUTS 3 EU regions, 2001–2018: (a) locational Gini index (dot line) and its non-spatial component (full line); (b) relative contribution of the spatial component to the overall geographical concentration

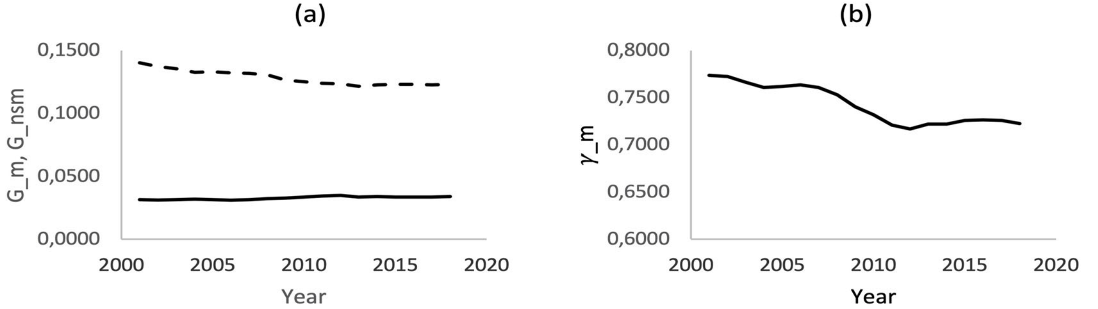

FIGURE 8 Geographical concentration of financial and business services in 1,323 NUTS 3 EU regions, 2001–2018: (a) locational Gini index (dot line) and its non-spatial component (full line); b) relative contribution of the spatial component to the overall geographical concentration

sector, the evolution of the overall concentration and its non-spatial component, together with the dynamic of the spatial component to of overall Gini.

Our evidence reveals that all the economic activities under consideration show a slight decline in the overall concentration with the only exception of industry across the 2001–2018 period. Hence, the decrease of the locational

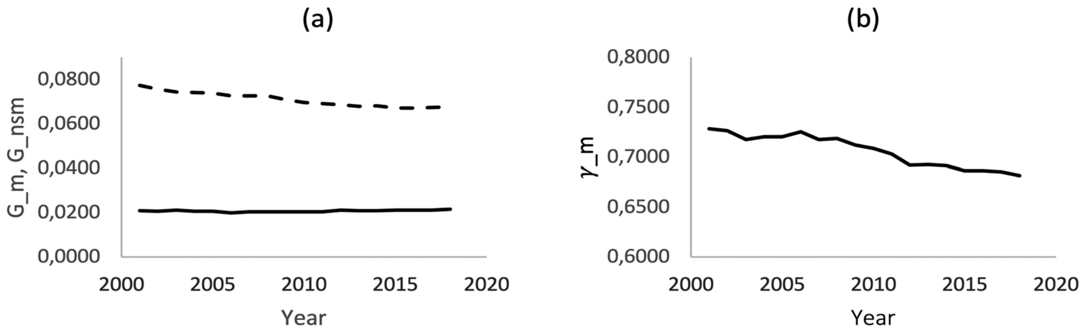

FIGURE 9 Geographical concentration of non-market services in 1,323 NUTS 3 EU regions, 2001–2018: a) locational Gini index (dot line) and its non-spatial component (full line); (b) relative contribution of the spatial component to the overall geographical concentration

Gini for each sector is mainly linked to a progressive reduction of the spatial component, as indicated by the lowering relevance of this component, with the only exception of industry. Generally, a tendency towards the reduction of the relative importance of the spatial interactions across regions during the years of the economic crisis has been reported in previous empirical analyses focused on income inequality (Márquez et al., 2019; Panzera & Postiglione, 2020). For the case of industry, an interesting evidence emerges since the increasing specialization is obtained due to an increasing contribution of the spatial part. Therefore, for industry geographical concentration appears to be more linked to neighbouring characteristics.

Our results for the EU are in line with previous literature in terms of spatial effects in concentration. Guimarães et al. (2011), for instance, embed spatial dependence by introducing a spatially augmented version of the EG index. However, if their approach preserves properties of the EG index, the calculation requires additional data at the firm level. Further, a deeper analysis of the spatial aspects is also highlighted in the proposal of Ferrante et al. (2020), who consider the level of spatial concentration with reference to the tourism sector of three countries (France, Italy, and Spain) using costs associated to transfers following different criteria. However, the impacts of different cost specifications on the index behaviour are still to be analysed (Ferrante et al., 2020).

