How Does Urban Spatial Structure Affect Productivity Growth? Evidence from Italian Municipalities

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Abstract. This paper analyses the relationship between the urban spatial structure and the productivity growth of 7,272 Italian municipalities over the period 2012-2018. We focused our attention on medium-sized cities, and, specifically, on whether proximity to them has an impact on the productivity growth of neighbouring areas. To capture their influence, we used a spatial lag model, and we built the spatial weight matrix by considering municipalities within a certain distance from them as neighbours. Moreover, in order to evaluate whether agglomeration has an impact on growth, both a-spatial concentration measures and spatial autocorrelation measures were included in the model. The results indicate that proximity to medium-sized cities has a positive effect on productivity growth; and that the more monocentric an area, the lower its productivity growth.

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1. Introduction

Italy is one of the most important and prosperous areas of the European Union, but there are still great disparities within the country. Italy's national economic development has always been accompanied by marked differences in regional performances (Calafati, 2009) and the North-South divide remains a persistent feature of this country's economic geography (Musolino, 2018). Nevertheless, the objective of strengthening economic and social cohesion is mentioned as one of the main priorities and aims of the Union. Indeed, Article 174 of the Treaty on the Functioning of the European Union (TFEU) states that 'the Union shall aim at reducing disparities between the levels of development of the various regions and the backwardness of the least favoured regions'.

In this context, the attempt to identify ways to overcome such disparities has led both academics and policymakers to investigate the links between urban spatial structure and productivity growth. In particular, an increasing number of studies have assessed the impact of monocentricity and polycentricity on economic productivity (e.g. Lee & Gordon, 2007, 2011; Meijers & Burger, 2010; Zhang *et al.*, 2017; Ouwehand *et al.*, 2021). However, mixed results emerged regarding the performance of different spatial structures. Indeed, while some studies find that a monocentric urban spatial structure leads to better results in terms of economic performance (e.g. Veneri &

Burgalassi, 2011; Li *et al.*, 2019), others find that polycentricity is more conducive to productivity (e.g. Meijers & Burger, 2010; Meijers, 2013; Veneri & Burgalassi, 2012).

From a policymaking perspective, understanding how different spatial structures affect economic performance can help both national and local policy makers to formulate more targeted policies, thereby contributing to reducing spatial disparities (Brezzi & Veneri, 2014).

Also the productivity advantages of large cities have long been recognized, and many studies have provided evidence on the existence and extent of agglomeration economies. However, urban growth comes at a cost: as cities become large, negative externalities such as congestion costs, pollution, labour crowding, and higher crime rates, begin to rise rapidly. Sometimes, these disadvantages (i.e. agglomeration diseconomies) are such that they make large cities less competitive (Parkinson *et al.*, 2015). This has prompted researchers and policymakers to pay attention to smaller cities as well. In particular, within the European context, attention has shifted to medium-sized cities and how they contribute to national growth and to the growth of surrounding areas.

The present study seeks to analyse the determinants of productivity growth in Italian municipalities, with a particular focus on proximity to medium-sized cities and agglomeration effects. The analysis covers 7,272 municipalities during the period 2012-2018.

The paper is structured as follows. The next section provides an overview of the existing literature on the topic and deals with the problem of measuring agglomeration. Section 3 introduces the case study and describes the empirical model as well as the variables included in it. Section 4 presents the results of the analysis. Finally, the last section draws the main conclusions and the policy implications of this study.

2. Agglomeration economies and productivity

The effects of agglomeration economies have been widely discussed and studied for more than a century. In particular, arguments concerning the benefits of spatial agglomeration on growth, productivity, and innovation have been extensively examined in several disciplines, including economic geography, urban economics, and new economic geography (De Dominicis, 2014).

The productivity advantages of cities and urban clusters characterized by a high density of firms and workers have long been recognized, and already drew the attention of Adam Smith (1776) and Alfred Marshall (1890). As early as 1776, Smith proposed for the first time the idea that greater productivity can be obtained through the division of labour, which in turn depends on the 'extent of the market' (Smith, 1776, p. 21), that is, the size of the market. However, it was Marshall (1890) who introduced the concept of 'industrial atmosphere' to describe the various advantages enjoyed by firms gathered together in a particular area, and who forwarded three main sources to explain why the agglomeration of economic activity may lead to improved aggregate economic results. Specifically, these sources are: *labour market pooling*, *input sharing*, and *knowledge spillovers*. In fact, according to Marshall, a densely populated local labour market (*labour market pooling*) enables a better match between an employer's needs and a worker's skills, lowering the risk for both. Moreover, the concentration of firms in a geographical area allows firms to share inputs (*input sharing*) and thus to reduce the costs of obtaining them. Finally, Marshall argued that geographical proximity facilitates the transmission of knowledge (*knowledge spillovers*).

More recently, additional sources have been suggested, including natural advantages, home market effects, consumption opportunities, and rent-seeking (Rosenthal & Strange, 2004).

However, according to Duranton and Puga (2004) Marshall's trinity is not a very useful basis for understanding the theoretical mechanisms underlying agglomerations, as they are actually three sources capturing the same mechanism (Duranton & Puga, 2004, p. 2066). Thus, they propose a taxonomy based on three mechanisms, namely *sharing*, *matching*, and *learning*. Indeed, a larger market enables a more efficient *sharing* of local infrastructures and facilities, a labour pool, or input suppliers. Another advantage of larger markets is that they lead to better *matching* between actors in a given space, such as buyers and suppliers or employers and employees. Finally, a larger market can also facilitate *learning*, for instance by encouraging the creation of new knowledge, as well as the development and widespread use of new technologies and business practices (Puga, 2010). However, as they stress, the results observed when analysing the effects of agglomeration economies are the same regardless of the mechanism, the so-called 'Marshallian equivalence' (Duranton & Puga, 2004).

Ciccone and Hall (1996) argue that the density of economic activity is crucial for explaining the variation of productivity, indeed, in their study across US states, they find that doubling employment density raises productivity by around 6 per cent. Subsequently, Ciccone (2002) enlarged the scope of his previous work by estimating agglomeration effects for the NUTS3 regions of France, Germany, Italy, Spain, and the UK, and found that the effects in these European countries are 'only slightly lower than the US and do not vary significantly across countries' (Ciccone, 2002, p. 225).

Nevertheless, subsequent empirical analyses using various data and methods have not always yielded consistent results. Indeed, while some studies find a positive relationship between national growth and the degree of spatial agglomeration, others do not (e.g. Sbergami, 2002; Bosker, 2007). For instance, Bosker's (2007) study of 208 regions across the EU for the period 1977-2002 finds that regions characterized by a dense concentration of economic activity grew more slowly than other regions. In a later study, Brülhart and Sbergami (2009) observe that agglomeration does boost national GDP growth, but only up to a certain level of economic development (around a per capita GDP of 10,000 USD). Furthermore, when examining the relationship between national productivity growth and the spatial agglomeration of economic activity across the EU-15 Member States, Gardiner *et al.* (2010) find mixed evidence that spatial agglomeration boosts growth. Indeed, according to the authors the precise results depend on the measure of agglomeration adopted and the spatial scale at which the analysis is conducted.

