Received: 3 May 2021 | Revised: 30 August 2021 | Accepted: 27 September 2021

DOI: 10.1111/rsp3.12482

ORIGINAL ARTICLE

Regional economic disparities, spatial dependence and proximity structures

Alfredo Cartone | Domenica Panzera | Paolo Postiglione

Department of Economic Studies, University G. d'Annunzio Chieti-Pescara, Pescara, Italy

Correspondence
Paolo Postiglione, Department of Economic Studies, University G. d'Annunzio Chieti-Pescara, Viale Pindaro 42, Pescara 66127, Italy.
Email: postigli@unich.it

[Correction added on 18 May 2022, after first online publication: CRUI funding statement has been added.]

Abstract

Since some decades, inequality has been attracting a growing interest within political debate as well as in theoretical and empirical studies. Considering inequality at a regional level offers useful insights for policy makers, facilitating the assessment of the effectiveness of strategies aimed at reducing regional disparities and helping in developing place-based actions. The study of regional inequality poses some relevant issues related to the spatial nature of data. In fact, dealing with georeferenced data implies the opportunity of considering the spatial interactions among regional units that are likely to play a role in shaping the inequality dynamics. Some studies have highlighted the importance of incorporating spatial effects in a traditional measure of inequality such as the Gini index. These studies are based on the definition of a proximity structure, which allows one to discriminate between the spatial and the non-spatial component of inequality. Different definitions of the proximity structure are likely to influence the spatial component of inequality. Those aspects are analysed in the present paper to offer more detailed insights in the territorial dimension of inequality. The measures and their decompositions are discussed in the case of European NUTS 3 regions.

KEYWORDS
economic disparities, neighbour regions, NUTS 3, spatial effects

JEL CLASSIFICATION
C18, C21, R12

1 | INTRODUCTION

During the last few decades, the quantification of income inequality, poverty and regional disparities have been attracting attention from different scholars (Andreano et al., 2021; Barrios & Strobl, 2009; Dunford, 1993; Williamson, 1965, among others).

The process of industrialization caused the increasing disparities between less developed regions and regions with higher productivity. Besides, the process of economic integration favoured international competition and the rise of income inequality (Beckfield, 2019). Finally, the economic crisis determined critical conditions that may have led to an increase in the overall gap between more and less developed regions (Brakman et al., 2015; Capello et al., 2015). However, if almost all European countries have been affected by the crisis, regions from the south and the east of Europe have suffered the most.

In this scenario, the reduction of regional disparities and the economic support to less-developed regions represent key objectives for institutions at all levels, including the European Union (EU; Iammarino et al., 2019). Since the introduction of cohesion as a paradigm of the European Community, the EU regional policies ground on a broader idea of cohesion, including social, economic and territorial dimensions. Those aspects remain priorities for its policy makers.

Addressing regional disparities requires considering a variety of methodological options to capture different socio-economic conditions. Additionally, economic development is deeply related to geography since specific features of a locality are crucial factors to promote or impede its growth and success. Accounting for specificities of territories implies rethinking policy interventions, putting aside ‘one-size-fits-all’ policies in favour of differentiated development strategies (Artelaris & Petrakos, 2016; Barca et al., 2012). However, if on the one hand absolute location of a regional unit is likely to impact on its economy, on the other hand, a relevant role is also played by its relative location (i.e., the influence of its neighbourhood).

Some more recent literature has been proposed in this direction. For example, Rey and Smith (2013), Márquez et al. (2019), and Panzera and Postiglione (2020) focused on the relevance of spatial effects while discussing the economic and social disparities, as the territorial dimension is seen as critical for tackling inequalities (Márquez et al., 2019).

Regional interconnections and the reciprocal influence between regions must be considered in order to analyse regional inequality. In fact, as for other economic phenomena, regional disparities are likely to be affected by the presence of neighbourhood effects in the form of spatial dependence (Anselin, 1988). Cultural, institutional and productivity factors may have influence on neighbours’ regions and the level of inequality in a region may not be independent from others (Gezici & Hewings, 2004). Those impacts have still received little attention in the EU, despite the increasing attention of policy makers to the effects of the integration process and the commitment to reduce regional disparities.

A further issue involves the definitions of linkages, connections and spatial relationships, which are pivotal to the measurement of neighbourhood effects. All the aforementioned contributions focus on indicators of spatial inequalities that are based on the definition of spatial connections in the form of a spatial proximity matrix, usually referred to as **W**.

The definition of the proximity structures (i.e., **W**) reflects specific hypotheses about the strength of regional interconnections and the spillover mechanisms. Still, the identification of imposed exogenous spatial relationships has been seen as critical (Corrado & Fingleton, 2012; Kelejian & Piras, 2014) and the impacts of different definitions of **W** are sometimes subordinated in the practice to other problems (e.g., model selection, Gibbons & Overman, 2012).

Following these considerations, in this paper we aim at measuring inequality at NUTS 3 level in the EU, while considering the impacts of regional interconnections using different definitions of proximity matrices. The purpose is two-fold. On the one side, we apply different indicators of spatial inequality in terms of different statistical options that can consider space while measuring regional disparities. On the other side, different weight matrices **W** are used and compared by considering their potential effects on interpretation and policy implications.

To give wider evidence, we focus on a fine spatial scale as the NUTS 3 level in the EU and the indicators of spatial inequality are obtained over the 2001–2019 period. The choice of a quite large number of years to analyse inequality is motivated by the need of considering years through increasing European integration, and the periods before and after the economic crisis started in 2007.

The methodological tools of our analyses are presented in Section 2; Section 3 illustrates the main empirical results that are discussed in Section 4. Finally, Section 5 concludes the paper.

2 | REGIONAL INEQUALITY AND THE SPATIAL DEPENDENCE EFFECT

Spatial effects have been introduced in the econometric literature for many years (Anselin, 1988), offering new possibilities for interpreting regional processes, as in the case of economic growth (LeSage & Fischer, 2008). As an example, the mechanism by which less developed regions tend to catch up to richer regional economies in the long run can be interpreted in the light of the regional interconnections and the subsequent spatial dependence effect between regional values (Elhorst et al., 2010; Ertur & Koch, 2007; Fischer, 2011; Panzera & Postiglione, 2014, 2021).

Despite its relevance, the spatial dependence effect has been often neglected in the literature on regional inequality measurement. Traditional inequality measures are invariant with respect to location and do not account for the geographical position of data. This implies that these measures are insensitive to any spatial permutation of data, and thus, given the gross domestic product (GDP) values, changing their geographical position does not impact on the inequality measure. This property is known as anonymity (Bickenbach & Bode, 2008; Panzera & Postiglione, 2020).

From a more statistical point of view, addressing the anonymity condition is relevant since proximity relationships among regional units could determine similarities or dissimilarities across regional GDP, and thus influence regional productivity and economic inequality. The role played by the geographical position of data, and thus by the potentially implied spatial dependence among observations in regional disparities, has only been addressed in more recent contributions (Arbia, 2001; Arbia & Piras, 2009; Márquez et al., 2019; Panzera & Postiglione, 2020; Rey & Smith, 2013).

Arbia (2001) proposes the distinction between spatial variability, which is invariant to permutations, and polarization, which refers to the geographical position of observations. Particularly, the author stresses the importance of developing indices that account for both aspects, suggesting several different approaches to combine measures of inequality and measures of spatial dependence. This paper can be considered as the starting point of this new interest for including the spatial effects in inequality measures. Some of these statistics are considered in the next subsection.

