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Social Indicators Research

An International and Interdisciplinary
Journal for Quality-of-Life Measurement

ISSN 0303-8300

Volume 148

Number 2

Soc Indic Res (2020) 148:379-394

DOI 10.1007/s11205-019-02208-7

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Measuring the Spatial Dimension of Regional Inequality: An Approach Based on the Gini Correlation Measure

Domenica Panzera¹ · Paolo Postiglione¹

Accepted: 9 October 2019 / Published online: 19 October 2019
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Abstract

Traditional inequality measures fail to capture the geographical distribution of income. The failure to consider such distribution implies that, holding income constant, different spatial patterns provide the same inequality measure. This property is referred to as anonymity and presents an interesting question about the relationship between inequality and space. Particularly, spatial dependence could play an important role in shaping the geographical distribution of income and could be usefully incorporated into inequality measures. Following this idea, this paper introduces a new measure that facilitates the assessment of the relative contribution of spatial patterns to overall inequality. The proposed index is based on the Gini correlation measure and accounts for both inequality and spatial autocorrelation. Unlike most of the spatially based income inequality measures proposed in the literature, our index introduces regional importance weighting in the analysis, thereby differentiating the regional contributions to overall inequality. Starting with the proposed measure, a spatial decomposition of the Gini index of inequality for weighted data is also derived. This decomposition permits the identification of the actual extent of regional disparities and the understanding of the interdependences among regional economies. The proposed measure is illustrated by an empirical analysis focused on Italian provinces.

Keywords Inequality measure · Spatial patterns · Spatial autocorrelation · Inequality decomposition

JEL Classification C1 · C18 · R1 · R12

1 Introduction

Income inequality is an important social issue and a major concern for governments. It has inspired a long tradition of theoretical and empirical research and policies to address poverty and disparities. At the European level, reducing disparities between countries, regions

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and social groups has inspired the European Union (EU) Cohesion Policy, and measures against poverty and social exclusion are among the specific objectives of the EU and its Member States (Molle 2007).

A number of studies that are concerned with the extent of inequality, its mechanisms and consequences have been proposed in the literature. For a review of the measures and methods that are frequently employed in the analysis of income inequality and income distribution, see among others, Heshmati (2006) and Cowell (2011). The study of income inequality implies considering the income distribution between individuals or between regions in a country. The measurement of regional inequality generally relies on differences in regional GDPs rather than on income differences between individual or households within a regional economy (Rey and Janikas 2005). When regional inequality is analysed, there are some additional issues that need to be considered because of the nature of georeferenced data and the possible spatial association relationships.

The literature on regional inequality has been mainly based on traditional inequality measures and focused on their geographical decomposition (see among others, Maxwell and Peter 1988; Tsui 1993; Fan and Casetti 1994; Kanbur and Zhang 1999; Nissan and Carter 1999; Azzoni 2001; Akita 2003; Beenstock and Felsenstein 2007). Studies on regional inequality based on composite indices resulting from the combination of multiple socio-economic indicators are also reported in the literature (Majumder et al. 1995; Quadrado et al. 2001; Parente 2019). Some contributions in the recent literature highlighted some specific limitations of the studies on regional inequality (Rey and Janikas 2005; Portnov and Felsenstein 2010). An important issue that has been poorly explored in the literature concerns the relationship between spatial dependence and global inequality (Rey and Janikas 2005). Spatial dependence refers to the similarity between observations that are collected at near geographical locations. Spatial dependence could play an important role in shaping the geographical distribution of regional GDP since it implies that similar values tend to cluster together in space. However, the geographical distribution of GDP is mainly neglected in the measurement of inequality. In fact, traditional inequality measures, such as the Gini index or generalized entropy measures, are insensitive to the geographical arrangements of GDP. This implies that, holding GDP constant, different spatial patterns can provide the same inequality measure. This property of inequality measures is known as anonymity (Bickenbach and Bode 2008). However, the joint consideration of measures of inequality and spatial dependence is desirable since it may reveal deeper insights about the distribution of regional GDP than would be possible using either measures alone (Rey and Janikas 2005).

The insensitivity of inequality measures to different spatial configurations has been addressed in a few recent contributions. Focusing on the relationship between measures of inequality and spatial dependence, Arbia (2001) suggested a number of approaches to combine them and developed some joint indexes. Arbia and Piras (2009) proposed a measure based on the linear correlation coefficient that accounts for both spatial autocorrelation and variability. An alternative approach towards considering the joint effect of inequality and spatial autocorrelation, which relies on a decomposition of the Gini index, has been proposed by Rey and Smith (2013). Lastly, a decomposition of the Theil index T , which is aimed at capturing the neighbourhood effect on global inequality, has been proposed by Márquez et al. (2019).

Following this line of research, the present paper introduces a new measure that permits the quantification of the relative contribution of spatial patterns to overall inequality. Our measure relies on the Gini correlation measure that was introduced by Schechtman and Yitzhaki (1987), and assesses the association between the regional GDPs and the average GDP in neighbouring regions. As such, our measure offers a new interpretation of the Gini

correlation that traditionally has been used in the decomposition of the Gini index based on the income source (Lerman and Yitzhaki 1985; Ogwang 2016), in portfolio analysis in finance (Schechtman and Yitzhaki 1987), and in other fields such as biological science (Ma and Wang 2012).