In their study, Rosenthal and Strange (2001), utilizing the Ellison and Glaeser index of agglomeration computed at the zip code, county, and state levels for the US, observe that the geographic scale of agglomeration varies according to the type of agglomeration force being examined. Indeed, they find that proxies for labour market pooling positively affect agglomeration at all levels of geography, while proxies for knowledge spillovers positively affect agglomeration only at the zip code level. Finally, proxies for input sharing positively affect agglomeration at the state level but have little effect on agglomeration at lower levels of geography.

In other studies, Rosenthal and Strange (2003), as well as Duranton and Overman (2005) find that agglomeration effects diminish quite rapidly with distance, typically within <50 km (Duranton & Overman, 2005). More recently, Artis *et al.* (2012) find that agglomeration economies do matter when explaining differences in economic performance across a sample of 119 British NUTS3 regions, however they observe that the agglomeration effect is smaller when variables proxying intangible assets are included in the model. They also suggest that 'improvements in local/regional transportation infrastructure that reduce the length of business and commuting journeys might boost labour productivity by means of increasing returns derived from transportation cost reductions, shared inputs and knowledge spillovers' (Artis *et al.*, 2012, p. 1186).

As a matter of fact, many countries have long operated some form of regional policy designed to remedy spatial disparities in economic development and welfare. For instance, since the founding of the European Union, regional policy has been viewed as a fundamental tool for ensuring economic and social integration among the Member States, which is indeed one of the key goals of the Union. Traditionally, the case for regional policies has been made on the basis of two arguments: social equity and economic efficiency (Gardiner *et al.*, 2010). According to the first of these, the spatial concentration of economic activity may be detrimental to some individuals, who would be socially disadvantaged in terms, for example, of job opportunities and access to public services, simply because they live in one region instead of another. At the same time, enduring regional disparities in economic activity, for instance in employment rates and productivity, are considered to be nationally inefficient, since the underutilization and underperformance of labour and capital in less prosperous regions mean that national wealth is lower than what it could be if those recourses were fully and more productively utilized. As a result, policies that foster the utilization and productivity of labour and capital in such regions should enhance the economic performance of these regions, and thus of the nation as a whole. Therefore, from this perspective, reducing regional inequalities benefits the national economy.

Nonetheless, recently, arguments have emerged suggesting that regional imbalance, and so the spatial concentration of economic activity and population in particular regions, may actually benefit national growth and therefore be nationally efficient (Martin, 2008; Gardiner *et al.*, 2010). Thus, this view suggests that policies aimed at reducing regional economic disparities can be detrimental to national efficiency.

Yet, in his recent works, Krugman (2009, 2011) himself suggests that perhaps, in the advanced economies, agglomeration may no longer be a prime source of growth-enhancing increasing returns that it once was. This may be different for developing countries, indeed, in his study Duranton (2016) estimates agglomeration effects for cities in Colombia, and finds an elasticity of wages with respect to city population of around 5 per cent. This means that moving from a city with 10,000 inhabitants to Bogotá with more than 7 million is associated with about 40 per cent higher wages.

2.1 Measuring spatial agglomeration

When it comes to assessing the impact of agglomeration on growth and productivity, a major issue concerns the measurement of agglomeration itself (Gardiner *et al.*, 2010, Nakamura & Paul, 2019). Specifically, researchers have adopted a number of different measures to assess geographic concentration (O'Donoghue & Gleave, 2004). However, as Bickenbach and Bode (2008) stress, 'choosing between different measures actually implies choosing between different definitions of concentration . . . rather than just choosing between different ways of measuring a single, uniform theoretical construct' (p.360). They also claim that this problem is worsened by the fact that studies differ in the sectoral and spatial scales of the data used to calculate the measures, but the scale selected affects the values of the measures as well as their interpretation. Thus, they suggest that measures of spatial concentration should be defined according to three characteristics: the *weighting scheme*, which defines the basic units adopted in the analysis, the *reference distribution*, which reflects the benchmark of no concentration, and, finally, the *projection function*, which specifies the range of values possible under the measure and reflects the researcher's relative emphasis on positive and negative as well as large and small deviations of the observed units from their reference.

Another issue stressed by Guillain and Le Gallo (2006) is that most concentration measures share one common weakness: 'they are aspatial in that geographical units under study are taken to be spatially independent of each other' (p.962). In other words, they point out that spatial units are treated identically, regardless of whether they are neighbours or distant, with the result that the role of spatial agglomeration may be misestimated. Thus, the authors suggest that an appropriate empirical methodology must capture two dimensions of agglomeration: the concentration in one spatial unit as well as the geographical pattern of the units, that is their spatial distribution in the study area. The aforementioned inability of most concentration measures to distinguish between different spatial arrangements had already been noted by White (1983) studying the phenomenon of residential segregation. Indeed, White called the 'checkerboard problem' (White, 1983) the problem that occurs when the value of a specific spatial unit is analysed neglecting the values of the same variable in its surrounding areas.

In addition to population density, indices borrowed from the literature on income inequality[1] are among the most widely used measures to quantitatively characterize the degree of concentration (Tsai, 2005; Bickenbach & Bode, 2008; Alonso-Villar & Del Río, 2013). An overview of some of the main concentration measures is presented below.

2.1.1 Population density

As already mentioned, the fact that productivity and wages are higher in larger and denser cities was first noted by Adam Smith (1776) and Alfred Marshall (1890), and has been confirmed by several modern empirical studies (Combes *et al.*, 2010). In particular, in the urban economics literature, efforts have been made to quantify the productivity gains from density (Duranton & Puga, 2020), and the measured elasticity with respect to density is typically between 0.04 and 0.10. (Combes *et al.*, 2010).

However, since the standard measure of population density, which is simply total population divided by total area, may be strongly influenced by the size of the geographical units (Kompil *et al.*, 2015), some have proposed an alternative measure of density called population weighted density (PWD). In fact, while raw population density gives the number of individuals per unit geographic area, so the density experienced by the average unit of land; population-weighted density gives the density at which the average citizen lives. Population weighted density is obtained by taking the weighted average of the density of all 'parcels' of land that comprise the area of interest, with each parcel weighted by its population (Kompil *et al.*, 2015), that is

$$PWD = \frac{\sum(P_i d_i)}{\sum P_i} \tag{1}$$

[1] It is important to note that, in the context of our analysis, in order to calculate the various concentration indices, instead of income per capita based on representative household surveys, we consider gridded population, that is the number of persons located in each cell of a regular grid.

where PWD is the population weighted density of the study area, and P_i and d_i the respective population and density of each parcel.