Conversely, the main advantage of our index consists in the simplicity of the approach and the need of only aggregated data for the construction. Furthermore, our indicator of concentration may be easily adopted to test significance of the spatial effects and can be compared to the standard locational Gini.

Discarding the size distribution of firms is a drawback implied using the locational Gini index calculated on *LQ*s. A possible solution, already highlighted by Guillain and Le Gallo (2010), may involve also considering the adjusted *LQ*s introduced by O' Donoghue and Gleave (2004) rather than the standard *LQ*s. These last quantities account for the employment in small and medium sized firm rather than considering only the total employment.

In this paper, the robustness of the G_{sm} indicator has been verified for different k-nearest neighbour proximity matrices ($k = 5, 10, 20$; see Appendix Table A3). The results appear robust, pointing, for every level of k considered, the prevalence of the spatial components as well as the presence of higher spatial concentration for the case of agriculture and industry.

5 | DISCUSSION

The second half of the latest century has been characterized by different opinions towards diversification and specialization (Caragliu et al., 2016). In this debate, it also emerged the need for a new view on spatial issues (e.g., a new "spatial grammar"; Gardiner et al., 2013, p. 924) to rethink sectoral policies and support more even growth.

In our results, we observed spatial patterns in different economic sectors across the EU. With regards to industry sector, this presents a good level of overall concentration, characterized by high impact of the spatial component since the beginning of the period (i.e., 2001). This component tends to increase over time.

The situation is quite different for the case of finance and business services, where the overall concentration faces a decrease because of the reduction of its spatial component. This result can be observed under two perspectives. On the one hand, the lower concentration of sectors characterized by a high valued added (as finance and business services) may lead more even growth. On the other hand, a decrease in the spatial component means that more peripheral regions could benefit less from propagation of high value added sectors (see, for the Italian case, Lazzeroni, 2010).

For agriculture, the overall level of concentration is quite constant over the period under analysis. What it is worth noting is that the spatial part represents a very large part of the overall concentration. Additionally, this ratio does not change over the years. The presence of territorial pattern in the agricultural sector is a well evidenced. However, this result stresses how agricultural vocation of some regions—particularly in the East—may cause a longer process of structural change in these areas.

The analysis offered adds evidence on the presence of spatial patterns in different economic sectors. It is evident that regional economic systems are heavily affected not only by temporal interdependencies but also by spatial ones (Cainelli et al., 2019). For example, peripheral regions closer to heavy specialized areas in one sector may be affected in case of crises (David et al., 2009).

Therefore, spatial indicators, as introduced in this paper, may be used to enlarge the interpretations of more recent trends and to support policies, as smart specialization, discussed in the European debate (Gardiner et al., 2020; McCann & Ortega-Argilés, 2015).

The spatial interconnections between regions should be carefully considered by policy-makers in designing plans or strategies. In fact, the presence of geographical patterns and neighbourhood effects may determine limited efficacy to local actions, whose effectiveness depends on the occurrences of neighbouring regions.

In light of our results, policy-makers should favour policies taken at regional level that can consider local characteristics (Rodríguez-Pose & Wilkie, 2017). Nevertheless, only considering the presence of spatial dependence at the overall level may lead to better coordinate multi-level governance and drive structural changes in accordance with the European Union strategies.

6 | CONCLUDING REMARKS

Spatial aspects have been often underrated in the scientific debate about concentration, despite the importance they assume in regional economics. In this paper, we propose a new interpretation of the locational Gini index to evaluate the presence of spatial dependence. Applying the rationale proposed by Panzera and Postiglione (2020), we derive a spatial version of the index whose properties are analysed and compared to other potential alternatives. A procedure to assess the statistical significance of the spatial measure is also introduced.

In the empirical application, we apply the spatial locational Gini to EU NUTS 3 regions, to observe the extent of spatial dependence in the analysis of geographical concentration for different economic sectors. The results highlight the dominance of the spatial component with respect to the non-spatial one throughout the period under consideration. However, the contribution from the spatial component to overall inequality appears to be heterogenous across sectors. The magnitude of the spatial component for industry sector increases over the period under analysis. Conversely, financial services sector is characterized by a continuous decrease of the spatial component. For the case of agriculture, the relevance of the spatial term keeps stable over time while compared to the non-spatial component.

