6

The Spatial Dimension of Inequality

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6.1 Foreword

The past few decades have seen an important surge in economic growth, but in some countries this phenomenon has been accompanied by a daunting degree of inequality in various forms, such as widening income gaps and greater poverty in many regions of the world. Disparities in living standards between people located in different regions reflect the so-called spatial inequalities (Keeley 2015). When living standards are proxied by income, the study of spatial inequality translates into the analysis of the spatial distribution of income.

In the economic theory developed in the middle of the last century, regional inequality was seen as a transitory phenomenon. According to the neoclassical growth theory (Solow 1956; Borts and Stein 1964), regional disparities tend to disappear as a consequence of a process of convergence between regions. In the same period, Kuznets (1955, 1963) formulated

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the "inverted-U" hypothesis that describes income inequality at different stages of economic development. From a historical perspective, Kuznets hypothesis argues that inequality started to rise with the advent of industrialization. In the beginning, relatively few people benefited from investments in physical capital. After a first period of development, more and more households, until then mainly employed in the agricultural sector, moved to the industrial sector, in which income was less evenly distributed than in the former sector. At this stage of development, inequality fell. Overall, the Industrial Revolution transformed largely rural and agrarian societies into industrialized urban ones. As pointed out by Lessmann (2014), Williamson (1965) adopted the same historical perspective to explain the origin of spatial inequality. Williamson asserts that the industrialization process "was driven by the discovery and utilization of natural resources such as coal and iron" Lessmann (2014, p. 35). Hence, in the first stage of the Industrial Revolution, regions endowed with those resources grew faster than the other regions and spatial (regional) inequality rose. At a later stage of the industrialization process, workers from poorer regions moved towards the richer regions offering more employment opportunities. One of the consequences of these migration flows was a rise of wages in origin regions and a fall of wages in destination regions. Hence, regional inequality fell, and the relationship between economic development and spatial inequality can again be graphically represented by an inverted-U curve. More recently, Piketty (2014), focusing on the relationship between income inequality and growth in the United States over the last decades, finds the opposite relationship to that indicated by Kuznets, that is, a U-shape relationship between income inequality and economic growth. The large increase of inequality in recent decades has been mainly driven by the rise in the global competition for skills, skill-biased technical change and the rise of information technologies. These huge transformations have not been accompanied by an adequate educational investment for large segments of the US labor force (Piketty and Saez 2014). This explains the recent growing inequality in the country.

At a global scale, Lakner and Milanovic (2016) produce the "elephant chart" that depicts changes in income distribution across the world

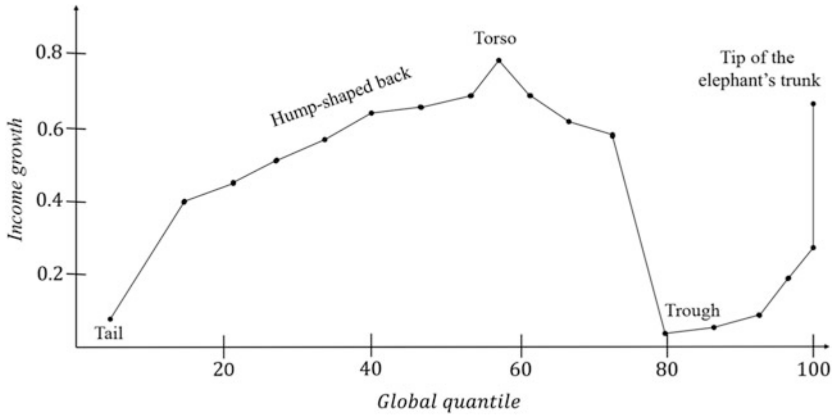

Fig. 6.1 The elephant chart (Lakner and Milanovic 2016). (Note: reproduced by the author)

between 1988 and 2008 (see Fig. 6.1). The elephant's tail indicates that the poorest people in the world are only slightly better off than in the past. The elephant's hump-shaped back shows the income growth of big countries, such as China and India, where millions of people have benefited from improvements in living standards. People having benefited more from economic growth in such countries are represented by the elephant's torso. The trough at the base of the elephant's trunk represents the income stagnation of poorer and middle classes mostly located in the advanced economies. The tip of the elephant's trunk represents the rise in income of the world's super-rich, mostly living in advanced countries. Overall, the elephant's chart suggests that globalization allowed poor countries to grow to the detriment of workers in rich countries.[1]

Beyond globalization, several studies identify other sources of income inequality in the world regions, such as the specific endowment of natural resources (Lessmann and Seidel 2017); agglomeration economies (Ciccone 2002); specific features of the workforce leading to productivity differences (Combes et al. 2008).