2.1.2 Coefficient of variation

One of the simplest measures of income inequality is the coefficient of variation (cv) which is calculated by dividing the standard deviation $\left(\sqrt{V}\right)$ of the income distribution by its mean $(\bar{y})$

$$cv = \frac{\sqrt{V}}{\bar{y}} \tag{2}$$

Since more equal income distributions have smaller standard deviations, cv will be smaller in areas with more equal societies. In particular, if all income recipients have the same income, cv will equal 0, since the standard deviation will be 0. However, the use of this coefficient has been somewhat limited, and this may be due to the fact that, unlike the Gini coefficient, it does not have an upper bound, making interpretation and comparison more difficult (Campano & Salvatore, 2006; De Maio, 2007). Furthermore, another limitation is that its components, namely, the standard deviation and the mean, may be extremely influenced by abnormally low or high income values (De Maio, 2007).

2.1.3 Gini coefficient

The Gini coefficient or Gini index (Gini, 1912) was introduced by Corrado Gini at the beginning of the twentieth century to measure personal income inequality. This index is probably the most widely used measure of income inequality, and it can be expressed in many different forms (Ceriani & Verme, 2012). For instance, the relative mean difference form of the Gini defines it as half of the relative mean absolute difference (Sen & Foster,1997)

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|}{2\,n^2\bar{x}} \tag{3}$$

where x_i is the value of variable x, typically income, observed at location $i = [1, 2, \dots, n]$ and $\bar{x} = (1/n)\sum_i x_i$. The Gini coefficient ranges from 0 to 1, where 0 represents complete equality, and 1 complete inequality.

2.1.4 Generalized entropy index

The generalized entropy index of inequality is defined as follows

$$GE_\alpha = \frac{1}{\alpha^2 - \alpha}\left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i}{\bar{y}}\right)^{\alpha} - 1\right] \tag{4}$$

where n is the population size, y_i is the income of the i-th individual, $\bar{y}$ is the average income, and α is a sensitivity parameter, whose value can be any real number, positive, zero, or negative. The more positive the α is, the more sensitive the index is to income differences at the top of the income distribution. On the other hand, the more negative the α is, the more sensitive the index is to income differences at the bottom of the income distribution. A special case of the generalized entropy index is the Theil index (Theil, 1967), which is obtained when $\alpha = 1$.

2.1.5 *Herfindahl index*

Another well-known measure of concentration is the Herfindahl index (e.g. Wheaton & Shishido, 1981; Henderson, 2003) which is simply the sum of the squares of the income shares

$$H = \sum_{i=1}^{n} s_i^2 \tag{5}$$

where s_i is the income share of person i.

2.1.6 *Moran Index*

The main problem with indices of concentration based on inequality measures is that they do not provide any spatial information about the values of interest, thus 'they do not take into account anything that is truly spatial' (Arbia, 2001, p. 272). As a result, traditional concentration measures are invariant to spatial permutations, i.e. they are invariant to changes in the geographical location of the considered data (Márquez *et al.*, 2019). This means that very different spatial patterns can give rise to the same concentration measure (Arbia & Piras, 2009). In order to better illustrate this problem, let's consider Table 1 which reports three different spatial patterns and their concentration estimates. In all three cases, out of a total of 100 pixels, 2 pixels have a population of 8 people (green), 10 pixels have a population of 4 people (yellow), 18 pixels have a population of 2 people (pink), and 70 pixels have a population of 1 person (grey). Thus, the only difference among the three cases is the spatial distribution of the population.

However, although it is quite obvious that spatial concentration is greater in case 1 than in case 2 or case 3, traditional concentration indices, such as the Gini index and the generalized entropy index, remain unchanged in the three cases. This means that none of them is capable of distinguishing among the three hypothetical situations. This example shows that considering spatial units identically, regardless of whether they are geographically distant or neighbours, leads to a measurement of agglomeration which is not reliable. In fact, if agglomeration effects spill over into neighbouring spatial units, agglomeration will then be underestimated (Guillain & Le Gallo, 2006).

A few studies have addressed the insensitivity of traditional concentration measures to different spatial configurations (e.g. Arbia, 2001; Dawkins, 2004; Arbia & Piras, 2009; Rey & Smith, 2013; Panzera & Postiglione, 2020). For instance, Arbia (2001) suggests that in order to capture all the various facets of spatial concentration, a-spatial concentration measures (like the ones described above) should be complemented by spatial autocorrelation measures, which can help assess the degree of spatial clustering of the distribution, that is the degree of spatial polarization.

Among the statistics developed to measure spatial autocorrelation, Moran's I is one of the most widely used (Arbia & Piras, 2009). This coefficient basically relates the value of a selected variable with its spatial lag, that is the value of the same variable in the neighbouring areas, and it is defined as follows

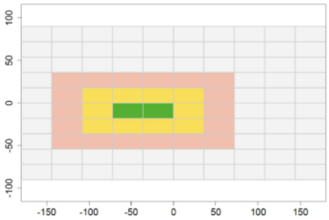
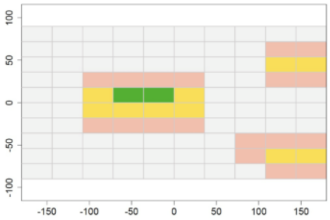
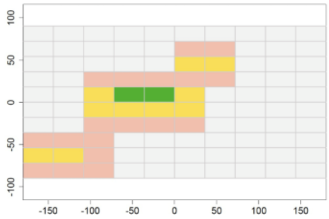
$$Moran = \frac{N}{\left(\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\right)} \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{6}$$

where N is the number of observations, $\bar{x}$ is the mean of the variable of interest, x_i is the value of variable x at location i, x_j is the value of variable x at location j, and w_{ij} is an element of the spatial weight matrix $\boldsymbol{W}$ that measures the 'closeness' between location i and location j. The Moran's I index ranges from -1 and +1. Positive values indicate positive spatial autocorrelation, and thus the spatial clustering of similar values; negative values indicate negative spatial autocorrelation, and thus tendency toward dispersion (i.e. clustering of dissimilar values); finally, values close to 0 indicate weak autocorrelation in the data.

For instance, if we go back to the cases displayed in Table 1, Moran's I assumes a higher value in case 1 (high polarization) than in case 2 and case 3. This means that the Moran coefficient is able to distinguish different clustering patterns.