2.1 | Measures of spatial inequalities

To assess economic disparities at the regional level, Márquez et al. (2019) have focused on the Theil index T, introducing its decomposition into spatial and non-spatial components. The spatial component reflects the influence that for each region comes from neighbour units. This component is referred to as the neighbourhood Theil index. By subtracting the neighbourhood Theil from the conventional Theil, a Specific Theil index that accounts for non-spatial inequality is defined.

Other contributions have been focused on the Gini index of inequality. Given a random variable X, expressing a quantity of interest (e.g., regional GDP per capita) that could be observed across N geographical units, Rey and Smith (2013) considered the Gini index G expressed in its relative mean difference form as:

$$G = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} |x_i - x_j|}{2N^2\mu}, \tag{1}$$

with μ denoting the mean of the values x_i of the variable X.

Denoted by w_{ij} the generic element of a binary spatial weight matrix expressing the proximity relationship between locations i and j, the authors rewrote the index in 1 as the sum of absolute differences between pairs of neighbouring observations (NG) and absolute differences between pairs of non-neighbouring observations (NNG) as:

$$G = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij} |x_i - x_j|}{2N^2\mu} + \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} (1 - w_{ij}) |x_i - x_j|}{2N^2\mu} = NG + NNG. \tag{2}$$

The expression in 2 allows the identification of a neighbour component NG (the first term on the right side) and a non-neighbour component NNG (the second term on the right side) of the Gini index. This reveals as the Gini traditional inequality index nests a measure of spatial autocorrelation. In fact, the element w_{ij}, when equal to one, allows the identification of neighbour values, so when the amount of positive spatial dependence strengthens, NNG should increase relative to the NG since the difference between values observed at non-neighbour locations should be greater. The result is the opposite in the presence of negative spatial dependence (Rey & Smith, 2013). The authors illustrated this decomposition by its application to US per capita income and found that the overall inequality is primarily explained by its spatial component (i.e., NNG).

A different approach to the decomposition of the Gini index has been recently proposed by Panzera and Postiglione (2020). This approach relies on the covariance-based formula of the Gini index, and on its decomposition in a spatial Gini index (G_s) and a non-spatial Gini, (G_{ns}) as:

$$G = \frac{2Cov(x, R_x/N)}{\mu_x} = G_s + G_{ns}, \tag{3}$$

where R_x is the rank assigned to the regional GDP value (such that $R_x = 1$ for the lowest value of regional GDP per capita and $R_x = N$ for the highest value) and all the other quantities are defined as above.

The spatial Gini index G_s is obtained by re-ranking the GDP values according to the rank assigned to the average GDP observed for neighbouring regions (R_{Wx}) and by considering the correlation between the regional GDP per capita and this new rank as:

$$G_s = \frac{2Cov(x, R_{Wx}/N)}{\mu_x}. \tag{4}$$

The spatial Gini index in 4 expresses the component of inequality that is determined by the spatial dependence effect. Since this component is obtained by a re-ranking of GDP values, it varies between $-G$ and G (Panzera & Postiglione, 2020). In practice, $G_s = G$ when the average GDP per capita in neighbour regions is ranked as the original GDP per capita value in the regions; $G_s = -G$ when the ranking of GDP per capita in neighbour regions is the opposite to the ranking of GDP per capita in the regions. When G_s reaches its maximum value, the overall inequality, measured by G, is totally defined by its spatial component. As the ranking of the regional GDPs becomes more dissimilar to the ranking of average GDPs in neighbour regions, the spatial component of inequality decreases, and it approaches its minimum value.

The non-spatial Gini index G_{ns} is defined as the difference between G and G_s, and expresses the component of inequality that is not influenced by re-ranking regions according to their spatial lag component (i.e., the idiosyncratic component). This term ranges between 0 and $2G$ (Panzera & Postiglione, 2020). The authors applied the proposed spatial decomposition to GDP per capita in Italy, evidencing the dominance of the spatial component with respect to the non-spatial one.

The decompositions in 2 and 3 rely on different definitions of the Gini index. While the formulation considered in 2 follows the standard interpretation of the Gini index as the area between the line of equality and the actual Lorenz curve, the covariance-based specification used in 3 focuses on the correlation between the variate values and their rank.

The latter approach offers an interesting interpretation of the Gini index as a constant times the regression coefficient (i.e., the slope of the regression line of the variable against its ranking) and it is useful to decompose the Gini measure of a variable into the Gini indices of each element making up the variable (Lerman & Yitzhaki, 1984). Differences also emerge in the spatial components identified according to these different approaches. While the spatial component in 2 is defined as the absolute difference between pairs of non-neighboring observations, the spatial component in 3 is focused on the correlation between the value that is observed for the reference unit and the ranking of the values observed for neighbouring regions (see Equation 4). Both these spatial components allow quantification of the degree of spatial autocorrelation, that is the tendence of GDP per worker values observed on neighbour regions to cluster together. Different proximity criteria can be used, based on geographical, social or economic distances. These proximity relationships are summarized in the matrix **W**. Different definitions of **W** might imply differences in the spatial component of inequality identified according to the approaches. Some possible different criteria used in the specification of the **W** are presented in the following section.

2.2 | Proximity matrices for the measurement of spatial inequality

As described in the previous section, in both the spatial Gini approaches it is necessary to identify a spatial proximity structure. The connectivity matrix **W** can be defined using different approaches. Following Getis (2009), the **W** matrices can be defined using the topological point of view, the theoretical point of view and the empirical point of view.

The topological point of view implies defining proximity matrices that are based on the actual configuration of spatial units. This criterion is used in the definition of proximity matrices based on the number of nearest neighbours, or on the length of the common borders.

The theoretical point of view implies defining proximity matrices based on exogenous criteria, as, for example, the matrices based on preconceived distance functions. The empirical point of view implies defining proximity matrices based on the spatial associations detected for the variable under study (e.g., proximity matrices based on measures of local spatial association). These three approaches have the common characteristics that only consider geographical information in the definition of connectivity structures.

However, besides geographical distance, other elements may play an important role. For example, Conley and Topa (2002) suggested the use of socio-economic distance. Catania and Billè (2017) adopted the concept of economic distance in several applications involving phenomena where the geographic distance is less relevant.

For instance, the economic structure of a region matters in determining growth dynamics and transitions, as well as the sectorial mix tends to be connected to long-term effects on economic growth (Paci & Pigliaru, 1997). Some authors (Ezcurra et al., 2005; Martínez-Galarraga et al., 2015) found that regions with close sectorial mix are affected by common trends in productivity and inequality. Moreover, regions that show similar structures in terms of sectors are characterized by close entrepreneurial culture, technological and institutional similarities (Koo, 2007).

In this paper, jointly with the standard geographical definition of proximity, we consider economic proximity that can generate horizontal spillovers and mutual effects linked to technological similarities, so that a shock in a region is likely to have consequences on economic inequality in closer regions (Harris et al., 2012; Moreno et al., 2005). Particularly, economic distance is obtained using some agricultural information. The choice of the share of the agricultural sector can synthetise the economic structure of the region as this can easily convey information about the development of the region itself (Paci & Pigliaru, 1997). Additionally, the consideration of agriculture is related to the great attention that the EU and the literature has given to territorial disparities at a lower level than NUTS 2 in Europe (Artelaris, 2021; Védrine & Le Gallo, 2021), as also motivated by the large number of policies that the EU delivered to tackle regional disparities for regions in transition.