[1]The elephant chart, as well as its interpretation, has been at the center of an economic and political debate. See Ravaillon (2018) for a discussion on this issue.

As pointed out by Lessmann and Seidel (2017), addressing the issue of spatial inequality is justified both by equity reasons and for the development of the economy as a whole. Inequality between regions or between neighborhoods of a same city can generate negative externalities and fuel social discontent, eventually leading to social unrest. When inequality between regions is accompanied by political, ethnic, language or religion divisions, social cohesion and political stability may be threatened (Kanbur and Venables 2005). On the efficiency side, Benabou (1993) shows that high income disparities, polarized between rich and poor, can create ghettos and can even bring about the complete collapse of the city's productive capacity. Finally, from a social welfare perspective, income inequality across regions generates a loss in social welfare according to Atkinson's (1970) approach to inequality measurement. This approach relies on the hypothesis of inequality aversion, that is, it would be socially desirable having a homogeneous distribution of income across regions, rather than regions exhibiting huge income disparities. Under the assumption of inequality aversion, society is willing to renounce a share of income to obtain an equitable distribution of it across regions. The higher inequality aversion, the higher the share society is willing to renounce.

The goal of this chapter is to describe and explain the research about income spatial inequality addressing different issues. The first part of the study is devoted to the measures of spatial inequality. Several measures have been designed for the purpose of measuring spatial inequality of income. These measures may be broadly classified as follows:

1. Decomposable measures of inequality implicitly assuming a partition of the population into geographical regions. Actually, these measures can be used to assess whatever phenomenon in which the population may be divided into a set of mutually exclusive and completely exhaustive subgroups, for example, on the basis of gender or ethnicity. The common trait of such measures is that when they are applied to measure spatial inequality, they are sensitive to the way the territory is divided.
2. Measures based on the individual location which present the advantage of being independent of the type of areal unit one uses to compute

spatial inequality. On the other hand, measures based on individual location require the availability of georeferenced data either at the individual level or at very small administrative units. Geocoded information is not always available in national databases.

The main features of these two classes of measures are presented in Sects. 6.2 and 6.3, respectively.

The second part of this chapter focuses on regional inequality mainly in Europe, highlighting specific aspects of methodology used to assess spatial inequality (Sect. 6.3). The third part discusses the causal relationship between spatial inequality and economic activity. The last section concludes.

6.2 Measures of Spatial Inequality Based on Decomposition Techniques

As mentioned above, decomposable indexes used to measure spatial inequality assume that the territory is divided into a finite number of areas that contain subgroups of the statistical population under examination. Two components of aggregate inequality are usually calculated: a weighted average inequality value for a given territorial area—the so-called within component—that broadly captures inequality occurring within the areal unit; a between-group component that captures the inequality due to variations in average incomes between areas.

Following the notation used by Brambilla et al. (2015), let I be the total inequality; W is the within component; B is the between-group term. The latter coincides with the spatial component of inequality expressed in absolute terms. It can also be expressed in relative terms, as a share of total inequality, B/I. Both measures, in absolute and relative terms, increase as spatial disparities between territorial areas become more acute. It is worth mentioning that in the literature on neighborhood effects, the between component is a measure of income segregation (Dawkins 2007; Wheeler and La Jeunesse 2008). In this chapter, the between component is a measure of spatial inequality, unless otherwise specified.