Table 1

Hypothesised spatial patterns

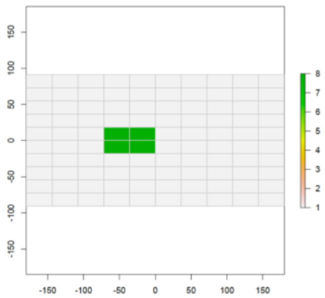
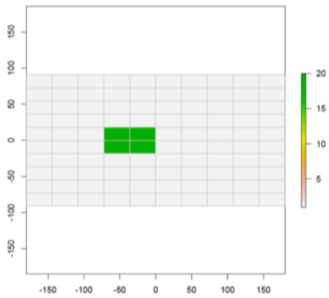
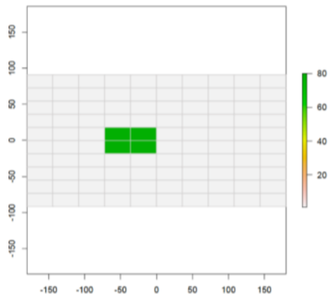
Metric	case 1	case 2	case 3
			
Total pop.	162	162	162
Total area	100	100	100
Pop. density	1.62	1.62	1.62
PWD	2.6543	2.6543	2.6543
Coeff. of var.	1.6925	1.6925	1.6925
Gini	0.3084	0.3084	0.3084
Gen. Entropy	0.1938	0.1938	0.1938
Herfindahl	0.0164	0.0164	0.0164
Moran	0.7092	0.4652	0.4908

Note. The 4 colours indicate different populations: grey, population of 1 inhabitant; pink, of 2 inhabitants; yellow, of 4 inhabitants; and green, of 8 inhabitants.

Nevertheless, not even autocorrelation measures alone are suitable for measuring spatial concentration since they are insensitive to the general variability of the phenomenon. To justify this statement, let's consider another example (Table 2). In all three cases, out of a total of 100 pixels, 96 pixels have a population of just 1 person, however, in the first case, the remaining 4 pixels (shown in green) have a population of 8 people each; in the second case, of 20 people; and in the last case, of 80 people. Indeed, a-spatial concentration measures assume higher values in case 3. On the other hand, the Moran coefficient remains unchanged in the three cases, which implies that it is not able to capture this difference.

Table 2

Hypothesised spatial patterns

Metric	case 1	case 2	case 3
			
Total population	128	176	416
Total area	100	100	100
Pop. density	1.28	1.76	4.16
PWD	2.7500	9.6364	61.7692
Coeff. of variation	1.9006	14.0024	242.0752
Gini	0.2100	0.4145	0.7292
Genalized Entropy	0.2059	0.5661	1.4156
Herfindahl	0.0215	0.0548	0.1485
Moran	0.3739	0.3739	0.3739

Note. In case 1, one green pixel represents a population of 8 people; in case 2 of 20 people; and in case 3 of 80 people.

2.2 Cities and economic performance

In the early 1990s, many researchers became interested in and began investigating the role played by cities in national economic performance. The interest in the analysis of the economic role of cities has continued to grow, especially among regional scientists, economic geographers and urban economists (Dijkstra *et al.*, 2013). Moreover, the evidence of a scarcity of public resources has heightened the debate on how each territory contributes or can contribute to national competitiveness. In particular, recent studies and reports clearly show the importance of paying attention to all cities, and not just to large capitals (e.g. Dijkstra *et al.*, 2013; Camagni *et al.*, 2015; Parkinson *et al.*, 2015; Cardoso & Meijers, 2016) which have long absorbed the attention of academics, researchers, and policy-makers. For instance, Parkinson *et al.* (2015) point out that the economic benefits of agglomeration are not unlimited, and argue that large capital cities can reach a point where diseconomies make them less competitive because of negative externalities such as congestion costs, labour crowding, land scarcity, pollution and high cost of living. They also present evidence that 'decentralizing responsibilities, powers and resources, spreading investment and encouraging high performance in a range of cities rather than concentrating on the capital city produces national benefits' (Parkinson *et al.*, 2015: 1057-1058).

In particular, in Europe, second-tier cities have been experiencing renewed interest within policy and research context (Cardoso & Meijers, 2016), where by 'second-tier cities' we mean those cities 'lacking the economic weight, political importance and attractive pull of first-tier cities (generally capitals) but still important enough to play a relevant role in national and international contexts' (Cardoso & Meijers, 2016, p.997). Indeed, while much of US literature has highlighted the importance of large metro areas in fostering economic growth, there is evidence that in Europe, over the last two decades, second-tier cities have often outperformed first-tier cities (Dijkstra *et al.*, 2013; Parkinson *et al.*, 2015). For instance, all of Austria's and Germany's second-tier cities outperformed their capitals in terms of annual GDP growth rates (Parkinson *et al.*, 2015). Of course, since European countries are very different culturally, politically and historically, even the economic performance of their second-tier cities differs significantly. For instance, a report on the subject by ESPON (2012) confirms this difference and associates it directly with the different national urban systems and, especially, with the different levels of centralisation. Indeed, second-tier cities tend to 'perform better in those countries which are less centralised and economically concentrated and where cities have greater powers, resources, and responsibilities' (ESPON, 2012, p.615), such as Germany. This is also confirmed by Cardoso and Meijers (2016) who find that 'second-tier cities perform better in more polycentric countries' (p.1011).

In addition to city size, the links between urban form and economic performance have long been recognized and studied within the urban economics literature (Parr, 1979; 1987). In fact, the spatial layout of cities is considered to have a significant impact on the rise of agglomeration and congestion costs, and, therefore, on a city's level of productivity, sustainability, and quality of life (Duque *et al.,* 2021). In particular, an increasing number of studies have assessed the impact of monocentricity and polycentricity on economic productivity (e.g. Lee & Gordon, 2007, 2011; Meijers & Burger, 2010; Zhang *et al.,* 2017; Ouwehand *et al.*, 2021), but mixed results emerged regarding the performance of different spatial structures. Nevertheless, since local governments can influence the locations of economic activities, urban infrastructure, and households, through various urban policies tools, such as land use regulations, it is crucial to understand which kind of spatial structure is more efficient in terms of economic performance.

2.3 Borrowed size versus agglomeration shadows

One possible explanation for the outperformance of second-tier cities in some countries is the concept of 'borrowed size', which explains how some cities are able to grow economically without physically expanding (Camagni *et al.*, 2015).

The concept of 'borrowed size' was first introduced by Alonso (1973) to describe the situation 'whereby a small city or metropolitan area exhibits some of the characteristics of a larger one if it is near other population concentrations' (Alonso, 1973, p.200). In particular, he suggests that small cities are able to retain many of the advantages related to their size, such as lower congestion costs, and, at the same time, to enjoy some of the benefits typical of large cities, through easy access to their larger neighbours. In other words, they can 'borrow' some of the agglomeration advantages of their larger neighbouring cities, but without incurring agglomeration costs (Burger *et al.*, 2015). Thus, size borrowing occurs when a city features urban functions and/or performance levels generally associated with larger cities. Moreover, Alonso (1973) noted that the processes of borrowed size are 'quite visible . . . in certain European urban patterns, such as those of Germany and the Low Countries, whose cities, quite small by our standards, apparently achieve sufficient scale for the functioning of a modern economy by borrowing size from one another' (Alonso, 1973, p. 200). Nevertheless, as Burger *et al.* (2015) suggest, the opposite can also occur, indeed competition from large cities can limit development and growth opportunities of neighbouring cities. This negative effect of larger urban centres over their surroundings is known as 'agglomeration shadow' and it is a prediction of New Economic Geography (NEG). The idea is that the existence of a comprehensive set of functions in a large and easily accessible centre reduces the need and opportunity for equivalent functions to emerge in surrounding places. Basically, larger cities cast a 'shadow' over their small neighbours, this means that their growth will be limited compared to an isolated city of the same size.