Further proximity matrices could be added to embed other economic interconnections (Boarnet, 1998). For example, transportation would offer a reliable insight into spillovers in the case of regional disparities. Equivalently, the similarities in the structure of human capital (e.g., in terms of skills) would add to the evidence. However, the use of those variables for building a proximity matrix for a large panel of regions at the NUTS 3 level is limited by data availability. Hence, a deeper analysis of those aspects could be conveyed in more local studies that could support policy makers (Díaz-Dapena et al., 2021).

Economic distance will be calculated as the differences between the shares s_i for each region, measured as the ratio between gross value added (GVA) per worker in agriculture and the overall GVA. As in Conley and Topa (2002), the Euclidean distance is used to obtain entries of **W** as:

$$w_{ij} = 1/Ec\,Dis_{ij} = 1/\sqrt{(s_i - s_j)^2}, \tag{5}$$

where $Ec\,Dis_{ij}$ is the economic distance calculated for each $i = 1 \dots N$ from each $j \neq i$.

Geographical and economic distances allow consideration of different interactions among regional units. If, on the one hand, geographical proximity could identify the influence among regional units that are contiguous or belonging to the same country, on the other hand, economic distances facilitate considering interactions among regional units with similar characteristics and economic structures.

3 | EMPIRICAL EVIDENCE

3.1 | Inequality in Europe at NUTS 3 level

The empirical analysis focuses on the regional inequality in terms of GDP per worker observed for 1,322 NUTS 3 EU regions across the period 2001–2019.

The level of GDP per worker in the regions under consideration, for 2001, 2010 and 2019, are displayed in Figure 1. Light colours denote lower values of GDP per worker, darker colours indicate higher GDP values. Data source for the EU regions is the publicly available ARDECO regional database.[1] GDP per worker shows a similar geographical distribution for the three different years across the period under consideration. Lower values of GDP per worker are mainly reported for Portugal and eastern regions, while higher values characterize regions in the north of Italy and in the north of Europe. The comparison across different years reveals a general increase of GDP values over time, as well as the persistence of regional economic disparities.

At the first stage, regional inequality among the EU NUTS 3 regions is measured by the standard Gini index before applying the two aforementioned spatial decompositions. The evolution of the overall regional inequality, measured by the Gini index G, during the period 2001–2019, is reported in Table 1.

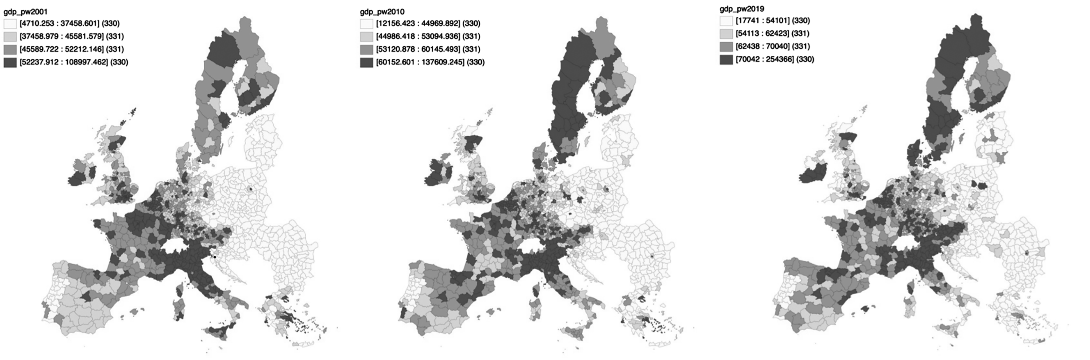

FIGURE 1 GDP per worker for 1,322 NUTS 3 regions (27 EU countries) for 2001, 2010 and 2019

TABLE 1 Gini index on GDP per worker 2001–2019 for 1,322 NUTS 3 EU regions

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
G	0.1746	0.1694	0.1651	0.1603	0.1601	0.1584	0.1569	0.1509	0.1478	0.1474
Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	
G	0.1452	0.1421	0.1403	0.1392	0.1412	0.1406	0.1389	0.1367	0.1341	

As presented in the table, the overall regional inequality in EU regions shows a decline across the period under consideration, decreasing from about 0.17 in 2001 to about 0.13 in 2019. The declining trend exhibited by the overall regional inequality is also shown in Figure 2.

The decreasing of G is also evident during the years of economic crisis. The decrease of inequality during a recession could be explained by the asymmetric growth trajectories that the European regional economies experienced. In fact, during this period, while the less developed regions have kept on converging toward richer regions, developed regions experienced a general income decline. Despite a general declining trend of regional inequality in GDP per worker, a deeper look at the territorial dynamics behind the G index should be considered. Therefore, to shed more light on the spatial dynamics of regional inequality, the Gini index is decomposed into its spatial and non-spatial components, following the approaches proposed by Rey and Smith (2013) and Panzera and Postiglione (2020), respectively. The analyses are performed using different criteria for the definition of the proximity matrix to assess potential differences.

3.2 | Spatial inequality at regional level using geographical proximity criteria

Geographical proximity is usually considered to define connections between regional units. Here, we start from a weight matrix **W** based on the inverse distance. The values assumed by the neighbour (NG) and the non-neighbour (NNG) components of G from Rey and Smith (2013) decomposition are reported in Table 2. The contribution of the spatial component to the overall inequality (NNG/G) is also shown in the table, together with the value of the Moran's I.[2]

Results reported in Table 2 highlight the dominance of the NNG component over the non-spatial component (i.e., NG) of inequality across the whole period. As it could be observed, the contribution of the spatial component to the overall inequality is stable during the period 2001–2019.

Different figures emerge from analysing the G_s/G ratio in Table 3. Also in this case, the spatial term still represents the larger part of the overall level of inequality. The impact of spatial inequality on the overall inequality

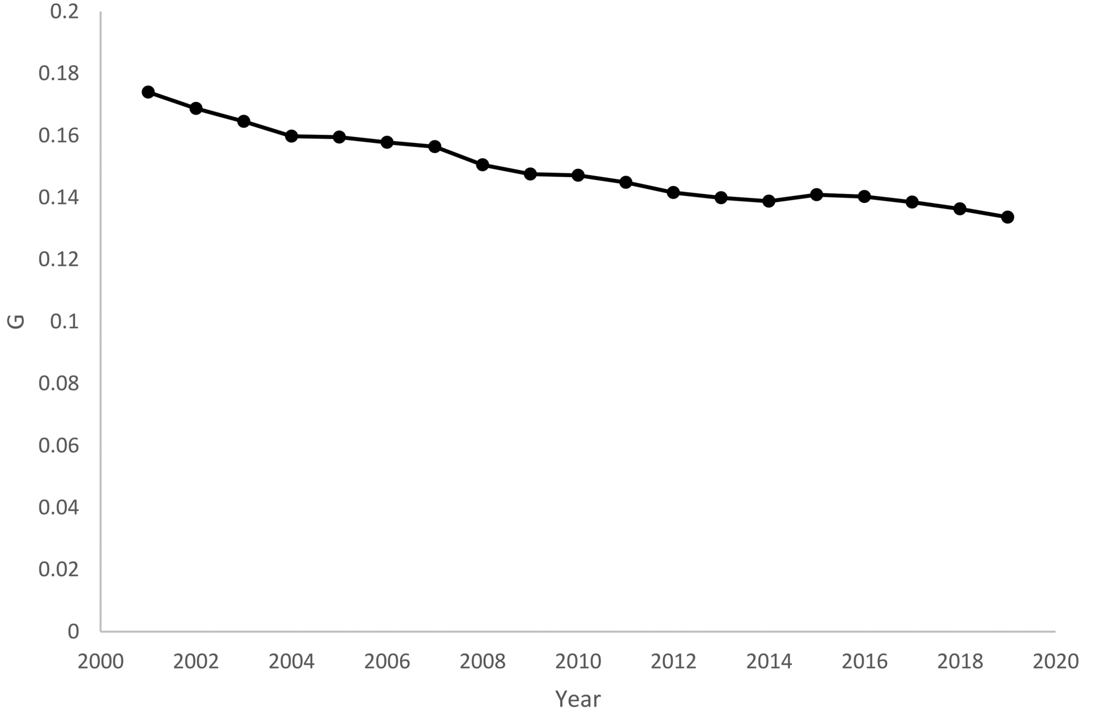

FIGURE 2 Gini index calculated on GDP per worker for 1,322 NUTS 3 EU regions, 2001–2019