Consider the following two extreme cases: first, all individuals living in the same area have equal income, then the within component is equal to zero and all difference in income is due to the spatial dimension measured by B. In the second opposite case, all areas exhibit the same average income and inequality is due only to the heterogeneous income distribution within areas. More generally, overall inequality may be thought to be the result of a certain degree of inequality within the territorial unit and between territorial units. Formally, overall inequality may be additively decomposable, as follows:

$$I = W + B. \tag{6.1}$$

Indices belonging to the Generalized Entropy Class (Theil 1967) are the only differentiable, symmetric and homogeneous inequality measures that can be additively decomposed in the within- and between-component (Bourguignon 1979; Cowell 1980; Shorrocks 1980). The indices belonging to this class may be formulated as follows:

$$E(\alpha) = \frac{1}{n\left(\alpha^2 - \alpha\right)} \sum_{i=1}^{n} \left[\left(\frac{y_i}{\overline{y}}\right)^{\alpha} - 1\right] \tag{6.2}$$

where $\alpha \in (-\infty; \infty)$ is the parameter that determines the specific form of the entropy index, as it is shown below; n is the total number of statistical units; y_i denotes the amount of income own by unit i; $\overline{y}$ is the average income.

When $\alpha = 0$, Eq. (6.2) becomes:

$$E(0) = \frac{1}{n} \sum_{i=1}^{n} \ln \frac{\overline{y}}{y_i}, \tag{6.3}$$

and it is called the mean logarithmic deviation or Theil's second measure.

When $\alpha = 1$, Eq. (6.2) becomes:

$$E(1) = \frac{1}{n}\sum_{i=1}^{n}\frac{y_i}{\overline{y}}\ln\frac{y_i}{\overline{y}}, \tag{6.4}$$

and it is called the Theil index.

Equations (6.3) and (6.4) are obtained by using a rule by de l'Hopital.[2] Notice that both indexes are not defined if there are zero incomes. The following index, called one-half of the squared coefficient of variation and obtained with $\alpha = 2$, can handle negative and zero incomes:

$$E(2) = \frac{1}{2n}\sum_{i=1}^{n}\left[\left(\frac{y_i}{\overline{y}}\right)^2 - 1\right], \tag{6.5}$$

The indices of the Generalized Entropy Class differ in their sensitivity to changes in different parts of the income distribution. Indices with a value of α close to zero are more sensitive to income differences in the lower tail; the Theil index ($\alpha = 1$) is equally sensitive to changes across the whole distribution; indexes with a value higher than 1 are more sensitive to differences in the upper tail.

Let us consider one of these indices from the Generalized Entropy Class, for instance, the Theil index, to show the decomposability according to a spatial criterion. Suppose that a territorial area is partitioned in m subareas mutually exclusive and completely exhaustive. Let s_j be the share of total income of each subarea; let T_j be the Theil index of each subarea; let $\overline{y}_j$ be the average income of each subarea; let $\overline{y}$ be the average income of the whole population. Equation (6.4) may be rewritten as follows (Haughton and Khandker 2009):

$$E(1) = \sum_{j=1}^{m} s_j T_j + \sum_{j=1}^{m} s_j \ln\frac{\overline{y}_j}{\overline{y}}, \tag{6.6}$$

[2]For further details, see Bellù and Liberati (2006, p. 50).

The first term of Eq. (6.6) is the sum of the Theil indices calculated for the different subareas, weighted by the subarea share on total income. This term represents the within component, that is, the part of inequality attributed to income differences within the same subarea. The second term is the Theil index associated with a distribution in which each individual receives the average income of his subarea. This component then represents the between component of the overall inequality.

The Gini index, perhaps the inequality index most commonly used by political institutions and international organizations, is not additively decomposable according to Eq. (6.6), unless a specific condition is met, that is, the relative position of each statistical unit in the subgroup is exactly the same in the total income distribution. In all other cases, the Gini coefficient may be decomposed in a between component, in a within component and in a third term called interaction or stratification term, which is due to the overlapping of regional income distributions (Bhattacharya and Mahalanobis 1967; Pyatt 1976; Yitzhaki and Lerman 1991).

Shorrocks and Wan (2005) apply the main indexes from the Generalized Entropy Class—$E(0)$, $E(1)$, $E(2)$—and the Gini index to assess spatial inequality in a large number of countries. They show that the correlation among $E(0)$, $E(1)$, $E(2)$ is quite high, ranging from 0.83 to 0.98, suggesting that the results obtained using one of these indexes are very similar to those arising from the other two indexes. The correlation with the Gini index is instead lower (around 0.7), and this is most likely due to their different decomposability.

Shorrocks and Wan (2005) also address the problem of the dependence of the spatial inequality assessment on the way the territory is divided. This issue is discussed in the next session.