Thus, the concepts of 'borrowed size' and 'agglomeration shadow' suggest that the population size of a particular city and its expected performance level are not necessarily related to each other, due to an advantage resulting from proximity to a larger city (borrowed size) or due to competition with larger urban centres (agglomeration shadow).

Burger *et al.* (2015) empirically explore these concepts, and find that it is more likely that 'larger cities cast a shadow over smaller neighbouring cities (as predicted by the New Economic Geography) rather than these smaller cities borrowing size from their larger neighbour (as suggested by Alsonso)' (p.1104). On the contrary, Phelps *et al.* (2001) investigate whether small firms located in small rural cities near London are able to borrow size from nearby larger urban areas, and find that these firms can locate in these cities and still access the specialized labour and informational external economies of their larger neighbours. Moreover, in their study, Partridge *et al.* (2009) explore population dynamics in the US and find that large urban centres tend to have positive growth effects for more proximate places of less than 250,000 people, rather than casting agglomeration shadows on them.

3. The Italian Scenario

Since the 1950s, the national economic development of Italy has been accompanied by marked differences in regional performances (Calafati, 2009); and in the last decades, despite a period of convergence (Terrassi, 1998; Iuzzolino *et al.*, 2011) especially in the years 1960-75, these differences have increased, mainly due to a decline of the poorest regions compared to the richest ones (OECD, 2020). At the provincial level, disparities among Italian provinces remain above the average of OECD countries (Figure 1). Since the economic crisis of 2008, provinces far from metropolitan areas have widened their productivity gap with metropolitan provinces, while provinces close to a metropolitan area have slightly narrowed the gap (OCED, 2020). Furthermore, compared to other countries, Italy has a higher concentration of population in small and medium-sized cities. Indeed, only 56% of the Italian population lives in cities of more than 50,000 inhabitants; this share is 8 percentage points lower than the EU average, and 19 percentage points lower than the OECD average (OECD, 2020).

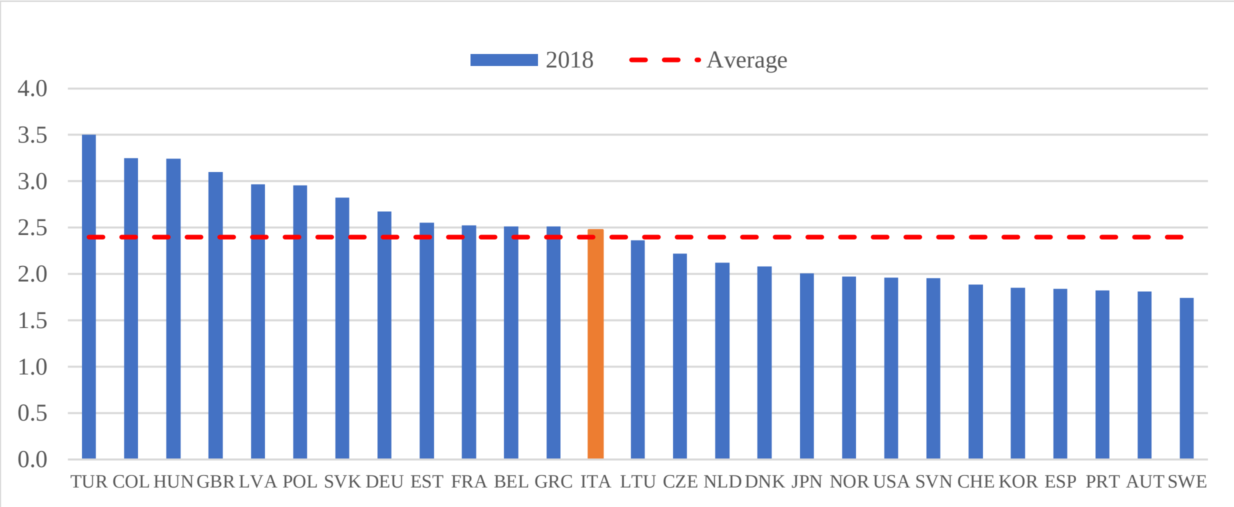


Figure 1. Index of disparity in GDP per capita, ratio of the top 20% richest provinces over the bottom 20% poorest provinces.
Note. A ratio of 3 means that the GDP of the most developed provinces accounting for 20% of the national population is three times as high as the GDP of the poorest provinces accounting for 20% of the national population. Own elaboration based on OECD data.

Given the strong fragmentation and the marked disparities of the Italian territory as well as the availability of data, we ran the empirical analysis at the municipality level. We considered the period 2012-2018 and we ended up considering 7,272 municipalities out of a total of 7,954 municipalities, due to some missing data and modifications in municipal boundaries. Note that, for convenience, in this study the terms 'city' and 'municipality' are used interchangeably.

Moreover, since one of the objective of our analysis is to detect agglomeration effects and to understand whether medium-sized cities have an impact on the productivity of their smaller neighbours, we classified municipalities into three types based on their population: as 'small' if their population is below 70,000; as 'medium-sized' if their population is between 70,000 and 125,000; and as 'large' if their population exceeds 125,000 inhabitants. Nearly 99% of the municipalities considered in the analysis have a population of less than 70,000 inhabitants. The biggest municipality is Rome with 2,820,219 residents, followed by Milan (1,395,980 residents) and Naples (954,318 residents); while the smallest one is Ribordone with only 49 residents, followed by Macra (55 residents), and Bergolo (56 residents). Moreover, the total number of medium-sized cities is 50, of which 23 are in Northern Italy, 11 in the Centre and 16 in the South.[2]

4. Empirical Model and Data Description

The econometric setup used in this in this work to estimate the impact of agglomeration on productivity growth is that of the β-convergence model. However, since the classic β-convergence model does not take spatial characteristics into account, i.e. it treats regions as if they were

[2] Regions belonging to Northern Italy are: Liguria, Lombardy, Piedmont, Aosta Valley, Emilia-Romagna, Friuli-Venezia Giulia, Trentino-Alto Adige, Veneto. Centre regions are Lazio, Marche, Tuscany and Umbria. Finally, among Southern Italian regions we have Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, plus the islands of Sicily and Sardinia.