TABLE 2 Neighbour (*NG*) and non-neighbour (*NNG*) components of the Gini index calculated for GDP per worker for 1,322 NUTS 3 EU regions in 2001–2019. Proximity matrix based on inverse distance

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
NG	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
NNG	0.1747	0.1693	0.1651	0.1603	0.1601	0.1583	0.1569	0.1510	0.1479	0.1474
NNG/*G*	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999
I	0.2066	0.2062	0.2088	0.2085	0.2061	0.2033	0.1975	0.1894	0.1822	0.1803
Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	
NG	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	
NNG	0.1452	0.1420	0.1403	0.1392	0.1411	0.1405	0.1389	0.1367	0.1341	
NNG/*G*	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	
I	0.1794	0.1797	0.1803	0.1855	0.1650	0.1630	0.1564	0.1476	0.1364	

declines over the period under analysis. Hence, the declining trend in overall inequality could be explained as a reduction of the spatial component of inequality.

The non-spatial term is slightly increasing in the period 2001–2019, revealing the increase of the idiosyncratic component of regional disparities which is masked by the decrease of the spatial inequality. This circumstance opens a challenging scenario for policy makers. In fact, it has been possible to provide a more homogeneous distribution of the GDP per capita by reducing the impact of the potential effects that one region has on the others. Furthermore, the reduction of disparities could involve the reduction of the idiosyncratic component of inequality, suggesting the importance of place-based policies, that accounts for the specific features that emerge at a very local level.

TABLE 3 Spatial (G_s) and non-spatial (G_{ns}) components of the Gini index calculated for GDP per worker for 1,322 NUTS 3 EU regions in 2001–2019. Proximity matrix based on inverse distance

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
G_s	0.1337	0.1296	0.1254	0.1204	0.1201	0.1178	0.1160	0.1100	0.1071	0.1050
G_{ns}	0.0411	0.0400	0.0398	0.0402	0.0406	0.0410	0.0409	0.0426	0.0407	0.0406
G_s/G	0.7650	0.7643	0.7592	0.7507	0.7493	0.7437	0.7385	0.7284	0.7234	0.7115
I	0.2066	0.2062	0.2088	0.2085	0.2061	0.2033	0.1975	0.1894	0.1822	0.1803
Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	
G_s	0.1047	0.1016	0.1010	0.1017	0.1019	0.1008	0.0987	0.0956	0.0914	
G_{ns}	0.0426	0.0408	0.0406	0.0394	0.0377	0.0399	0.0403	0.0412	0.0429	
G_s/G	0.7189	0.7124	0.7179	0.7290	0.7168	0.7125	0.7069	0.6959	0.6785	
I	0.1794	0.1797	0.1803	0.1855	0.1650	0.1630	0.1564	0.1476	0.1364	

TABLE 4 Neighbour (*NG*) and non-neighbor (*NNG*) components of the Gini index calculated for GDP per worker for 1,322 NUTS 3 EU regions in 2001–2019. *K*-nearest neighbours proximity matrix with $k = 10$

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
NG	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
NNG	0.1746	0.1693	0.1650	0.1602	0.1600	0.1583	0.1569	0.1509	0.1478	0.1473
NNG/G	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996
I	0.4736	0.4647	0.4708	0.4686	0.4620	0.4561	0.4517	0.4350	0.4276	0.4027
Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	
NG	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	
NNG	0.1451	0.1419	0.1402	0.1396	0.1411	0.1405	0.1388	0.1366	0.1341	
NNG/G	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996	
I	0.3975	0.3973	0.3992	0.4037	0.3736	0.3696	0.3578	0.3433	0.3213	

Further, calculation of the spatial indicators of inequalities is supplied for other proximity matrix specifications. Following, we use a *k*-nearest specification at different levels of *k* and start considering ten neighbours for each region. The results for the Rey and Smith (2013) spatial and non-spatial Gini are shown in Table 4.

The results in Table 4 suggest that the *NNG* is again a very large part of the overall inequality measured by the Gini index. Additionally, values are in line with the results of Table 2 obtained with the inverse-distance specification, even if the levels for Moran's *I* are a bit higher. Results obtained for the G_s (Panzera & Postiglione, 2020) are summarized in Table 5.

The decreasing trend in the spatial inequality component calculated in Table 3 is confirmed in the case of *k*-nearest proximity matrix wit $k = 10$ (see Table 5). Hence, the interpretation seems not to change if a different proximity matrix is used. Additionally, robustness is further checked for a different level of *k* and both techniques are performed by setting $k = 20$. Results for the *NNG* are summarized in Table 6, while the outputs for the G_s are presented in Table 7.

From Tables 6 and 7, it can be observed how the level of the spatial component is in line with previous specifications of the proximity matrix. Only a slight reduction in the level of the spatial part is individuated for the G_s when *k* is set to a very wide number of neighbours. In the case of the *NNG*, the spatial indicator reports lower sensitiveness to the identification of the spatial matrix. However, this does not show great variability over time, oppositely to the G_s component. Not being the geographical proximity, the only criterium to define the **W** matrix, an example of economic distance will be considered in the following section.

TABLE 5 Spatial (G_s) and non-spatial (G_{ns}) components of the Gini index calculated for GDP per worker for 1,322 NUTS 3 EU regions in 2001–2019. *K*-nearest neighbours proximity matrix with $k = 10$

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
G_s	0.1457	0.1412	0.1371	0.1326	0.1319	0.1303	0.1292	0.1227	0.1197	0.1177
G_{ns}	0.0291	0.0282	0.0280	0.0277	0.0283	0.0281	0.0278	0.0283	0.0282	0.0297
G_s/G	0.8333	0.8332	0.8302	0.8269	0.8232	0.8226	0.8226	0.8121	0.8094	0.7981
I	0.4736	0.4647	0.4708	0.4686	0.4620	0.4561	0.4517	0.4350	0.4276	0.4027
Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	
G_s	0.1165	0.1139	0.1147	0.1121	0.1149	0.1135	0.1114	0.1082	0.1040	
G_{ns}	0.0287	0.0281	0.0279	0.0272	0.0263	0.0271	0.0276	0.0287	0.0302	
G_s/G	0.8022	0.8016	0.8011	0.8042	0.8137	0.8070	0.8016	0.7905	0.7746	
I	0.3975	0.3973	0.3992	0.4037	0.3736	0.3696	0.3578	0.3433	0.3213	

TABLE 6 Neighbour (*NG*) and non-neighbour (*NNG*) components of the Gini index calculated for GDP per worker for 1,322 NUTS 3 EU regions in 2001–2019. *K*-nearest neighbours proximity matrix with $k = 20$