In our proposal, the Gini correlation measure is used to identify the extent to which spatial dependence affects the regional inequality. As a further result, the proposed measure introduces regional importance weighting in the analysis. This aspect has been mainly neglected from the studies on spatially based income inequality measures. Since we are dealing with regional data, GDP per capita is assumed to be the regional average income. To consider how many individuals this average represents, we consider GDP data that are weighted by population shares, and develop a measure that relies on the Gini index for weighted data as a measure of inequality (Mookherjee and Shorrocks 1982). A decomposition of the Gini coefficient for weighted data into its spatial and non-spatial components is also derived.

The proposed measure is applied in an empirical analysis of regional inequality in Italian provinces. Italy is characterized by a marked North–South dualism that is associated with relevant regional disparities. Accounting for spatial dependence in the analysis of such economic structures could improve the information that is derived from traditional inequality measures.

The remainder of this paper is organized as follows. Section 2 discusses the problem of the insensitivity of inequality measures to different spatial configurations of GDP. Section 3 introduces the proposed measure, gives some background information and presents its interpretation. In Sect. 4, the empirical analysis focused on regional inequality in Italian provinces is presented. Concluding remarks are given in Sect. 5.

2 Income Inequality and the Role of Space

The anonymity condition implies that traditional inequality measures are permutationally invariant, which means that very different spatial patterns can give rise to the same inequality measure.

With respect to the regional data, we consider the Gini index for weighted data G^w ,¹ where the GDP per capita for each region is weighted by the population share in the region with respect to the overall (i.e., national) population (Mookherjee and Shorrocks 1982; Yitzhaki and Schechtman 2013).

Figure 1(a) shows the geographical distribution of regional GDP per capita for the 110 Italian provinces in 2011, and (b) shows the geographical distribution that is obtained by randomly assigning the GDP per capita values to Italian provinces. The darker colours are used to indicate the provinces with higher GDP per capita, and the light colours refer to those with lower GDP per capita. The geographical distributions in Fig. 1 correspond to two different spatial patterns: the more agglomerated distribution is in (a) and the more dispersed distribution is in (b).

¹ See Sect. 3 for further details about the Gini index for weighted data.

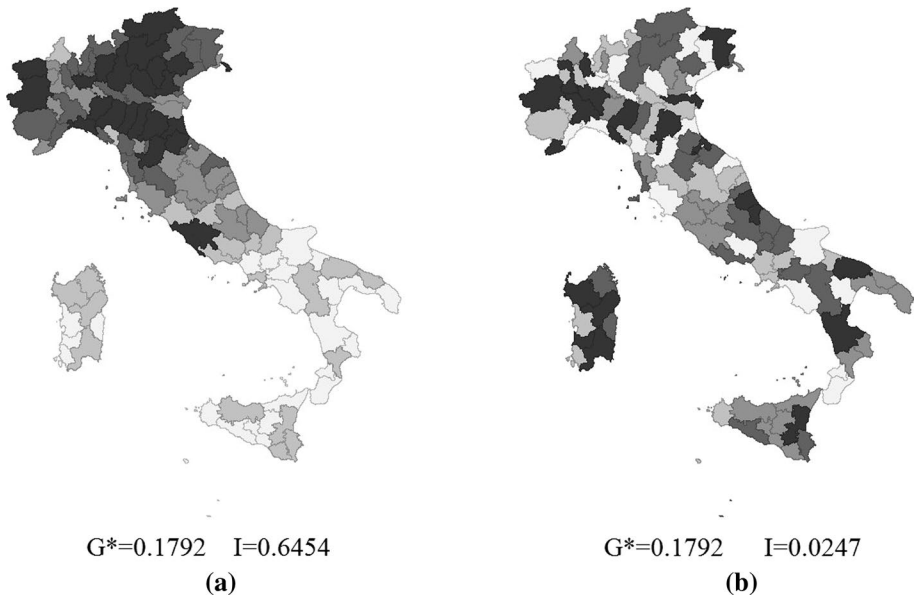


Fig. 1 Gini index G^* and Moran's I computed for GDP per capita—Italian provinces (2011) **a** Real spatial distribution of regional GDP per capita, and **b** spatial distribution obtained by a random permutation of regional GDP per capita

In addition, they are characterized by different degrees of spatial autocorrelation, as measured by Moran's I^2 (Moran 1950), while exhibiting the same level of inequality, as measured by the Gini index.

This evidence brings up the importance of defining a measure that accounts for these differences and focuses on both inequality and spatial autocorrelation. Neglecting the spatial features of data in the measurement of inequality might mask important information about the actual disparities that are experienced by regional units. Thus, it becomes desirable to define a measure that is able to capture both the non-spatial variability, which is invariant to permutations, and the role of geographical location in economic inequality.

The particular geographical location of data is determined by the presence of positive or negative spatial associations, which makes consideration of the spatial dependence effect in the measurement of inequality relevant.