6.2.1 Spatial Inequality and the Modifiable Areal Unit Problem

Shorrocks and Wan (2005) argue that for a given population size, the between component, on average, tends to become larger as the number of regions in which the territory is divided increases. Novotný (2007) outlines this point. He argues that the between component, expressed both in absolute and relative terms, does not decrease but does not necessarily increase with the number of regions. For example, if inequality is measured between urban and rural areas—hence the territory under analysis is divided in only two "regions"—the between component is expected to be high. This suggests that also the manner of partition into regions matters. Novotný (2007) recommends following some basic principles in order to divide the spatial area being analyzed in an appropriate way. First, the division should be such that the subareas are contiguous and roughly comparable according to the area size. Second, "the essentially functional nature of a socio-geographical area should be taken into account" (Novotný 2007, p. 566). In particular, cities or metropolitan areas should not be separated by their surrounding peripheries.

Beyond the relationship between spatial inequality and the number of subareas, Novotný (2007) addresses the issue about the relationship between spatial inequality and population and area size of subunits in the case in which the Theil index Eq. (6.6) is used to assess inequality. In his paper, the Theil index is applied to assess inequality in 46 countries observed over a very long period, from 1820 to 2003. It turns out that the rank order correlation between spatial inequality indicators—B and B/I—and the area size turns out to be not statistically significant. A weak positive correlation exists instead between spatial inequality expressed in absolute terms—B—and population considered as a measure of the region size. Moreover, the value of the Theil index turns out to be dependent on the number of regions for which it is calculated.

The sensitivity of the results to the choice of spatial scale is a special case of the Modifiable Areal Unit Problem (MAUP) that arises when the spatial analysis is applied to the same data, but different aggregation schemes are used. The assessment of spatial inequality changes when the scale of the aggregation units changes (Openshaw 1984; Wong 2009). The MAUP can take two forms: the *scale effect* and the *zone effect.* The scale effect implies that the analysis using data aggregated, for example, by census tract will provide different results than the same analysis carried out on data aggregated by municipality. The zone effect arises when the scale of analysis is fixed but the shape of the aggregation units changes.

For example, the assessment of spatial inequality using data aggregated into one-mile grid cells will differ from the assessment based on one-mile hexagon cells.

It is worth emphasizing that the MAUP affects all phenomena having a spatial characterization, hence this problem has been addressed in different fields, in particular in the literature of income segregation. The next session briefly presents the approach developed by this strand of literature to handle with MAUP. Then I will show how this approach has been recently adopted to measure spatial inequality.

6.3 Measures of Spatial Inequality Based on Individual Location

In the last decades, several studies on income segregation have developed measures that do not depend on the type of areal unit one uses to assess segregation. These measures are individually based, that is, they consider the local environment surrounding each person. There are basically two approaches to construct individually based measures. The first approach constructs the local environment of each individual by expanding a variable-width buffer around each individual location. The fact that the radius is allowed to vary reflects different geographical scales. For example, Reardon et al. (2008) define the local environment of each individual using four radii ranging from 500 meters to 4 kilometers. They correspond to local environments ranging from a neighborhood pedestrian in size to those that are considerably larger, similar in some cases to large high-school attendance zones. The concentric local environments aggregate the k-nearest neighbors that are used to calculate different scale-dependent measures of segregation. Once such measures of segregation are calculated, they are used to compute a *spatial segregation profile*, which is a curve that depicts the level of segregation at a range of spatial scales. Reardon et al. (2008) apply this methodology to assess residential segregation in of the 40 largest metropolitan areas of the United States.

The second approach, developed by Östh et al. (2015), uses the population size, instead of the radius, for measuring neighborhood scale.

The authors argue that the key variable to define the size of a city is its population. In the same vein, segregation measures should be "based on individualized neighborhoods with the same population count to compare segregation levels across urban areas and across countries" (Östh et al. 2015, p. 45).