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
NG	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
NNG	0.1746	0.1694	0.1651	0.1603	0.1601	0.1583	0.1569	0.1509	0.1479	0.1474
NNG/*G*	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996
I	0.4103	0.4024	0.4072	0.4068	0.4005	0.3957	0.3915	0.3739	0.3610	0.3379
Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	
NG	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	
NNG	0.1452	0.1420	0.1403	0.1392	0.1411	0.1405	0.1389	0.1367	0.1341	
NNG/*G*	0.9995	0.9995	0.9995	0.9995	0.9995	0.9995	0.9995	0.9995	0.9995	
I	0.3341	0.3329	0.3340	0.3400	0.3100	0.3055	0.2939	0.2810	0.2601	

TABLE 7 Spatial (G_s) and non-spatial (G_{ns}) components of the Gini index calculated for GDP per worker for 1,322 NUTS 3 EU regions in 2001–2019. *k*-nearest neighbours proximity matrix with $k = 20$

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
G_s	0.1420	0.1372	0.1335	0.1288	0.1279	0.1264	0.1247	0.1185	0.1156	0.1138
G_{ns}	0.0329	0.0325	0.0317	0.0317	0.0324	0.0321	0.0324	0.0326	0.0323	0.0337
G_s/G	0.8120	0.8091	0.8080	0.8026	0.7972	0.7843	0.7842	0.7843	0.7814	0.7713
I	0.4103	0.4024	0.4072	0.4068	0.4005	0.3957	0.3915	0.3739	0.3610	0.3379
Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	
G_s	0.1125	0.1095	0.1083	0.1081	0.1060	0.1081	0.1060	0.1030	0.1000	
G_{ns}	0.0328	0.0326	0.0321	0.0313	0.0313	0.0326	0.0330	0.0338	0.0354	
G_s/G	0.7742	0.7705	0.7716	0.7756	0.7786	0.7682	0.7626	0.7528	0.7364	
I	0.3341	0.3329	0.3340	0.3400	0.3100	0.3055	0.2939	0.2810	0.2601	

3.3 | Spatial inequality at regional level using economic distance

After examining different options for geographical distance, we also provide an analysis to exploratively assess the use of proximity based on economic variables. In the econometric literature, there is a progressive attempt to go beyond the definition of connectivity between regions in terms of geographical distance. Socio-economic distances have been conceptualized in less recent times (Conley & Topa, 2002) and, over the last years, more authors have tried to specify distances based on a variety of different economic quantities (Catania & Billè, 2017; Fiorelli et al., 2021, among others).

For the definition of weight matrices using economic variables, we consider distance between the share of agricultural sector of different regions. This economic distance is calculated between regions over the whole Europe, since this also allows us to assess if similarities in the economic structure after the EU integration have caused patterns in terms of GDP inequality. Also, developing a **W** matrix based on economic distances allows us to evaluate the sensitivity of the spatial inequality measures to different proximity structures obtained using 'the geography' or 'the economics.'

In the following tables, results for the economic distance (Ec Dis) are reported.

In Table 8, results are presented for the Rey and Smith (2013) indicators, while in Table 9 the evidence from applying Panzera and Postiglione (2020) measures is reported. In both tables, the result shows how the level of the

TABLE 8 Neighbour (*NG*) and non-neighbour (*NNG*) components of the Gini index calculated for GDP per worker for 1,322 NUTS 3 EU regions in 2001–2019. Economic distance

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
NG	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
NNG	0.1745	0.1693	0.1650	0.1602	0.1600	0.1582	0.1568	0.1508	0.1478	0.1473
NNG/*G*	0.9994	0.9994	0.9994	0.9994	0.9994	0.9994	0.9994	0.9994	0.9993	0.9994
I	0.2268	0.2127	0.2195	0.2416	0.2432	0.2694	0.2514	0.2283	0.2268	0.2480
Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	
NG	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	
NNG	0.1451	0.1419	0.1402	0.1391	0.1410	0.1404	0.1388	0.1366	0.1340	
NNG/*G*	0.9994	0.9994	0.9994	0.9994	0.9994	0.9994	0.9994	0.9994	0.9994	
I	0.2375	0.2476	0.2079	0.2616	0.2381	0.1998	0.2315	0.1829	0.1879	

TABLE 9 Spatial (G_s) and non-spatial (G_{ns}) components of the Gini index calculated for GDP per worker for 1,322 NUTS 3 EU regions in 2001–2019. Economic distance

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
G_s	0.0798	0.0802	0.0808	0.0786	0.0796	0.0783	0.0769	0.0724	0.0707	0.0729
G_{ns}	0.0950	0.0893	0.0844	0.0818	0.0806	0.0801	0.0802	0.0786	0.0772	0.0746
G_s/G	0.4566	0.4731	0.4892	0.4901	0.4968	0.4940	0.4893	0.4793	0.4783	0.4939
I	0.2375	0.2476	0.2079	0.2616	0.2381	0.1998	0.2315	0.1829	0.1879	0.2375
Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	
G_s	0.0720	0.0701	0.0697	0.0713	0.0706	0.0701	0.0692	0.0669	0.0643	
G_{ns}	0.0733	0.0720	0.0707	0.0681	0.0707	0.0706	0.0698	0.0699	0.0700	
G_s/G	0.4953	0.4933	0.4961	0.5115	0.4995	0.4986	0.4981	0.4890	0.4787	
I	0.2375	0.2476	0.2079	0.2616	0.2381	0.1998	0.2315	0.1829	0.1879	

NNG is very similar if compared with other spatial configurations based on geographical proximity, but this still accounts for a large part of the overall inequality. Conversely, for the G_s the level of the spatial component is lower when compared with the figures obtained for geographical proximity.

A reduction of the spatial interactions term when different distances from the geographical are considered is coherent with Conley and Topa (2002) for the social distance. In this circumstance, this reduction may be connected to the nature of the underlying spillovers. By only considering horizontal spillovers due to distance in terms of sectorial mix, not the whole interactions are embedded into economic **W**. In fact, vertical spillovers may represent a part of the regional externalities. Despite the latter being still important, an analysis at NUTS 3 level would require highly complex input/output linkages (Capello, 2009).

However, a magnitude around 50% for the contribution of the spatial component to the overall inequality suggests that there is a considerable effect of the economic distance between more 'agricultural' regions and more developed areas, even if the EU promoted progressive integration. Thence, European programs might have reduced structural differences across the EU, but the result confirms how the distance in terms of sectorial mix still matters in the regional level of inequality, also at a low scale.

4 | DISCUSSION

By applying the two different spatial methodologies, we observe that the results lead to a better assessment of regional inequalities. An in-depth understanding of spatial features is required to guide actions at all levels and to develop 'place-sensitive' policies for a more cohesive EU. Hence, policy makers should be more aware of the underlying territorial framework (Iammarino et al., 2019).

The analysis of disparities at a detailed geographical level (i.e., NUTS 3) can let us define very ad hoc strategies (Díaz-Dapena et al., 2021). First, a deeper understanding of what is going on within the larger regions (NUTS 2) could be required to be more effective. Second, an analysis of the spatial features that emerge at a detailed scale strengthens key concepts as spatial justice and territorial cohesion (Medeiros & Rauhut, 2020; Panzera & Postiglione, 2020). Lastly, spatial indicators point towards a local approach to tackle inequality as the use of spatial statistics could give a wider picture (Cartone & Postiglione, 2021).

When using the Rey and Smith (2013) indicator, the relevance of the spatial component is estimated very high, and remains stable over time. Conversely, while considering the Panzera and Postiglione (2020) indicator, the figures of the ratio G_s/G are quite different and show a decreasing trend for all the **W** matrices. However, all results confirm how spatial patterns have their relevance on the overall inequality.