The importance of incorporating spatial dependence into inequality measures has been highlighted in some recent contributions. Focusing on the spatial concentration, Arbia (2001) emphasized the importance of developing indices that combine spatial autocorrelation and measures of variability, and suggested a number of different approaches. By making use of a series of empirical examples, the author showed that the spatial concentration consists of two different features as the a-spatial variability, which is invariant to permutations, and the polarization that refers to the geographical location of observations. To summarize these different aspects of spatial concentration, the author suggested combining

² Moran's I computed for GDP per capita, y_i can be expressed as follows: $I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} (y_i - \mu_y)(y_j - \mu_y)}{\sum_i (y_i - \mu_y)^2}$, where n denotes the number of observations, w_{ij} is the element of the proximity matrix and $\mu_y = \sum_i y_i / n$.

the measures of the a-spatial concentration, such as the Gini index, or other measures of variability, with measures of spatial autocorrelation (like Moran's I) or measures of local association (like the Getis-Ord statistic) that measure polarization. The author gave some suggestions about the combination of these measures.

Arbia and Piras (2009) introduced a new class of measures that incorporates the ideas of both a-spatial concentration and spatial agglomeration. This class of measures is defined as the linear correlation coefficient between a random variable X that corresponds to n spatial units, and a random variable X^* that corresponds to the permutation of the n values of X , which maximizes a measure of positive spatial association. Formally, we have the following:

$$\lambda = \frac{\sum_{i=1}^n (X_i - \mu)(X_i^* - \mu)}{\sum_{i=1}^n (X_i - \mu)^2} \quad (1)$$

where μ denotes the mean of X_i . This class of measures accounts for both the a-spatial concentration (the variance in the denominator) and spatial correlation (the numerator). The authors discussed the properties of this measure and approximate sampling theory. They also identified some possible extensions of the proposed statistic, such as its use for the comparison of the concentration of the same variable measured over two different time periods or in two different countries, and its extension to other measures of inequality (see Arbia and Piras 2009).

Rey and Smith (2013) considered the Gini index G in its relative mean difference form, and rewrote the sum of all pairwise differences as the sum of absolute differences between pairs of neighbouring observations and absolute differences between pairs of non-neighbouring observations. Formally, we have the following:

$$G = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} |x_i - x_j|}{2n^2 \mu} + \frac{\sum_{i=1}^n \sum_{j=1}^n (1 - w_{ij}) |x_i - x_j|}{2n^2 \mu} \quad (2)$$

where w_{ij} denotes the generic element of a binary spatial weight matrix expressing the proximity relationship between locations i and j .

This decomposition facilitates the identification of a neighbouring component, NG , (i.e., the first term on the right side) and a non-neighbouring component, NNG , (i.e., the second term on the right side) of the Gini index G , and reveals that this index nests a measure of spatial autocorrelation. In fact, when the amount of positive spatial autocorrelation strengthens, the second term should increase relative to the first since the value similarity in space would be greater. The result is the opposite in the presence of negative spatial autocorrelation (Rey and Smith 2013).

The contribution of Márquez et al. (2019) is focused on the Theil index T . Aiming at determining the explicit contribution of spatial regional patterns to inequality, the authors identified a neighbourhood Theil index that provides a measure of inequality that only considers the information from the neighbouring regions. The identification of the neighbourhood Theil index allows one to separate the a-spatial and the spatial components of inequality. In fact, by subtracting the neighbourhood Theil from the conventional Theil, a Specific Theil index that accounts for non-spatial inequality is defined. The neighbourhood Theil index completely depends on the concept of the neighbourhood and its quantification. Furthermore, it requires that the underlying spatial process be isotropic and significant; i.e., it is different from one that is derived by a completely random spatial process. Both these conditions make the

replacement of the GDP in a region by the average GDP in neighbouring regions possible (see Márquez et al. 2019).

Following the idea of a complementarity between inequality and spatial autocorrelation, in this paper, we propose a measure that facilitates the assessment of the relative contribution of spatial patterns to a given pattern of income inequality. Our contribution is aimed at extending the previous works in this area. Our measure relies on the Gini index as a measure of global inequality. Using regional data, we focus on the Gini index that is computed using weighted data, and introduce a measure that can be interpreted as the ratio between a spatial Gini and this weighted Gini index. The introduced spatial Gini expresses the correlation between the regional GDP per capita and the same variable that is spatially lagged. As with the measure that was proposed by Arbia and Piras (2009), our index is thus defined as a ratio between a measure of spatial autocorrelation and a measure of variability. In the proposal by Arbia and Piras (2009), they state that assessing the extent of spatial autocorrelation requires the determination of the spatial configuration that maximizes some spatial autocorrelation statistics. Our measure only requires the prior identification of the neighbouring regions for each spatial unit. As with the spatial decomposition that was proposed by Rey and Smith (2013), our contribution is focused on the Gini index of inequality. However, in our approach, a weighting scheme reflecting the relative importance of each region in the whole economy is considered, and the spatial relationships are defined using a single vector of weights.

In the contribution of Márquez et al. (2019), the spatial component is quantified by considering only the information that is related to the neighbouring regions. In contrast, in our approach, the spatial Gini is based upon the correlation between the value that is observed for the reference unit and the values that are observed for the neighbouring regions.

3 The Proposed Measure: Background, Definition and Interpretation

The presence of positive or negative spatial associations impacts the geographical distribution of data. These associations should be considered in the analysis of regional inequality to properly understand the differences in the GDP distributions. The importance of jointly considering the spatial dependence and inequality requires the definition of a single measure that could account for both of these aspects. The measure that is proposed in this paper is defined as a special case of the Gini correlation index that was introduced by Schechtman and Yitzhaki (1987).