independent from each other (e.g. Rey & Montouri, 1999; Dall'Erba & Le Gallo, 2008), we included a spatially lagged term of the dependent variable (Arbia *et al.*, 2005). As a result, our model takes the following form

$$\frac{1}{T}\ln\left(\frac{y_{i,t}}{y_{i,0}}\right)= \alpha+\beta\ln(y_{i,0})+ \gamma X+\rho\boldsymbol{W}\left[\frac{1}{T}\ln\left(\frac{y_{i,t}}{y_{i,0}}\right)\right]+ \varepsilon_{i,0} \tag{7}$$

where T is the total number of years of the observed period, $y_{i,0}$ and $y_{i,t}$ are respectively the initial and final productivity levels for municipality i[3], α is a constant term, β is the convergence coefficient, X is a matrix of additional explanatory variables, γ is the vector of the parameters. Finally, ρ is the parameter of the spatially lagged dependent variable $\boldsymbol{W}\left[\frac{1}{T}\ln\left(\frac{y_{i,t}}{y_{i,0}}\right)\right]$ that captures the interaction effect showing the degree to which the productivity growth rate in one region is affected by the growth rates of its neighbouring regions (Arbia *et al.*, 2005), and $\varepsilon_{i,0}$ is the independently and identically distributed error term. The parameter β is expected to be negative, because if there is a negative relationship between the growth rate of productivity $\frac{1}{T}\ln\left(\frac{y_t}{y_0}\right)$, and the initial level of productivity y_0, then the hypothesis of convergence holds: less productive regions will tend to grow faster than more productive ones. Moreover, if parameters belonging to vector γ are jointly equal to 0, absolute convergence holds; otherwise, conditional convergence is assumed (Monfort, 2008).

The next sections will describe in detail the dependent variable as well as the explanatory variables included in our empirical model, and provide information regarding the construction of each of them and the data sources drawn upon. For what concerns the spatial weights matrix W, we used a row-standardized inverse distance weights matrix. However, as W was determined endogenously, it will be presented and explained in Section 5.

4.1 Dependent variable

We proxy productivity growth by looking at the average growth of income per employee over the period 2012-2018, which represents the dependent variable and is given by

$$\frac{1}{6}\ln\left(\frac{y_{2018}}{y_{2012}}\right) \tag{8}$$

where 6 is the number of years in the period of interest, y_{2018} is the average income per employee in 2018, while y_{2012} is the average income per employee in the base period (i.e. 2012). The income per employee was calculated by dividing the total income at the municipal level by the number of persons employed in the municipality. For what concerns data sources, income data were retrieved from the Italian Ministry of Economy and Finance website; while the total number of persons employed from the Statistical Atlas of Municipalities of the Italian National Institute of Statistics (ISTAT).

Figure 2 shows the average growth in productivity over the years considered in the analysis. The situation is very fragmented, with negative growth rates especially in the southern areas of the country.

[3] 'Municipality' refers to the 50km area around each municipality, which will be explained in detail in Section 4.2.4.

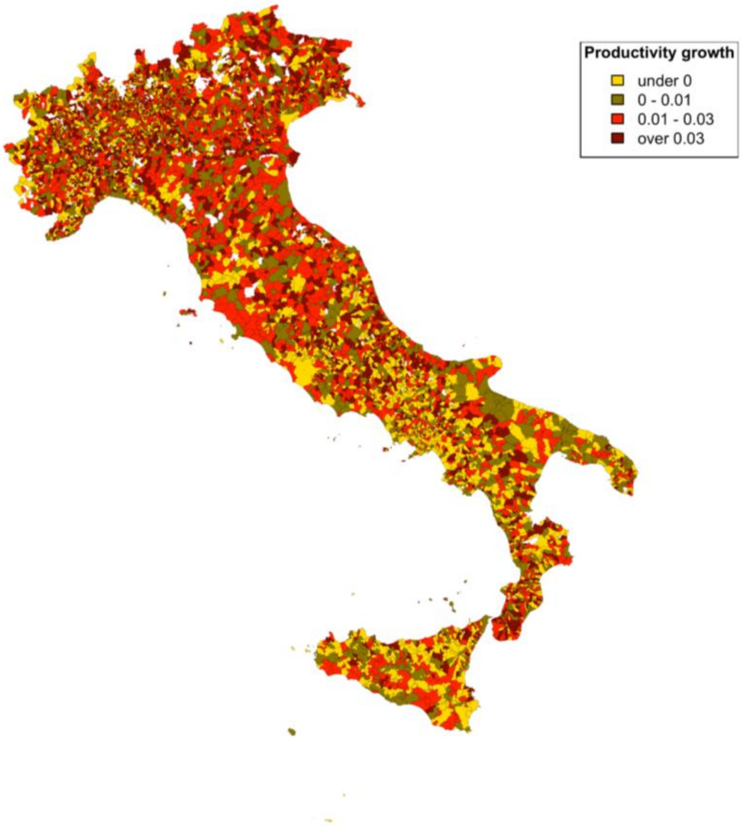


Figure 2. Productivity growth over the years 2012-2018.

4.2 Explanatory variables

4.2.1 Initial level of productivity

Following Barro and Sala-i-Martin (1991, 1992) we used the initial level of productivity (i.e. productivity in 2012) to control for economic convergence across municipalities. Indeed, the inclusion of this variable in the model allows to determine whether less productive municipalities grew faster than more productive ones during the study period.

4.2.2 Minimum distance from tollgates

The spatial distribution of infrastructure, including the highway network, affects land use and demographics (Zeng *et al*., 2019). For instance, Garcia-López *et al*. (2015) analyse the effects of highways on suburbanization of Spanish cities, and find that each highway ray leads to a population growth of 20% in the suburbs, especially in suburban municipalities where ramps were located. Duranton and Turner (2012) estimate that in the United States employment grows faster in cities with more interstate highway-kilometres and suggest that interstate highways reduce per capita income disparities among US cities.

Moreover, empirical evidence suggests that commuting, job searching and information flows deteriorate with distance and travel effort (Gerritse & Arribas-Bel, 2018), thus good access to highways produce user benefits because it reduces such costs. A few studies have also analysed the role of highways on productivity growth (e.g. Aschauer, 1990; Fernald, 1999; Holl, 2016; Zheng, 2007; Duranton & Turner, 2012), and found a positive relationship between them.

Therefore, we decided to create an accessibility index for each municipality, to determine which one has an easier access to the highway network. The measure we used is based on the potential accessibility indicator developed by ESPON (2007) and Osland (2010), and defines the accessibility of municipality i as follows

$$A_i = \exp(-\gamma\, d_{ij}) \tag{9}$$

where A_i is the accessibility of municipality i, and $\exp(-\gamma\, d_{ijs})$ is a distance decay function, with d_{hjs} being the minimum distance expressed in meters between municipality i and the tollgate located in municipality j. The value of parameter γ has been set to 0.045, meaning that nearby locations are given greater weight than remote ones (ESPON, 2007).