The differences in the interpretation of the two measures should be carefully considered. On the one side, the spatial term calculated in *NNG* is a spatial expansion of the standard Gini index, due to the effect of positive (or negative) spatial autocorrelation in the spatial lag of x (in our case, the GDP per worker). Hence, this measure is directly linked to the extent of the spatial autocorrelation embedded into the objective variable and, consequently, the *NNG* is obtained by splitting the Gini coefficient in its spatial and non-spatial part. Conversely, in the Panzera and Postiglione (2020) decomposition, the spatial part is obtained by a reformulation of the Gini coefficient as a rank correlation. The G_s indicator of inequality evidences the reciprocal influence between values of GDP per worker observed on neighbour regions, by re-ranking the GDP per worker using its spatial lag. Thence, this can be considered as an explicit indicator of territorial inequality, as its absolute value rises when the lack of spatial uniformity is more evident.

Although technical, those features may constitute the basis for accurate interpretation of inequality in the EU. The application of those indicators over several years shows that the declining inequality may be attributed to a reduction of the spatial term. This circumstance may be positively linked to the progressive EU integration. However, invariant level of specific inequality poses challenges for policy makers at all levels (including the

European) to also address inequality and disparities 'within regions' and granular growth dynamics (Urso et al., 2019).

An additional issue for the measurement of spatial inequality regards the proximity structure. When looking at the trends for different spatial configuration, both applications show similar patterns. Therefore, the adoption of several spatial structures does not dramatically change the results. While the *NNG* remains more stable over time, the G_s retains its descending trend, which has an impact on the overall level after the crisis (Agnello & Sousa, 2012). Those features make spatial measures of inequality appear as robust to different proximity specifications.

Changes can be highlighted when using economic distance. In the current study, a matrix based on regional sectorial mix has been used to an explorative aim. However, the results show some new insight on how the economic distance between more developed regions and less developed regions may affect inequality. In Figure 3, results from Table 9 are graphically reappraised. It can be observed that an initial surge in the effects of sectorial mix distance happened in 2001. Nevertheless, this effect shows a decline later until a stop in 2008, the year in which economic effects of the financial crisis became more evident. Again, the spatial effects due to economic distance between regions rose evidently with a spike in 2014. Subsequently, a new declining trend started after 2014, when the more severe effects of the crisis were partially left behind.

Indeed, the structural similarities determine interdependencies between regions, affecting the inequality dynamics. In the case of the G_s, its magnitude describes how the level of inequality is due to an uneven distribution of sectorial mix throughout the EU. Generally, the results support the idea that economic distance may give further empirical evidence for the pivotal problems of path dependencies and economic transitions (Martin & Sunley, 2006; Paci & Pigliaru, 1997). Moreover, the interpretations in the case of economic distance highlight the flexibility of spatial measures of inequality for policy makers to evaluate crucial aspects using 'more economic' **W**s.

The results also give insights into the policy scenario of the EU. The debate about regional inequality in Europe has attracted greater consideration in the last few years. The Cohesion Policy represents an elective instrument for

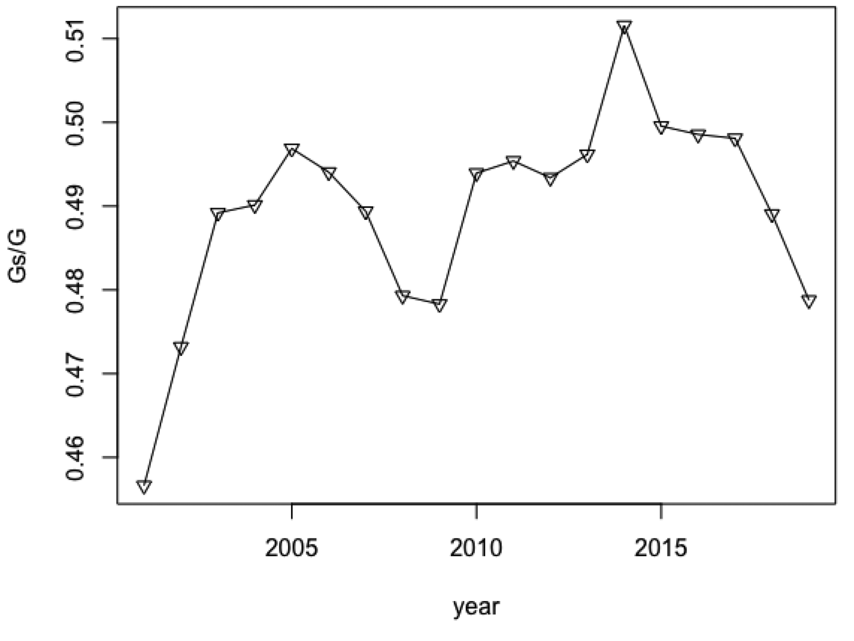

FIGURE 3 G_s/G index calculated on GDP per worker using an economic distance **W** matrix. 1,322 NUTS 3 EU regions, 2001–2019

European policy makers to reduce regional disparities. Further, in more recent years this debate has benefited from new tools for the evaluation of underlying economic mechanisms, as for spillovers, externalities and local peculiarities.

Usual mechanisms of adjustment that should guarantee more equity while preserving economic performance remain difficult to ignite (Iammarino et al., 2019). For example, restrictions on people flows are expected to reduce positive effects of migration on the reduction of inequalities (Partridge et al., 2012), as well as the impact of migration not being territorially invariant (Di Berardino et al., 2021). In this direction, the use of spatial indicators may help to shed more light on some mechanisms that drive spatial inequality as, for instance, knowledge spillovers in less advanced sectors that could slow transition.

However, a deeper consideration should be given to the study of the impact of the economic distance in spatial inequality measures. The use of economic distance for weight matrices is more common in other types of regional analyses (Kang & Dall'erba, 2016). From our results, it is evident that a considerable magnitude for the spatial component is also obtained using economic distances. Particularly, we observed that regions that tend to be more 'agricultural' share a common path of inequality. This may lead policy makers to directly act on those factors that inhibit transition and help to develop a deeper vocation towards more productive sectors, to fill the gap with more advanced regions.

Finally, the idiosyncratic term could also be of interest to policy makers. Whenever this term results as considerable, the presence of within region inequalities should be further addressed (Rodríguez-Pose & Wilkie, 2017).

5 | CONCLUSION

In this paper, a larger focus on the role of the spatial dependence in the analysis of regional inequality in the EU has been presented. Specifically, we tried to shed more light on the consequences of spatial dependence in the traditional inequality measures, applying spatial analysis in the EU at NUTS 3 level.

The collected evidence shows how discarding the spatial interactions among neighbouring regional units result in a considerable loss of details. In fact, over recent years, the contribution of spatial inequality slightly decreased, which is consistent with a European strategy lead by the need for more integrations. However, even in the aftermath of the economic crises, the non-spatial (i.e., idiosyncratic) inequality figures remain stable, which leads to a broader consideration of very specific causes of inequality at low scale.

Analysts and European policy makers should take into account not only the overall level of inequality, but also isolate specific components of inequality to act in critical situations. Particularly, the effects due to geographical position of the data retrieve additional information on significative geographical patterns.

We extended the discussion using two spatial indicators of inequalities, and we performed the analyses for different proximity structures. Hence, the two methodological approaches are tested for different **W** matrices. By comparing the different spatial configurations, the empirical analysis highlights the dominance of the spatial component on the idiosyncratic component, where a geographical component is used.

Finally, two major future research lines emerge. First, a deeper analysis at very local level (e.g., municipalities) could be considered if data at a lower scale are available for a considerable set of European regions. Second, research in terms of spatial indicators of inequalities could be further addressed in future studies, also extending inferential properties of those methodologies, and considering other proximity matrices that include other economic phenomena or a combination of those.