The Gini correlation is a measure of association between two random variables, which is based on the covariance between one variable and its cumulative distribution function.

Let X and Y be two random variables with continuous distribution functions F_X and F_Y , respectively, and a continuous bivariate distribution $F_{X,Y}$. The Gini correlation is a not symmetric measure of association between X and Y . It can be specified in the following two forms, depending on which variable is given in its actual values and which is expressed through its cumulative distribution function:

$$\Gamma(x, y) = \frac{\text{Cov}(x, F_Y(y))}{\text{Cov}(x, F_X(x))} \quad (3)$$

or

$$\Gamma(y, x) = \frac{\text{Cov}(y, F_X(x))}{\text{Cov}(y, F_Y(y))}. \quad (4)$$

As Eqs. (3) and (4) show, the Gini correlation between two variables is expressed as the ratio of two covariances. The covariance in the numerator is computed between one variable and the cumulative distribution function of the other, and it corresponds to the Gini covariance between the variables. The covariance in the denominator is computed between the variable and its cumulative distribution function and represents a measure of variability. In fact, as showed by Schechtman and Yitzhaki (1987), the covariance in the denominators of Eqs. (3) and (4) corresponds to one-fourth of the Gini's mean difference, which is a measure of dispersion (see also, Stuart 1954).

The properties of the Gini correlation are a mixture of the properties of the Pearson and Spearman correlations and have been detailed by Schechtman and Yitzhaki (1987), who defined a point estimator and derived its large sample properties (see also Schechtman and Yitzhaki 1999; Yitzhaki and Schechtman 2013). The main properties of the index are listed below: (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), which proposed some applications of the Gini correlation index in economics and finance.

The use of the Gini correlation for assessing the role that is played by a specified spatial configuration in the income distribution has been proposed by Dawkins (2007) in the field of income segregation, which refers to the uneven geographic distribution of households with different income levels within an area. This irregularity produces a pattern of inequality. The measures of income segregation do not generally consider the spatial arrangement of neighbourhoods, thus giving rise to the checkerboard problem³ (see White 1983; Morrill 1991; Dawkins 2004, 2007).

To address this last issue, Dawkins (2007) introduced a new spatial ordering index S_r . Two main spatial ordering schemes are emphasized by Dawkins (2007), including the nearest neighbour spatial ordering and the monocentric spatial ordering. The nearest neighbour spatial ordering assigns to each neighbourhood income the rank that is associated with the income per capita of the neighbourhood's nearest neighbour. Conversely, in the monocentric spatial ordering, a new variable Z , expressing the distance from a given point within the region to the centroid of each neighbourhood, is defined. Then, the neighbourhood incomes are ranked in ascending or descending order based on Z .

Based on these alternative spatial reranking schemes, the spatial ordering index S_r is expressed as the ratio between a spatial reranked Gini index, G_r , and a Gini index of between-neighbourhood income segregation, G_B (see Dawkins 2007), as follows:

$$S_r = \frac{G_r}{G_B} = \frac{Cov(y_j, \bar{R}_{j(n)})}{Cov(y_j, \bar{R}_j)} \quad (5)$$

with $G_r = (2/Y)Cov(y_j, \bar{R}_{j(n)})$ and $G_B = (2/Y)Cov(y_j, \bar{R}_j)$, where Y is the aggregate household income that is earned by the residents of the region, y_j is the aggregate household

³ In the segregation literature, the checkerboard problem refers to the failure to distinguish between different patterns of income segregation, ranging from clustered to spatially random, using common segregation measures.

income that is earned by the residents of the neighbourhood j , \bar{R}_j is the average rank of the income per capita that is earned by neighbourhood j within the overall neighbourhood income per capita distribution, and $\bar{R}_{j(n)}$ is the average spatial rank of the per capita income that is earned by neighbourhood j . For further details, see Dawkins (2007).

Following Dawkins (2004, 2007), in this paper, we propose an index to evaluate the impact of the spatial dependence on inequality, which is defined starting with the Gini correlation measure that is defined in Eqs. (3) and (4).

Specifically, we introduce a measure that is defined as the Gini correlation between the variable Y and its spatial lag WY , where Y denotes the regional GDP per capita and W is a row-standardized spatial weight matrix that summarizes the proximity relationship between regional units. The spatially lagged variable expresses a weighted average of the values of Y that are observed for neighbouring regions.

Assuming, as a first simple working hypothesis, that all regional units are equally weighted (i.e., have the same population share), our measure, which is denoted as γ , can be specified as the ratio between the covariance of each observation of Y and the rank R_{WY} of the observations of WY and the covariance between Y and its own rank R_Y . It is as follows:

$$\gamma(y, Wy) = \frac{Cov(y, R_{WY}/n)}{Cov(y, R_Y/n)} \tag{6}$$

Denoted with n the number of observations, the expressions R_Y/n and R_{WY}/n represent the empirical estimates of the cumulative distribution functions of Y and WY , respectively (Yitzhaki and Lerman 1991), when the observations are equally weighted.

In Eq. (6), the numerator corresponds to the Gini covariance between Y and WY and provides a measure of spatial autocorrelation, while the denominator expresses the variability in the regional GDP per capita.