4.2.3 Employment in the secondary sector

An analysis carried out by the Italian institute for local finance and economy (IFEL) concerning the economic specialization of Italian municipalities, shows that 58.7% of the Italian municipalities are specialized in the primary sector, 31.4% in the secondary sector, and 9.9% in the tertiary sector. A municipality can be defined as ‘specialized’ if its ratio is higher than the same ratio calculated at the national level. However, if we focus on the gross value added share of the different sectors, the construction and the manufacturing industries play a key role for the Italian national economy. Indeed, while the agricultural sector accounted for 2% of the national value added in 2018, the industrial sector accounted for nearly 24% (ISTAT, 2018). Thus, given that the main objective of this study is to analyse productivity at the municipal level, we decided to include the employment in the secondary sector, expressed as a share of total employment. The number of people employed in the secondary sector was obtained by summing the employees in the manufacturing and in the construction industries. These data were drawn from the Statistical Atlas of Municipalities.

4.2.4 Agglomeration measures

Following Arbia (2001) we used a-spatial concentration measures to characterize quantitatively the degree of equal distribution of the population, and the Moran coefficient to assess the degree of clustering. In fact, as already mentioned in Section 2, these two measures capture different facets of spatial concentration: a-spatial concentration measures provide useful information about the extent to which population is concentrated in a limited number of areas (Arbia, 2001; Guillain and Le Gallo, 2006), but they do not take into account whether those areas are close together or far apart, a feature that can be captured by the Moran coefficient, which is indeed able to distinguish between different degrees of spatial polarisation (Arbia, 2001). Specifically, based on the definition, the Moran coefficient is expected to be high, intermediate, and low, for monocentric, polycentric and decentralised sprawling forms respectively (Tsai, 2006).

In order to compute agglomeration measures as precisely as possible, we relied on the Global Human Settlement Population Grid (GHS-POP), which is the newest global raster population data, released in 2018 by the European Commission Joint Research Centre. The GHS-POP depicts the distribution and density of the population, expressed as the number of people per cell. These data are produced in an equal-area projection in grids of 250 m and 1 km spatial resolution, and are available for the target years 1975, 1990, 2000 and 2015. The GHS-POP disaggregates residential population estimates for smallest census unit provided by the Center for International Earth Science Information Network (CIESIN) for the years of interest. The disaggregation is based on built-up areas as mapped by GHSL for the same years. It is within each census unit and proportional to the share of built-up area of the census unit in that cell. This means that if a cell contains 3% of the total amount of built-up area within a census unit, it will be allocated 3% of the total population. Since we covered the period 2012-2018 we considered the data for the year 2015, and we used the 250m resolution.

For instance, Figure 3 depicts the GHS-POP raster layer of the municipality of Brescia, while Figure 4 shows the Moran scatterplot on the left-hand side, and the map of the quadrants on the right-hand side. In the Moran scatterplot, the population of a grid cell is on the horizontal axis, whereas its spatially lagged counterparts are on the vertical axis. The upper-right and the lower-left quadrants represent positive spatial autocorrelation, that is similar values at neighbouring locations; while the lower-right and upper-left quadrants correspond to negative spatial autocorrelation, that is dissimilar values at neighbouring locations. The Moran scatterplot can be augmented with a regression line, which has Moran's I as slope and which can be used to identify the presence of outliers (i.e. points far away from the line). Thus, if we look at the maps of the quadrants, red represents the high-high quadrant (i.e. high-population areas surrounded by high-population areas); blue represents the low-low quadrant (low-population areas surrounded by low-population areas); pink represents the high-low quadrant (i.e. high-population areas surrounded by low-population areas); and grey represents the low-high quadrant (i.e. low-population areas surrounded by high-population areas). Therefore, Figure 4 shows that Brescia is characterised by high-population areas surrounded by areas with similar values in the city centre (red), and by low-population areas surrounded by areas with similar values in the surroundings (blue).

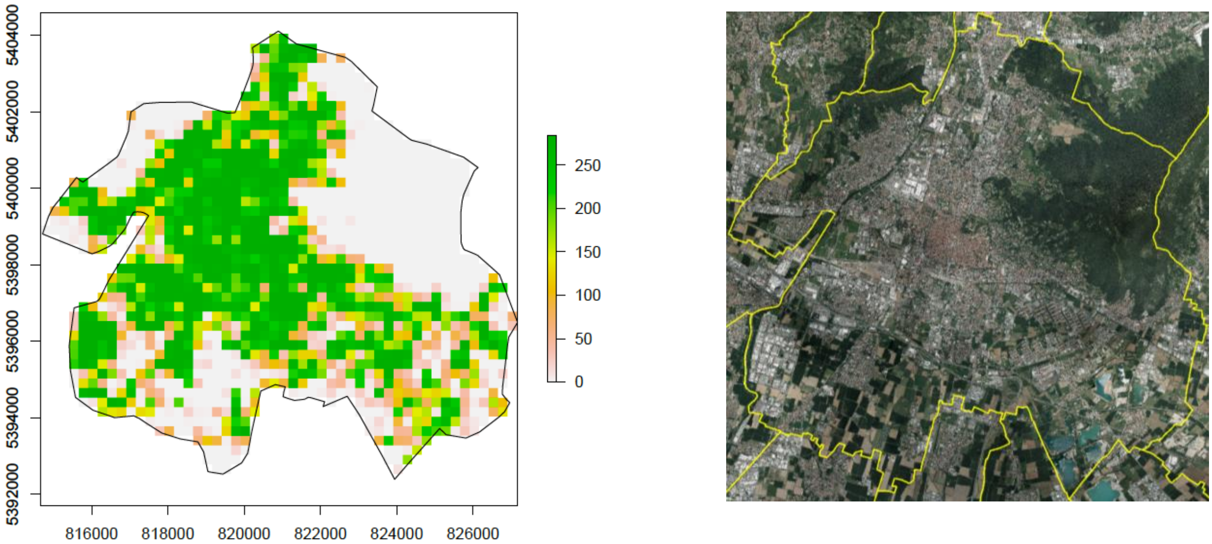


Figure 3. Municipality of Brescia.
Note. The map is based on GHS-POP raster data, while the satellite image is from the geoportal of the province of Brescia.