ACKNOWLEDGEMENT

Open Access Funding provided by Universita degli Studi Gabriele d'Annunzio Chieti Pescara within the CRUI-CARE Agreement.

ORCID

Alfredo Cartone https://orcid.org/0000-0002-1709-1493
Domenica Panzera https://orcid.org/0000-0002-0699-6983
Paolo Postiglione https://orcid.org/0000-0002-2798-4519

ENDNOTES

[1] Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy (ARDECO, https://ec.europa.eu/knowledge4policy/territorial/ardeco-database_en) maintained by the European Commission's Joint Research Centre.

[2] Moran's I computed for GDP per worker, x_i, can be expressed as follows: $I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(x_i - \mu_x)(x_j - \mu_x)}{\sum_i (x_i - \mu_x)^2}$, where all the quantities are defined as above. Moran's I ranges between -1 and 1, assuming negative values in the presence of clustering of dissimilar values and positive values otherwise.

REFERENCES

Agnello, L., & Sousa, R. M. (2012). How do banking crises impact on income inequality? *Applied Economics Letters*, *19*, 1425–1429. https://doi.org/10.1080/13504851.2011.631885

Andreano, M. S., Benedetti, R., Piersimoni, F., & Savio, G. (2021). Mapping poverty of Latin American and Caribbean countries from heaven through night-light satellite images. *Social Indicators Research*, *156*, 533–562. https://doi.org/10.1007/s11205-020-02267-1

Anselin, L. (1988). *Spatial econometrics: Methods and models*. Kluwer Academic Publishers.

Arbia, G. (2001). The role of spatial effects in the empirical analysis of regional concentration. *Journal of Geographical Systems*, *3*, 271–281. https://doi.org/10.1007/PL00011480

Arbia, G., & Piras, G. (2009). A new class of spatial concentration measures. *Computational Statistics & Data Analysis*, *53*, 4471–4481. https://doi.org/10.1016/j.csda.2009.07.003

Artelaris, P. (2021). Regional economic growth and inequality in Greece. *Regional Science Policy & Practice*, *13*, 141–158. https://doi.org/10.1111/rsp3.12363

Artelaris, P., & Petrakos, G. (2016). Intraregional spatial inequalities and regional income level in the European Union: Beyond the inverted-U hypothesis. *International Regional Science Review*, *39*, 291–317. https://doi.org/10.1177/0160017614532652

Barca, F., McCann, P., & Rodríguez-Pose, A. (2012). The case for regional development intervention: Place-based versus place-neutral approaches. *Journal of Regional Science*, *52*, 134–152. https://doi.org/10.1111/j.1467-9787.2011.00756.x

Barrios, S., & Strobl, E. (2009). The dynamics of regional inequalities. *Regional Science and Urban Economics*, *39*, 575–591. https://doi.org/10.1016/j.regsciurbeco.2009.03.008

Beckfield, J. (2019). *Unequal Europe: Regional integration and the rise of European inequality*. Oxford University Press.

Bickenbach, F., & Bode, E. (2008). Disproportionality measures of concentration, specialization and localization. *International Regional Science Review*, *31*, 359–388. https://doi.org/10.1177/0160017608319589

Boarnet, M. G. (1998). Spillovers and the locational effects of public infrastructure. *Journal of Regional Science*, *38*, 381–400. https://doi.org/10.1111/0022-4146.00099

Brakman, S., Garretsen, H., & van Marrewijk, C. (2015). Regional resilience across Europe: On urbanization and the initial impact of the great recession. *Cambridge Journal of Regions, Economy and Society*, *8*, 141–148. https://doi.org/10.1093/cjres/rsv005

Capello, R. (2009). Spatial spillovers and regional growth: A cognitive approach. *European Planning Studies*, *17*, 639–658. https://doi.org/10.1080/09654310902778045

Capello, R., Caragliu, A., & Fratesi, U. (2015). Spatial heterogeneity in the costs of the economic crisis in Europe: Are cities sources of regional resilience? *Journal of Economic Geography*, *15*, 951–972. https://doi.org/10.1093/jeg/lbu053

Cartone, A., & Postiglione, P. (2021). Principal component analysis for geographical data: The role of spatial effects in the definition of composite indicators. *Spatial Economic Analysis*, *16*, 126–147. https://doi.org/10.1080/17421772.2020.1775876

Catania, L., & Billè, A. G. (2017). Dynamic spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of Applied Econometrics*, *32*, 1178–1196. https://doi.org/10.1002/jae.2565

Conley, T. J., & Topa, G. (2002). Socio-economic distance and spatial patterns in unemployment. *Journal of Applied Econometrics*, *17*, 303–327. https://doi.org/10.1002/jae.670

Corrado, L., & Fingleton, B. (2012). Where is the economics in spatial econometrics? *Journal of Regional Science*, *52*, 210–239. https://doi.org/10.1111/j.1467-9787.2011.00726.x