In a recent work, Andreoli and Peluso (2018) use the radius approach to assess spatial inequality. They propose a new spatial index of inequality based on the income heterogeneity within the local environment of each individual. To show their methodology, some basic notation is first introduced. Individuals are indexed by i, with $i = 1, \ldots n$. They are endowed with an income y_i. The radius of the local environment is denoted by d, while d_i denotes the set of individuals located within the local environment of individual i. The average income of the local environment of individual i is $\mu_{id} = \frac{1}{n_{id}} \sum_{j \epsilon d_i} y_j$, where n_{id} is the number of individuals located in the i's local environment. The index is a function of the average deviation of income from the i's income, divided by the average income in the local environment. Deviations from the average income are considered in absolute value. Formally:

$$\varDelta_i = \frac{1}{\mu_{id}} \sum_{j \epsilon d_i} \frac{\left| y_j - y_i \right|}{n_{id}} \tag{6.7}$$

The inequality index, denoted by NI, is defined as follows:

$$NI = \frac{1}{2} \sum_{i=1}^{n} \frac{1}{n} \varDelta_i \tag{6.8}$$

The index combines the average variabilities observed in the environment of all individuals. The average $\varDelta_i$ is divided by 2 in order to rescale the index between 0 and 1. A value of the index equal to 0 indicates the absence of inequality since all incomes are equal. A value equal to 1 implies that in each individual neighborhood one individual has all the income. Hereafter, the inequality index defined by Eq. (6.8) will be indifferently called the NI inequality index or the Local Inequality index.

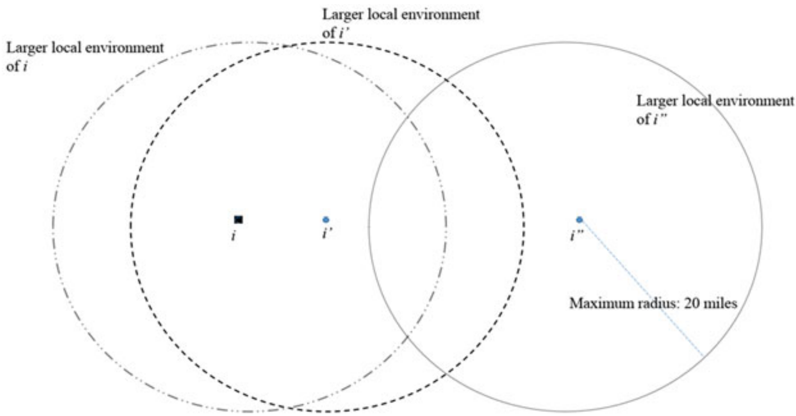

Fig. 6.2 Individual local environment. (Note: Spatial location of three individuals. The largest local environment is depicted for each individual. Individuals *i* and i' are each located in at least the largest local environment of the other, while individual i'' is outside the local environments of the other two)

The *NI* inequality index is used to derive a *local inequality curve* that depicts the level of inequality at a range of spatial scales. This methodology is applied to assess inequality in American metropolitan areas over the last 35 years. The radius ranges from 0.2 miles to 20 miles, similarly to what was done by Reardon et al. (2008). The main results are twofold: first, local inequality has substantially increased over the period 1980–2014; second, inequality patterns are highly heterogeneous across American cities.

Notice that Δ_i is a measure of the average variability of incomes depurated from the average amount of income in the local environment of individual *i*. Let us consider the following example with three individuals, i, i' and i''. Individuals i and i' are distant one from the other 0.1 miles, while i'' is distant from i and i' more than 20 miles. The location of the three individuals is represented in Fig. 6.2. As the maximum radius in Andreoli and Peluso's (2018) application is 20 miles, the income of i'' does not affect either the value of Δ_i or the value of $\Delta_{i'}$.

Now, suppose that the income of i'' doubles or becomes ten times bigger. The value of $\Delta_{i''}$ remains unchanged as well as the value of the

NI inequality index. This means that the *NI* inequality index does not capture the wider gap in income between the first two individuals—i, i' and i''. Andreoli and Peluso (2018) address this point by proposing a further inequality index that corresponds to the Gini coefficient calculated over the average incomes observed in the local environments of i, i' and i''. In equivalent terms, the second inequality index they propose is the Gini coefficient applied to the distribution of average incomes $\left(\mu_{id}, \mu_{i'd}, \mu_{i''d}\right)$.

The Gini coefficient increases when the income of i'' or becomes ten times bigger.