Accounting for spatial dependence sheds light on the underlying geographical distributions of sectors. In the use of the spatial decomposition, we stress how policies can have different effects when different spatial patterns are present. Lastly, identifying the role of spatial interactions in the distribution of economic activities at finer geographical scales could help in developing policies in accordandce with the overall EU strategis. To this aim, a more accurate consideration of the modifiable areal unit problem should be part of future research.

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ENDNOTES

[1] The Gini correlation measure between two variables X and Y, $\Gamma(x,y)$, satisfies the following main properties: 1) $-1 \leq \Gamma(x,y) \leq 1$ for all (x,y); 2) if y is a monotonically increasing (decreasing) function of x, then both $\Gamma(x,y)$ and $\Gamma(y,x)$ will equal to $+1(-1)$; 3) if x and y are statistically independent, then $\Gamma(x,y) = \Gamma(y,x) = 0$; 4) $\Gamma(x,y) = -\Gamma(-x,y) = -\Gamma(x,-y) = -\Gamma(-x,-y)$; 5) $\Gamma(x,y)$ is invariant under a strictly monotonic transformation of y; and 6) $\Gamma(x,y)$ is invariant under scale and location changes in x. The proof of these properties is given in Schechtman and Yitzhaki (1987).

[2] The list of EU countries is: Austria, Belgium, Bulgaria, Cyprus, Czech, Germany, Denmark, Estonia, Greece, Spain, Finland, France, Croatia, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherlands, Poland, Portugal, Romania, Sweden, Slovenia, Slovakia, United Kingdom.

[3] The Moran's I is calculated as $I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(x_i - \mu_x)(x_j - \mu_x)}{\sum_i (y_i - \mu_x)^2}$, where all the quantities are defined as above.

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APPENDIX A

TABLE A1 Spatial locational Gini different economic sectors in 1,323 EU NUTS 3 regions, 2001–2009. k-nearest neighbour contiguity matrix $(k = 10)$. p-values in brackets

	2001	2002	2003	2004	2005	2006	2007	2008	2009
Agriculture, forestry and fishing (A)	0.2729 (0.000)	0.2693 (0.000)	0.2691 (0.000)	0.2636 (0.000)	0.2652 (0.000)	0.2636 (0.000)	0.2623 (0.000)	0.2615 (0.000)	0.2628 (0.000)
Industry (except construction, B – E)	0.0825 (0.000)	0.0850 (0.000)	0.0869 (0.000)	0.0901 (0.000)	0.0914 (0.000)	0.0930 (0.000)	0.0943 (0.000)	0.0961 (0.000)	0.0959 (0.000)
Construction (F)	0.0567 (0.000)	0.0554 (0.000)	0.0568 (0.000)	0.0548 (0.000)	0.0558 (0.000)	0.0540 (0.000)	0.0532 (0.000)	0.0478 (0.000)	0.0405 (0.000)
Wholesale and retail trade, transport, accommodation and food service, information and communication (G – J)	0.0443 (0.000)	0.0429 (0.000)	0.0423 (0.000)	0.0403 (0.000)	0.0390 (0.000)	0.0378 (0.000)	0.0373 (0.000)	0.0370 (0.000)	0.0356 (0.000)
Financial and business service (K – N)	0.1087 (0.000)	0.1062 (0.000)	0.1043 (0.000)	0.1013 (0.000)	0.1016 (0.000)	0.1013 (0.000)	0.1001 (0.000)	0.0985 (0.000)	0.0938 (0.000)
Non-market services (O – U)	0.0564 (0.000)	0.0550 (0.000)	0.0535 (0.000)	0.0535 (0.000)	0.0533 (0.000)	0.0527 (0.000)	0.0522 (0.000)	0.0523 (0.000)	0.0506 (0.000)

TABLE A2 Spatial locational Gini for different economic sectors in 1,323 EU NUTS 3 regions, 2010–2017. k-nearest neighbour contiguity matrix $(k = 10)$. p-values in brackets