Di Berardino, C., D'Ingiullo, D., Furia, D., & Cartone, A. (2021). Immigration diversity and regional economic growth. *Economia Politica*. https://doi.org/10.1007/s40888-021-00226-8
Díaz-Dapena, A., Fernández Vázquez, E., Rubiera Morollón, F., & Viñuela, A. (2021). Mapping poverty at the local level in Europe: A consistent spatial disaggregation of the AROPE indicator for France, Spain, Portugal and the United Kingdom. *Regional Science Policy & Practice*, *13*, 63–81. https://doi.org/10.1111/rsp3.12379
Dunford, M. (1993). Regional disparities in the European community: Evidence from the REGIO databank. *Regional Studies*, *27*, 727–743. https://doi.org/10.1080/00343409312331347915
Elhorst, J. P., Piras, G., & Arbia, G. (2010). Growth and convergence in a multi-regional model with space-time dynamics. *Geographical Analysis*, *42*, 338–355. https://doi.org/10.1111/j.1538-4632.2010.00796.x
Ertur, C., & Koch, W. (2007). Growth, technological interdependence and spatial externalities: Theory and evidence. *Journal of Applied Econometrics*, *22*, 1033–1062. https://doi.org/10.1002/jae.963
Ezcurra, R., Gil, C., Pascual, P., & Rapún, M. (2005). Regional inequality in the European Union: Does industry mix matter? *Regional Studies*, *39*, 679–697. https://doi.org/10.1080/00343400500213473
Fiorelli, C., Cartone, A., & Foglia, M. (2021). Shadow rates and spillovers across the Eurozone: A spatial dynamic panel model. *Empirica*, *48*, 223–245. https://doi.org/10.1007/s10663-020-09483-5
Fischer, M. M. (2011). A spatial Mankiw-Romer-Weil model: Theory and evidence. *The Annals of Regional Science*, *17*, 419–436. https://doi.org/10.1007/s00168-010-0384-6
Getis, A. (2009). Spatial weights matrices. *Geographical Analysis*, *41*, 404–410. https://doi.org/10.1111/j.1538-4632.2009.00768.x
Gezici, F., & Hewings, G. J. (2004). Regional convergence and the economic performance of peripheral areas in Turkey. *Review of Urban & Regional Development Studies*, *16*, 113–132. https://doi.org/10.1111/j.1467-940X.2004.00082.x
Gibbons, S., & Overman, H. G. (2012). Mostly pointless spatial econometrics? *Journal of Regional Science*, *52*, 172–191. https://doi.org/10.1111/j.1467-9787.2012.00760.x
Harris, R., Moffat, J., & Kravtsova, V. (2012). In search of 'W. *Spatial Economic Analysis*, *6*, 249–270. https://doi.org/10.1080/17421772.2011.586721
Iammarino, S., Rodríguez-Pose, A., & Storper, M. (2019). Regional inequality in Europe: Evidence, theory and policy implications. *Journal of Economic Geography*, *19*, 273–298. https://doi.org/10.1093/jeg/lby021
Kang, D., & Dall'erba, S. (2016). An examination of the role of local and distant knowledge spillovers on the US regional knowledge creation. *International Regional Science Review*, *39*, 355–385. https://doi.org/10.1177/0160017615572888
Kelejian, H. H., & Piras, G. (2014). Estimation of spatial models with endogenous weighting matrices, and an application to a demand model for cigarettes. *Regional Science and Urban Economics*, *46*, 140–149. https://doi.org/10.1016/j.regsciurbeco.2014.03.001
Koo, J. (2007). Determinants of localized technology spillovers: Role of regional and industrial attributes. *Regional Studies*, *41*, 995–1011. https://doi.org/10.1080/00343400601142746
Lerman, R., & Yitzhaki, S. (1984). A note on the calculation and interpretation of the Gini index. *Economics Letters*, *15*, 363–368. https://doi.org/10.1016/0165-1765(84)90126-5
LeSage, J. P., & Fischer, M. M. (2008). Spatial growth regressions: Model specification, estimation and interpretation. *Spatial Economic Analysis*, *3*, 275–304. https://doi.org/10.1080/17421770802353758
Márquez, M. A., Lasarte-Navamuel, E., & Lufin, M. (2019). The role of neighbourhood in the analysis of spatial economic inequality. *Social Indicators Research*, *141*, 245–273. https://doi.org/10.1007/s11205-017-1814-y
Martin, R., & Sunley, P. (2006). Path dependence and regional economic evolution. *Journal of Economic Geography*, *6*, 395–437. https://doi.org/10.1093/jeg/lbl012
Martínez-Galarraga, J., Rosés, J. R., & Tirado, D. A. (2015). The long-term patterns of regional income inequality in Spain, 1860–2000. *Regional Studies*, *49*, 502–517. https://doi.org/10.1080/00343404.2013.783692
Medeiros, E., & Rauhut, D. (2020). Territorial cohesion cities: A policy recipe for achieving territorial cohesion? *Regional Studies*, *54*, 120–128. https://doi.org/10.1080/00343404.2018.1548764
Moreno, R., Paci, R., & Usai, S. (2005). Spatial spillovers and innovation activity in European regions. *Environment and Planning (a): Economy and Space*, *37*, 1793–1812. https://doi.org/10.1068/a37341
Paci, R., & Pigliaru, F. (1997). Structural change and convergence: An Italian regional perspective. *Structural Change and Economic Dynamics*, *8*, 297–318. https://doi.org/10.1016/S0954-349X(96)00077-X
Panzera, D., & Postiglione, P. (2014). Economic growth in Italian NUTS 3 provinces. *The Annals of Regional Science*, *53*, 273–293. https://doi.org/10.1007/s00168-014-0628-y
Panzera, D., & Postiglione, P. (2020). Measuring the spatial dimension of regional inequality: An approach based on the Gini correlation measure. *Social Indicators Research*, *148*, 379–394. https://doi.org/10.1007/s11205-019-02208-7
Panzera, D., & Postiglione, P. (2021). The impact of regional inequality on economic growth: A spatial econometric approach. *Regional Studies*. https://doi.org/10.1080/00343404.2021.1910228

Partridge, M. D., Rickman, D. S., Olfert, M. R., & Ali, K. (2012). Dwindling US internal migration: Evidence of spatial equilibrium or structural shifts in local labor markets? *Regional Science and Urban Economics*, *42*, 375–388. https://doi.org/10.1016/j.regsciurbeco.2011.10.006

Rey, S. J., & Smith, R. J. (2013). A spatial decomposition of the Gini coefficient. *Letters in Spatial and Resource Sciences*, *6*, 55–70. https://doi.org/10.1007/s12076-012-0086-z

Rodríguez-Pose, A., & Wilkie, C. (2017). Revamping local and regional development through place-based strategies. *Cityscape*, *19*, 151–170.

Urso, G., Modica, M., & Faggian, A. (2019). Resilience and sectoral composition change of Italian inner areas in response to the great recession. *Sustainability*, *11*, 2679. https://doi.org/10.3390/su11092679

Védrine, L., & Le Gallo, J. (2021). Does EU Cohesion Policy affect territorial inequalities and regional development? In D. Rauhut, F. Sielker, & A. Humer (Eds.), *EU cohesion policy and spatial governance*. Edward Elgar Publishing. https://doi.org/10.4337/9781839103582.00022

Williamson, J. G. (1965). Regional inequality and the process of national development: A description of the patterns. *Economic Development and Cultural Change*, *13*, 3–45. https://doi.org/10.1086/450136

How to cite this article: Cartone, A., Panzera, D., & Postiglione, P. (2022). Regional economic disparities, spatial dependence and proximity structures. *Regional Science Policy & Practice*, *14*(5), 1034–1050. https://doi.org/10.1111/rsp3.12482

DOI: 10.1111/rsp3.12482

Resumen. Desde hace algunas décadas, la desigualdad ha venido suscitando un interés creciente en el debate político y en los estudios teóricos y empíricos. El estudio de la desigualdad a nivel regional ofrece una perspectiva útil para los responsables políticos, facilitando la evaluación de la eficacia de las estrategias destinadas a reducir las disparidades regionales y ayudando a desarrollar acciones basadas en el lugar. El estudio de la desigualdad regional plantea algunas cuestiones relevantes relacionadas con la naturaleza espacial de los datos. De hecho, el uso de datos georreferenciados supone la oportunidad de considerar las interacciones espaciales entre las unidades regionales que probablemente desempeñen un papel en la configuración de la dinámica de la desigualdad. Algunos estudios han destacado la importancia de incorporar los efectos espaciales en una medida tradicional de desigualdad como el índice de Gini. Estos estudios se basan en la definición de una estructura de proximidad, que permite discriminar entre el componente espacial y el no espacial de la desigualdad. Es probable que las diferentes definiciones de la estructura de proximidad influyan en el componente espacial de la desigualdad. Estos aspectos se analizan en este artículo para ofrecer una perspectiva más detallada de la dimensión territorial de la desigualdad. Las medidas y su desagregación se analizan con el caso de las regiones europeas NUTS 3.

抄録: ここ数十年の間に、政治的な議論や理論的・実証的研究において、不平等に対する関心が高まっている。地域レベルでの不平等を検討することは、政策立案者に有益な洞察を提供し、地域格差の縮小を目的とした政策の有効性の評価を容易にし、地域ベースの活動を支援する。地域格差の研究は、データの空間的性質に関連する重要な問題を提起する。実際、地理参照データを扱うことは、不平等のダイナミクスの形成に関連しているとみられる地域単位間の空間的相互作用を検討する機会を意味する。ジニ係数などの伝統的な不平等の尺度に空間効果を組み込むことの重要性を明らかにした研究もある。これらの研究は近接性の構造の定義に基づいており、不平等の空間的な構成要素と非空間的な構成要素を区別することを可能にする。近接性の構造の他の定義は、不平等の空間的な構成要素に影響を与える可能性が高い。本稿では、これらの側面を分析し、不平等の地域的側面について詳細に解明する。ヨーロッパNUTS 3地域の事例を用いて、その測度と分解を考察する。