In their paper, American cities are assessed on the basis of both the Neighborhood Index and the Gini Index specified above. The results clearly identify four groups of cities:

1. Cities with a low value of the Local Inequality Index and a low value of the Gini index (Cities LL). These cities are called even cities (see figure 3 in the original paper) since the local inequality individually based is low and income is quite evenly distributed across all the local environments.
2. Cities with a low value of the Local Inequality Index and a high value of the Gini index (Cities LH). These cities are called polarized cities since the biggest disparities are between neighborhoods while the distribution of income within each neighborhood is quite low. Detroit and Washington show such a pattern of inequality.
3. Cities with a high value of the Local Inequality Index and a low value of the Gini index (Cities HL). These cities are called mixed cities since neighborhoods exhibit a quite similar average income while the main source of income heterogeneity is within neighborhood. Among the 50 largest metropolitan areas, San Francisco and Miami belong to this group.
4. Cities with a high value of the Local Inequality Index and a high value of the Gini index (Cities HH). These cities are called unstable cities since inequality is high both at the local level as well as between neighborhoods. Los Angeles, New York and Chicago show such a

pattern of inequality. The authors argue that other factors other than income, such as ethnicity, play a role in widening income disparities.

It is worth mentioning that the local inequality index (6.8) discussed so far, as well as the inequality measures presented in Sect. 6.2.1 are purely descriptive. In a further paper, Andreoli and Peluso (2019) extend their approach by transposing their measure of spatial inequality on the inferential ground. More specifically, they provide unbiased estimators of the *NI* index and its standard error. In this way, they are able to make statements about inequality in American cities beyond the confines of the sample used.

In the next section, we review the literature about spatial inequality focusing on specific issues arising from the empirical analysis.

6.4 Spatial Inequality in Europe and Empirical Methods

This section focuses on regional inequality mainly in Europe highlighting specific aspects of methodology used to assess spatial inequality.

Several studies support the evidence of convergence between European countries in relatively recent years. For instance, Ezcurra et al. (2007) show the presence of a process of regional convergence in terms of inequality within the European Union between 1993 and 1998. Moreover, they find that income inequality across households decreased in 40% of the regions considered. Most of these regions are the less-developed of the EU and are mainly located in the less-developed countries. This reduction in inequality especially in the less-developed countries is interpreted as a positive result of the structural funds on personal-income distribution. Ezcurra et al. (2007) also show that the measure of inequality considered in their analysis, that is, the Gini index, varies considerably across regions and that it is spatially nonstationary. The lowest value is 0.1961 for Thüringen while the highest value is twice the lowest and it is observed for Açores. The existence of spatial autocorrelation in the regional distribution of inequality is verified on the basis of the Moran's

I and Geary's c global tests that correlate the value of a variable with the value of the same variable in neighbor regions (Cliff and Ord 1973, 1981; Haining 1990). The Moran's I is related to the Peason's correlation coefficient since it represents the deviations of the values of a variable by its mean. In formal terms:

$$I = \frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{i,j}} \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{i,j}\left(y_i - \overline{y}_i\right)\left(y_j - \overline{y}_j\right)}{\sum_{i=1}^{N}\left(y_i - \overline{y}_i\right)} \tag{6.9}$$

where N is the number of regions indexed by i and j; y is the Gini index; $\overline{y}$ is the Gini average value; $w_{i,j}$ is an element of a weights matrix $\boldsymbol{W}$ of $N \times N$ size. The calculated Moran's I varies between −1 (negative autocorrelation) and 1 (positive autocorrelation). A positive (negative) coefficient corresponds to a value of Moran's I that is larger (lower) than its theoretical mean equal to $\frac{-1}{N-1}$.

The Geary's c measures the difference between values of the variable at nearby locations. It is defined as

$$c = \frac{(N-1)}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{i,j}} \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{i,j}\left(y_i - y_j\right)^2}{2W\sum_{i=1}^{N}\left(y_i - \overline{y}_i\right)^2} \tag{6.10}$$

where W is the sum of all $w_{i,j}$. The value of Geary's c varies between 0 (positive autocorrelation) and some unspecified value close to 2 (strong negative autocorrelation).

The results of Ezcurra et al. (2007) provide a very strong evidence of spatial dependence. The distribution of the Gini index is not random across regions but tends to be clustered, with regions having relatively high (low) value of the Gini index and neighbor regions having high (low) values as well. The highest Gini coefficient values are observed in regions of Ireland, the UK, and some of the southern European countries. The lowest values are found in central and Northern European countries.