Since the Gini index G can be expressed as twice the covariance between a variable and the rank of the variable divided by its mean (see Lerman and Yitzhaki 1984; Schechtman and Yitzhaki 1987), the index $\gamma(y, Wy)$ can be rewritten as the ratio between a spatial reranked Gini G_s^4 and the classic Gini index G :

$$\gamma(y, Wy) = G_s/G \tag{7}$$

where

$$G_s = \frac{2Cov(y, R_{WY}/n)}{\mu_y} \tag{8}$$

and

$$G = \frac{2Cov(y, R_Y/n)}{\mu_y} \tag{9}$$

where μ_y is the mean of the variable Y .

⁴ The term spatially reranked Gini, or simply spatial Gini, is borrowed from Dawkins (2004). In Dawkins (2004), this terminology is referred to the Gini index of residential segregation.

As previously mentioned, when dealing with regional data, the GDP per capita, which is assumed to be representative of the whole region, should be weighted by the region’s population to account for how many individuals this GDP per capita represents. This entails introducing a regional importance weighting in the analysis, which could be achieved by assigning the population shares $\pi_i = p_i / \sum_i p_i$ to each regional value y_i where p_i is the total population of region i ; $i = 1, 2, \dots, n$; and $\sum_i \pi_i = 1$.

When using weighted data, Lerman and Yitzhaki (1989) suggested substituting the empirical cumulative distribution function in the covariance-based Gini formula with a quantity that reflects the idea of the midpoint of the cumulative distribution. Specifically, when each observation, y_i , is associated with the weight, π_i , the rank R_Y/n in (9) can be replaced by the following quantity (Lerman and Yitzhaki 1989):

$$F_Y^*(y_i) = \sum_{j=0}^{i-1} \pi_j + \pi_i/2 \quad i = 1, 2, \dots, n \tag{10}$$

where $\pi_0 = 0$.

Using the estimate of $F_Y(y)$ from (10), we can calculate the weighted covariance between y and $F_Y(y)$, and, hence, the Gini index for weighted data as follows:

$$G^* = \frac{2Cov(y, F_Y^*(y))}{\mu_y^*} = \frac{2 \sum_{i=1}^n \pi_i (y_i - \mu_y^*) (F_Y^*(y_i) - \bar{F}^*)}{\mu_y^*} \tag{11}$$

where $\mu_y^* = \sum_i \pi_i y_i$, and $\bar{F}^* = \sum_i \pi_i F_Y^*(y_i)$.

Following the same approach, a weighted version of the spatial Gini in (8) can be derived. The unweighted spatial Gini in (8) is based upon the covariance that is computed between the GDP per capita in each region and the rank that is associated with the weighted average GDP per capita in neighbouring regions divided by the number of observations. To introduce the proposed weighted version of the spatial Gini, the GDP per capita values, y_i , are reordered according to the non-decreasing order of the values assumed by the weighted average GDP per capita in neighbouring regions, Wy_i . Therefore, the rank R_{WY}/n in (8) is replaced by the quantity $F_{WY}^*(Wy_i)$, which is defined similarly to Eq. (10). The weighted version of G_s is thus specified as follows:

$$G_s^* = \frac{2Cov(y, F_{WY}^*(Wy))}{\mu_y^*} = \frac{2 \sum_{i=1}^n \pi_i (y_i - \mu_y^*) (F_{WY}^*(Wy_i) - \bar{F}_w^*)}{\mu_y^*} \tag{12}$$

where $\bar{F}_w^* = \sum_i \pi_i F_{WY}^*(Wy_i)$.

The weighted version of our index $\gamma(y, Wy)$ can be thus specified as follows:

$$\gamma^*(y, Wy) = \frac{G_s^*}{G^*} = \frac{Cov(y, F_{WY}^*(Wy))}{Cov(y, F_Y^*(y))} \tag{13}$$

Since, as discussed by Dawkins (2004), a spatial Gini index that is produced by a reranking will always be bounded above by the original Gini index and below by the negative value of the Gini index, the index G_s^* is bounded below by $-G^*$ and above by G^* , and the following relation holds (see Dawkins 2004):

$$G^* = G_s^* + G_{ns}^* \quad (14)$$

Here G_{ns}^* , where $0 \leq G_{ns}^* \leq 2G^*$, captures the component of the inequality that is not due to a specified pattern of spatial dependence. Equation (14) thus expresses the decomposition of the Gini index in its spatial and non-spatial components, and the relative contribution of the spatial component to the overall inequality is quantified by the measure $\gamma^*(y, Wy)$.

As previously mentioned, our measure, regardless of the weights used, ranges between -1 and 1 (Schechtman and Yitzhaki 1999; Ogwang 2016). When the ranking of WY is identical to the original ranking of Y , $G_s^* = G^*$, $G_{ns}^* = 0$ and $\gamma^*(y, Wy) = 1$, thus indicating that the overall inequality is completely explained by the given pattern of spatial dependence. As the ranking of the regional GDPs (i.e., Y) becomes more dissimilar to the ranking of average GDPs in neighbour regions (i.e., WY), the spatial component of inequality decreases and it approaches its minimum value of $-G^*$, when the average GDPs in neighbour regions are ranked as the opposite with respect to the original order of regional GDPs. In this case, the non-spatial component of inequality reaches its maximum value of $2G^*$ and $\gamma^*(y, Wy) = -1$. When Y and WY are uncorrelated, we have that $G_s^* = 0$, and, thus, $G^* = G_{ns}^*$ and $\gamma^*(y, Wy) = 0$, thus indicating that the overall inequality is completely explained by its non-spatial component.