	2010	2011	2012	2013	2014	2015	2016	2017
Agriculture, forestry and fishing (A)	0.2642 (0.000)	0.2633 (0.000)	0.2650 (0.000)	0.2674 (0.000)	0.2639 (0.000)	0.2622 (0.000)	0.2588 (0.000)	0.2570 (0.000)
Industry (except construction, B – E)	0.0962 (0.000)	0.0980 (0.000)	0.0985 (0.000)	0.1004 (0.000)	0.1026 (0.000)	0.1035 (0.000)	0.1051 (0.000)	0.1055 (0.000)
Construction (F)	0.0367 (0.000)	0.0347 (0.000)	0.0313 (0.000)	0.0288 (0.000)	0.0292 (0.000)	0.0302 (0.000)	0.0303 (0.000)	0.0318 (0.000)
Wholesale and retail trade, transport, accommodation and food service, information and communication (G – J)	0.0354 (0.000)	0.0359 (0.000)	0.0360 (0.000)	0.0363 (0.000)	0.0364 (0.000)	0.0356 (0.000)	0.0350 (0.000)	0.0352 (0.000)
Financial and business service (K – N)	0.0917 (0.000)	0.0895 (0.000)	0.0886 (0.000)	0.0880 (0.000)	0.0889 (0.000)	0.0897 (0.000)	0.0896 (0.000)	0.0893 (0.000)
Non-market services (O – U)	0.0495 (0.000)	0.0487 (0.000)	0.0476 (0.000)	0.0470 (0.000)	0.0471 (0.000)	0.0461 (0.000)	0.0461 (0.000)	0.0462 (0.000)

TABLE A3 Spatial locational Gini G_{sm} and γ_m for different economic sectors in 1,323 EU NUTS 3 regions (2018) by using different levels of k of the k -nearest neighbour contiguity matrix. p-values in brackets

	G_{sm}			γ_m		
	$k = 5$	$k = 10$	$k = 20$	$k = 5$	$k = 10$	$k = 20$
Agriculture, forestry and fishing (A)	0.2535					
(0.000)	0.2510					
(0.000)	0.2454					
(0.000)	0.8409	0.8334	0.8150			
Industry (except construction, B – E)	0.1072					
(0.000)	0.1068					
(0.000)	0.1038					
(0.000)	0.7491	0.7466	0.7254			
Construction (F)	0.0322					
(0.000)	0.0336					
(0.000)	0.0350					
(0.000)	0.3784	0.3945	0.4113			
Wholesale and retail trade, transport, accommodation and food service, information and communication (G – J)	0.0361					
(0.000)	0.0351					
(0.000)	0.0341					
(0.000)	0.6344	0.6168	0.5993			
Financial and business service (K – N)	0.0877					
(0.000)	0.0892					
(0.000)	0.0885					
(0.000)	0.7107	0.7227	0.7172			
Non-market services (O – U)	0.0453					
(0.000)	0.0462					
(0.000)	0.0455					
(0.000)	0.6682	0.6817	0.6711			

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Resumen. Las interacciones espaciales entre unidades regionales pueden influir en la distribución geográfica de las actividades económicas. Muchas medidas tradicionales de la concentración geográfica no logran captar este aspecto, ya que no son sensibles a las permutaciones de la posición espacial de las regiones. Este artículo propone un enfoque para la medición de la concentración geográfica de las actividades económicas que tiene en cuenta las interacciones espaciales entre las regiones. El índice Gini local se dividió en componentes espaciales y no espaciales, de modo que se presenta una nueva interpretación del índice. La medida se aplica para evaluar la concentración geográfica de diferentes sectores económicos para 1.323 regiones NUTS 3 de la Unión Europea durante el período 2001–2018.

抄録: 地域単位間の空間的相互作用は、経済活動の地理的分布に影響を与える可能性がある。従来の地理的集中度の測定法の多くは、この側面を捉えることができず、地域の空間位置の順列に非感受性である。本稿では、地域間の空間的な相互作用を考慮した、経済活動の地理的集中度の測定法を提案する。立地ジニ係数を空間的成分と非空間的成分に分解するという、新しい方法で指標を解釈する。2001~2018年のEUの1,323のNUTS3の区画における様々な経済セクターの地理的集中度を、この測定法を用いて評価する。