The analysis carried out by Hoffmeister (2009) considers the European Union divided according to different criteria. More specifically, the EU area is divided on three geographical levels and the decomposition of the inequality measure used in the analysis is made accordingly as I will show below. The main aim of the study is to evaluate the effectiveness of social policies in Europe. The first geographical level is such that European countries are divided in two groups: the first group includes the original 15 countries in the EU prior to 1 May 2004 (EU15); the second group includes the ten countries that joined the EU in 2004 (AC10).[3] These two parts of Europe exhibit a huge income gap. The second level is the country, in which the national government is responsible for social policy in the EU and plays a key role in the redistribution of income across individuals within the country. The third level is subnational and corresponds to the Eurostat Nomenclature of Territorial Units for Statistics (NUTS) classification level.[4] Each region, on average, covers between 3 and 7 million of people. Such regions are the main recipients of resources from the EU's and Member States' regional policies. The index used for the analysis is the mean logarithmic deviation defined by (1.3). The decomposition is repeated three times on the different geographic levels described above. The results reveal that European countries converged during the second half of the 1990s at all investigated geographic levels, then between EU15 and AC10; throughout the countries, and throughout individuals within countries. From his findings, Hoffmeister (2009) draws the conclusion that social policies promoting balanced spatial development may have played a role in this process of convergence.

More recently, Mussini (2017) shows that income inequality between EU regions overall decreased from 2007 to 2011. The analysis is based on the Gini index, used to measure inequality in absolute and relative terms. The Gini index of absolute inequality is broken down into three components explaining the role played by population change, re-ranking, and changes in absolute income disparities between regions.

Widening the boundaries of the supranational entity from the EU to OECD countries, Arnold and Blöchliger (2016) find that inequality has been decreasing between countries over the period 1995–2013. Within-country disparities have instead widened. The measures used to assess inequality are the coefficient of variation, the Gini coefficient and the

[3]The ten countries that joined EU in 2004 are: the Czech Republic, Cyprus, Estonia, Hungary, Latvia, Lithuania, Malta, Slovakia, Slovenia, and Poland.

[4]The NUTS classification is a hierarchical system for dividing up the economic territory of the EU.

range. The coefficient of variation and Gini coefficient exhibit a similar pattern of decreasing inequality over time due to the catching up of less developed regions. The range provides another type of information. It shows an increasing pattern up to 2004, indicating that the gap between the most equal (lowest Gini coefficient) regions and the most unequal (highest Gini coefficient) has widened from 1995 to 2004, then started to reduce and thereafter started to decline.

The amount of inequality between regions and the level of GDP within a country are negatively related, indicating that countries in the sample lie on the downward-sloping side of the Kuznets (1955) curve. The same finding is found by Novotný (2007) for EU. In the next section, the relationship between spatial inequality and economic activity is further investigated.

6.5 The Causal Relationship Between Spatial Inequality and Economic Activity

Several studies investigate the relationship between regional inequality and economic growth without addressing the problem of simultaneity of these two variables. Most of them show the magnitude and the sign of the correlation without identifying the causal relationship between inequality and economic growth. A recent paper by Lessmann and Seidel (2017) addresses this issue, analyzing the causal impact of spatial inequality on economic activity in a large number of countries. Their methodology is inspired by Easterly (2007) and Henderson et al. (2017) and consists in adopting an instrumental variable approach. The instruments are purely exogenous natural factors of development, such as geography, climate and resource endowments, which contribute to determine the physical setting of a location and the output production independently of man-made factors. These instruments are called first-nature determinants of development (Krugman 1993) and they differ from other factors that are man-made and are endogenous to economic activity, geography and spatial inequality. Man-made factors, called second-hand factors, contribute to determine markets size effects, factor mobility and infrastructure.

According the New Economic Geography,[5] the exogenous first-nature factors are the original cause of agglomeration of economic activity in a specific area. The effects of first-nature factors may be amplified or mitigated by man-made factors.

Economic activity at the regional level is proxied by nightlights, as in Henderson et al. (2017). Inequality is measured by the Gini index formulated as follows:

$$G_j = 1 + \frac{1}{n_j} - \frac{2}{y_j n_j^2} \sum_{i=1}^{n_j} \left(n_j + 1 - i\right) y_{ij}, \tag{6.11}$$

where y_{ij} is the nightlight in cell i in country j; n_j is the number of grid cells attributed to country j. The authors adopt a weighted formula of the Gini index, in which the weights are the amounts of land mass inside each grid cell. This implies that grid cells with huge water areas contribute less in determining inequality than cells with bigger amounts of land.