As with the measure that was introduced by Arbia and Piras (2009), our index is defined as a ratio between a measure of spatial autocorrelation and a measure of variability. Note that the weighted Gini covariance in the numerator of our measure expresses the correlation between the variable Y and its spatial lag WY . The Gini mean difference in the denominator of our measure shares many properties with the variance considered by Arbia and Piras (2009), but can be more informative with respect to the properties of distributions that depart from normality (see Yitzhaki 2003). Furthermore, in the measure that was proposed by Arbia and Piras (2009), assessing the extent of spatial autocorrelation requires determining the spatial configuration that maximizes some spatial autocorrelation statistics. In contrast, our measure only requires the prior identification of the neighbouring regions for each spatial unit. Furthermore, our measure is flexible enough to incorporate different proximity definitions.

As with the measure that was proposed by Rey and Smith (2013), our measure relies on the Gini index as measure of inequality. However, unlike Rey and Smith (2013), we consider the Gini index using weighted data. This introduces the differences in the contribution of regional economies to overall inequality into the analysis. This aspect has been mainly neglected in the previous literature on Gini based spatial inequality measures.

4 Empirical Illustration

The proposed measure is illustrated using empirical analysis that is focused on the income inequality in Italian provinces, that correspond to the NUTS 3 level of the official EU classification. We consider regional GDP per capita data over the period of 2000–2015. The source of the data is the EUROSTAT dataset.

To illustrate the characteristics of our index, we first need to consider a spatial reranking of the geographical distribution of GDP per capita. To this end, Fig. 2 shows a comparison between the geographical distribution of regional GDP per capita in Italian provinces for 2011 (a) and the geographical distribution that is obtained by assigning the average GDP per capita of neighbouring provinces to each province (b). The spatial weight matrix W that

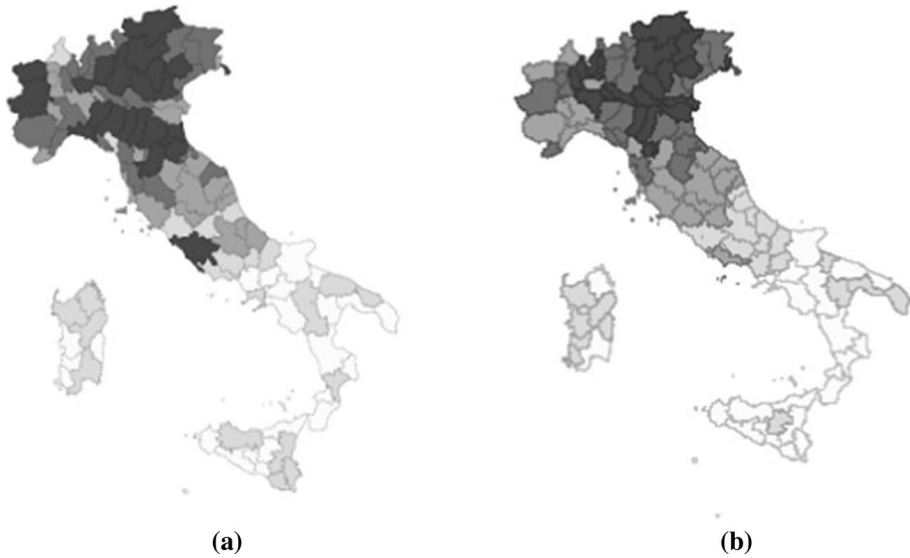


Fig. 2 Comparison between **a** the real spatial distribution of regional GDP per capita and **b** the spatial re-ranking based on the weighted average of neighbouring GDPs—Italy NUTS 3, year 2011

Table 1 Decomposition of the Gini Index G^* for different patterns of spatial dependence (regional GDPs per capita, Italy NUTS 3, year 2011)

$W = 5$ nearest neighbours	$W = 7$ nearest neighbours	$W = 10$ nearest neighbours
$G^* = 0.1792$	$G^* = 0.1792$	$G^* = 0.1792$
$G_s^* = 0.0944$	$G_s^* = 0.1002$	$G_s^* = 0.0935$
$G_{ns}^* = 0.0848$	$G_{ns}^* = 0.0790$	$G_{ns}^* = 0.0857$
$\gamma^*(y, Wy) = 0.5268$	$\gamma^*(y, Wy) = 0.5591$	$\gamma^*(y, Wy) = 0.5218$

is used in the definition of the proximity relationship is based on the k nearest neighbours' criterion, where $k = 5$.

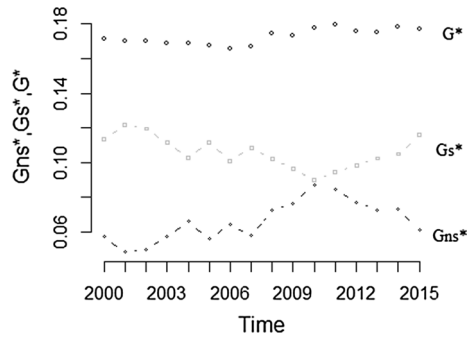
The weighted version of the measure that is proposed in Sect. 3 is computed by comparing the original order of regional GDPs in (a) with the re-ranking of the regional units based on (b). The weights that are assigned to y and Wy are assigned based on the share of the population in each region π_i (see Sect. 3). The values of $\gamma^*(y, Wy)$ are reported in Table 1, along with the values of the overall weighted Gini index G^* and its spatial and non-spatial components. The results in Table 1 are also calculated using the diverse specifications of the matrix W that are based on different numbers of neighbours.

As Table 1 indicates, the results are stable for the different numbers of neighbours that are used in the definition of W . For any specification of the spatial weight matrix, we have positive values of the spatial Gini G_s^* . A positive value of G_s^* reveals a positive association between Y and WY . This result indicates the presence of positive spatial autocorrelation. For any specifications of the spatial weight matrix, the spatial component of the Gini index G^* is slightly larger than the non-spatial component G_{ns}^* . This indicates that for Italian provinces, the global inequality is explained by both of these components roughly to the same extent. This result is confirmed by the value of $\gamma^*(y, Wy)$.

Table 2 Spatial and non-spatial components of inequality for Italian provinces 2000–2015

Year	2000	2001	2002	2003	2004	2005	2006	2007
G^*	0.1712	0.1701	0.1697	0.1687	0.1687	0.1675	0.1654	0.1668
G_s^*	0.1136	0.1216	0.1195	0.1113	0.1027	0.1114	0.1010	0.1087
G_{ns}^*	0.0576	0.0485	0.0502	0.0574	0.0660	0.0561	0.0644	0.0581
$\gamma^*(y, Wy)$	0.6636	0.7149	0.7042	0.6598	0.6088	0.6651	0.6106	0.6517
I	0.7389	0.7335	0.7441	0.7434	0.7366	0.7236	0.7203	0.7218
Year	2008	2009	2010	2011	2012	2013	2014	2015
G^*	0.1746	0.1732	0.1775	0.1792	0.1755	0.1754	0.1781	0.1770
G_s^*	0.1021	0.0964	0.0902	0.0944	0.0983	0.1024	0.1049	0.1158
G_{ns}^*	0.0725	0.0768	0.0873	0.0848	0.0772	0.0730	0.0732	0.0612
$\gamma^*(y, Wy)$	0.5848	0.5566	0.5082	0.5268	0.5601	0.5838	0.5890	0.6542
I	0.6502	0.6100	0.6263	0.6454	0.6332	0.6630	0.6770	0.6695

Fig. 3 Gini index G^* (points), spatial component (grey dashed line), and non-spatial component (black dashed line)—Italy NUTS 3, 2000–2015



Moreover, these results reveal that a positive spatial autocorrelation leads to increasing inequality because it gives rise to clusters of similar incomes. This result is consistent with some key findings in the regional inequality literature that revealed the presence of a positive relationship between the measures of inequality and the degree of spatial autocorrelation (Rey 2004; Rey and Janikas 2005).

The results that are displayed in Table 1 reveal that the percentage impact of the spatial component to overall inequality is always higher than 50%. Some differences emerge if we consider a longer time period.

Table 2 shows the decomposition of the Gini Index G^* into its spatial and non-spatial components for the period of 2000–2015. The values of Moran’s I , which are computed for the provincial GDP per capita, and the values of $\gamma^*(y, Wy)$ are also reported. The values of the Gini index G^* , and of its spatial and non spatial components, for the period of 2000–2015, are also depicted in Fig. 3.

As Table 2 indicates, for each year in the period under investigation, the spatial component of inequality is larger than the non-spatial component one (see also Fig. 3). The positive impact of the pattern of spatial autocorrelation to the overall inequality results in high values of $\gamma^*(y, Wy)$, which are also depicted in Fig. 4. The presence of a positive spatial association is also confirmed by high values of the Moran’s I . The value of the spatial component of

Fig. 4 Relative contribution of spatial patterns to global inequality—Italy NUTS 3, 2000–2015

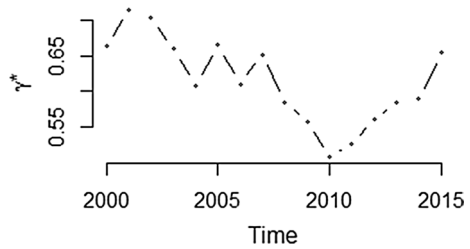


Table 3 Neighbour and non-neighbour components of inequality for Italian provinces 2000–2015

Year	2000	2001	2002	2003	2004	2005	2006	2007
G^*	0.1712	0.1701	0.1697	0.1687	0.1687	0.1675	0.1654	0.1668
NG^*	0.0008	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009
NNG^*	0.1704	0.1692	0.1688	0.1678	0.1678	0.1666	0.1645	0.1659
Year	2008	2009	2010	2011	2012	2013	2014	2015
G^*	0.1746	0.1732	0.1775	0.1792	0.1755	0.1754	0.1781	0.1770
NG^*	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011	0.0011
NNG^*	0.1735	0.1721	0.1764	0.1781	0.1744	0.1743	0.1770	0.1759

inequality and its impact on the overall inequality declines starting from 2008, as shown in Table 2 (see also Fig. 4). Our measure $\gamma^*(y, Wy)$ reaches its minimum value in 2010, and it increases starting from 2011. Note that the dynamics of our measure are consistent with the values of Moran’s I , which show a decline starting from 2008.