Equation (6.11) is also used to calculate the Gini coefficient considering predicted incomes from first-nature geography. Predictions are from linear regression and a machine learning algorithm (random forest). The latter is a more flexible tool than the former since accounts for potential nonlinearity between physical geography and the outcome variable. Moreover, it admits interdependent relationship between first-nature variables, that is, each explanatory variable may affect the others. This is not the case for the ordinary least squares model. The predicted values of the Gini coefficient enter as explanatory variable in the auxiliary regression of the two-stage equation model, as explained below.

The empirical strategy consists in estimating a two-stage equation model. In the first equation, first-nature characteristics are the predictors of spatial inequality, in addition to other variables. More precisely, the log spatial inequality observed in country j is regressed on:

[5]Venables (2005) provides the following definition of the New Economic Geography: "*The New Economic geography provides an integrated and micro-founded approach to spatial economics. It emphasizes the role of clustering forces in generating an uneven distribution of economic activity and income across space. The approach has been applied to the economics of cities, the emergence of regional disparities, and the origins of international inequalities.*"

- An instrumental variable, denoted by *GIV*, based on predicted incomes from the first-nature geography
- A set of first-nature factors averaged on the country level and denoted by *GEO*
- A set of control variables, *X*, used in some of the specifications; a world region fixed effect, denoted by γ

$$\log\left(\mathrm{G}_j\right) = \beta_0 + \beta_1 GIV_j + \beta_2 GEO_j + \beta_i \sum_i X_{ij} + \gamma + \varepsilon_j, \tag{6.12}$$

The predicted values, $\hat{G}$, of spatial inequality are used in the second-stage regression in which the dependent variable is the log light density *Y* in country *j*[6] :

$$\log\left(\mathrm{Y}_j\right) = \tilde{\beta}_0 + \tilde{\beta}_1 \hat{G}_j + \tilde{\beta}_2 GEO_j + \tilde{\beta}_i \sum_i X_{ij} + \gamma + \eta_j, \tag{6.13}$$

The authors point out that predicted spatial inequality, $\hat{G}_j$, based on the first-nature characteristics, is a strictly exogenous variable since it does not depend on second-nature man-made factors. Then one can be confident that the exclusion restriction is satisfied.

The empirical model is applied to investigate the causal relationship between economic activity and spatial inequality in 184 countries over the period 2008–2012. The analysis is cross-section because of very low variability of geographic variables. Data are averaged over the 5 years to avoid bias due to extreme weather events or other local shocks. The data used by Lessmann and Seidel (2017) are gridded in order to neglect any administrative boundaries that are subject to political influences.

[6]Equations (6.2) and (6.3) correspond to equations (3) and (4), respectively, in the original paper.

The results show a highly significant negative relationship between spatial inequality and economic activity. This means that the higher the spatial inequalities, the lower the economic activity in the country. A 0.01 unit increase in the Gini coefficient determines a reduction in economic activity ranging between 1.7% and 3.8%, depending on specification and prediction method.

Lessmann and Seidel (2017) implicitly provide the direction for further research. Indeed, the authors claim that the paper does not causally identify those factors moderating the negative relationship between spatial inequality and economic activity. They suggest that infrastructure as well as equalization payments may counteract the disadvantages arising from poor first-nature geographic characteristics. A detailed causal investigation on economic activity still remains to be done.

6.6 Concluding Comments

Research on spatial economics has generally provided several important insights to the understanding of inequality patterns across regions. For instance, it has been able to quantify the importance of spatial inequality in determining overall income differentiation. Other sources of inequality are gender, age, ethnicity or education. As noted by Kanbur (2006), if one or more of these sources are not randomly distributed across space, the between-group component does not properly reflect the significance of space as a determinant of inequality. This concern provides the direction for further research. The analysis of spatial inequality could be associated with the analysis of traits mentioned above that contribute to socioeconomic stratification. The result would be a deeper comprehension of regional inequality and its determinants (Novotný 2007). A full and complete knowledge of regional disparities is essential for policy makers to identify appropriate policy actions to reduce spatial inequality. Such policies would be able to deal with the relative importance of different drivers of regional disparities.

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