These results seem to have some important implications. First, the decrease of G_s^* , starting from 2008, reveals that the spatial spillovers are less evident during the economic crisis. Second, the simultaneous increase of the non-spatial component of the Gini index reveals an effective increase in the inequality, which is masked by the values of G^* that remain fairly stable during all the periods under investigation (see Fig. 3).

Our results are in agreement with the empirical findings of the analysis that was given by Márquez et al. (2019). The authors, focusing on income inequality among European NUTS 3 regions, found a decrease of the relative importance of the neighbourhood component (as measured by the neighbourhood Theil index) and thus an increase in the specific component of inequality (measured by the specific Theil index) for the period of 2007–2014.

In Table 3, the spatial decomposition of the Gini index, which was proposed by Rey and Smith (2013), is presented. Specifically, we consider a weighted version of the decomposition given in Eq. (2), which is defined as follows:

$$G^* = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \pi_i \pi_j |y_i - y_j|}{2n^2 \mu_y^*} + \frac{\sum_{i=1}^n \sum_{j=1}^n (1 - w_{ij}) \pi_i \pi_j |y_i - y_j|}{2n^2 \mu_y^*} \tag{15}$$

with all variables being identical to those that are specified above. The first term on the right side represents the neighbouring component NG^* , and the second one is the non-neighbouring component NNG^* . The NNG^* component can be interpreted as the spatial component of G^* that varies in the same direction as the positive spatial autocorrelation

(Rey and Smith 2013). Both these components, which are computed for Italian provinces over the period of 2000–2015, are reported in Table 3.

The results that are reported in Table 3 show a relevant positive contribution of the spatial component (NNG^*) to overall inequality. The non-spatial component is fairly stable over the period under investigation.

Compared with these results, our measure seems to better emphasize the fluctuations of the spatial and non-spatial inequality over the period under investigation. Compared to the non-spatial component NG^* , the non-spatial Gini, G_{ns}^* , permits one to better appreciate the actual extent of the inequality and to isolate the role of spatial dependence in regional disparities. Compared to the spatial component NNG^* of index G^* defined in Eq. (15), the spatial Gini index G_s^* , that we introduced in Eq. (12), exhibits a trend that is more coherent with the evolution, over the period 2000–2015, of the spatial dependence pattern, as measured by the Moran's I . In fact, the Pearson's correlation coefficient between G_s^* and Moran's I , over the 16 years, is 0.7424, while the Pearson's correlation coefficient calculated between NNG^* and I is -0.7624 . A strong positive relationship between our measure $\gamma^*(y, Wy)$ and the Moran's I is also reported, with a Pearson's correlation coefficient between these measures equal to 0.8381. In this sense, our measure, $\gamma^*(y, Wy)$, that expresses the relative contribution of spatial dependence to a given pattern of regional inequality, assumes values that appear more coherent with the values of Moran's I .

5 Conclusion

Dealing with regional inequality requires considering the role of spatial proximity in shaping the income distribution. However, traditional inequality measures disregard the geographical location of data, and different spatial patterns may provide the same inequality measure.

To address this issue, this paper proposed an approach to assess the relative contribution of a given spatial pattern to overall inequality. We introduced a measure that is defined using the regional GDP and the same variable that is spatially lagged, which is inspired by the Gini correlation (Schechtman and Yitzhaki 1987). Our measure, which is defined as $\gamma^*(y, Wy)$, accounts for both the inequality and spatial autocorrelation and is the subject of an interesting interpretation as the ratio between the spatial reranked Gini index and the overall Gini index of inequality. Unlike most of the spatially based inequality indexes that have been proposed in the literature, our measure accounts for the different contributions of regions to the overall inequality. In fact, in the definition of our measure, we focus on a specification of the Gini index for weighted data. A decomposition of the Gini index in its spatial and non-spatial components is also derived.

The proposed approach is applied to analyse the regional economic inequality for Italian provinces over the period of 2000–2015. The empirical evidence showed a relevant contribution of the spatial dependence effect in shaping the inequality in Italian provinces. The spatial component contributes to the total inequality more than the non-spatial component for the period of 2000–2008, and it loses its relative importance during the economic crisis years. In fact, starting from 2008, we noted an increase in the relative importance of the non-spatial inequality. Our empirical findings are consistent with the empirical result of the study by Márquez et al. (2019).

Compared to the measure that was proposed by Rey and Smith (2013), our index appears to be more able to differentiate the contributions of the spatial and non-spatial

components of inequality, thereby highlighting a trend that is more consistent with that of Moran's I .

This empirical evidence confirmed that the joint consideration of the spatial autocorrelation and income inequality produces important complementarities and offers insights that are not obtainable when these aspects are analysed alone. These results reveal that the proposed measure could be useful in assessing the actual extent of inequality, even in the presence of outstanding economic performances (Paredes et al. 2016). Furthermore, our measure is flexible enough to be applied at different geographical scales. The opportunity to identify the role of the spatial dependence relationship in driving income inequality at fine geographical scales is essential to providing useful information for location-based policies that are aimed at reducing income inequality (Márquez et al. 2019).

Future research could further explore the properties of the proposed measure. Interesting areas for future research involve analysing the impact of different neighbourhood definitions and developing an inferential framework for the proposed measure.

Acknowledgements This study was financed by the project H2020 IMAJINE which has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 726950.

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