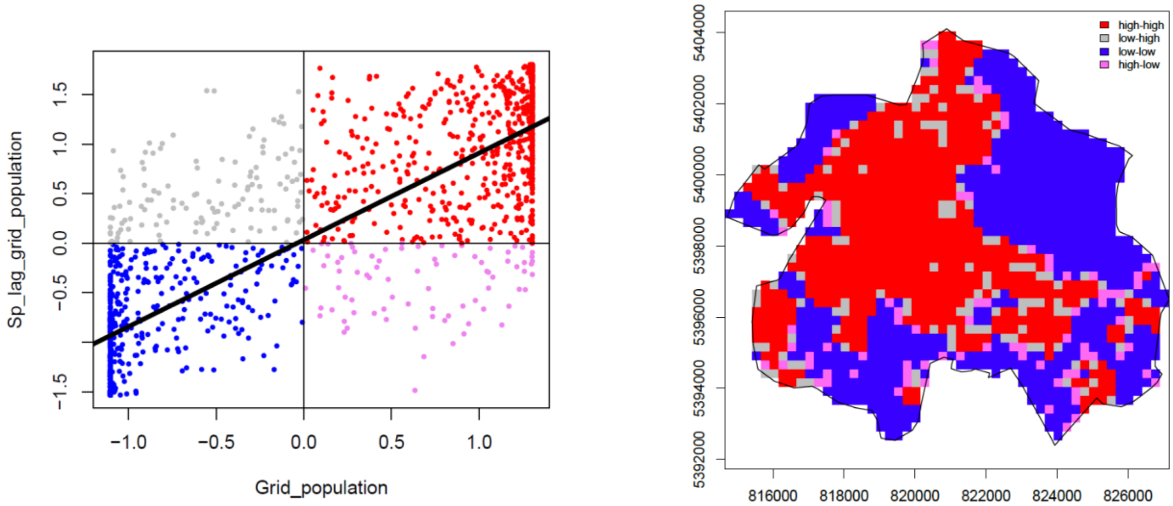


Figure 4. Moran scatterplots and Moran scatterplot maps.
Note. Own elaboration based on GHS-POP raster data.

However, since one of the objectives of this study is to evaluate agglomeration effects, we decided to calculate all the aforementioned measures for each municipality but considering a radius of 50 km from the centroid of each of them (e.g. Figure 5). This is justified by the fact that some municipalities are too small for agglomeration effects to be seen and analysed properly, and by the results of Duranton and Overman (2005) that show that agglomeration effects typically hold within a distance of less than 50 km.

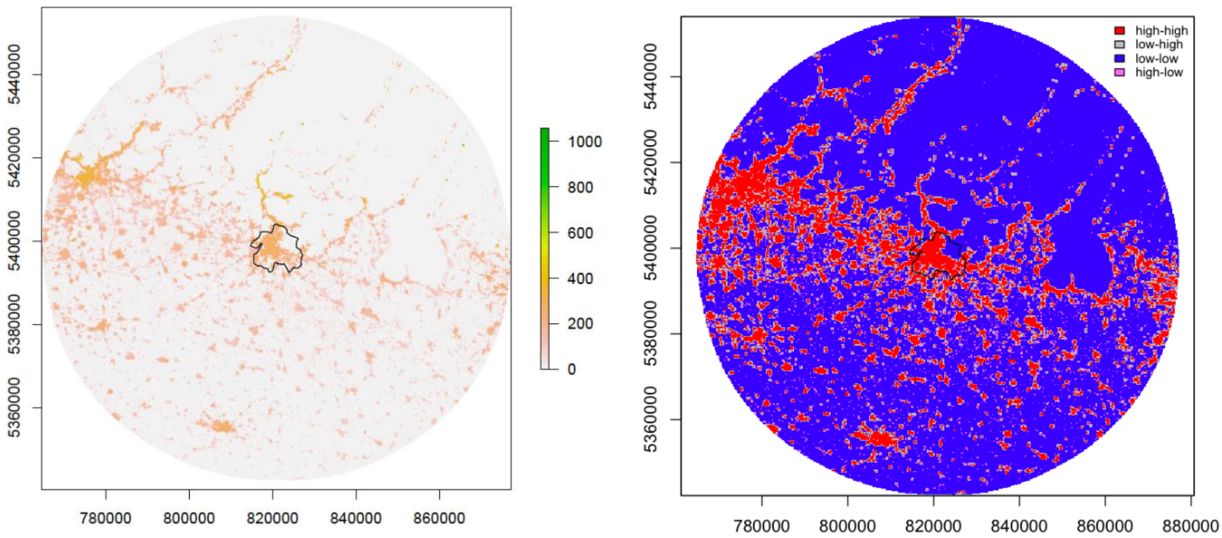


Figure 5. GHS-POP layer and Moran scatterplot map of Brescia, considering a 50km radius.
Note. Own elaboration based on GHS-POP raster data.

Finally, descriptive statistics for the utilized variables are in Appendix A.

5. Results

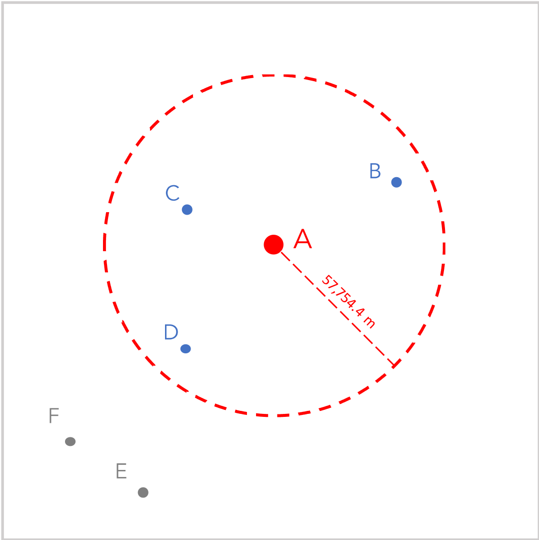
The inclusion of the spatial lag term in our model leads to an endogeneity problem, this implies that traditional econometric techniques, like the ordinary least square (OLS), may lead to biased and inconsistent estimates (Balta-Ozkan *et al.*, 2015). Therefore, either the maximum likelihood (ML) estimation method (Ord, 1975), or the instrumental variable estimation (GS2SLS) method (Kelejian & Prucha, 1998, 1999) need to be employed in order to obtain consistent estimators (Dettori *et al.*, 2012; Balta-Ozkan *et al.*, 2015). Specifically, the ML approach was preferred to the GS2SLS because, in the latter approach, the endogeneity problem is accounted for by using the spatially lagged exogenous variables WX as instruments but, as among our regressors we have agglomeration and a-spatial concentration measures based on an area of 50 km around each municipality (i.e. in the neighbouring municipalities), we risk double counting. Indeed, the spatial lag of these variables is explicitly accounted by these same variables.

As already mentioned in Section 3, we used a row-standardized inverse distance weights matrix, and given that one of the objectives of this study was to understand the role of medium-sized cities in fostering economic growth, we built the matrix considering their sphere influence. In particular, as shown in Figure 6, we considered as neighbours all those municipalities within a threshold distance from a medium-sized city. This means that, spatial linkages hold not only between municipalities and the medium-sized city, but also between municipalities within the sphere influence. We consider this conceptualization useful to capture the immediate effects of a medium-sized city on the surrounding areas as well as the effects mediated by other municipalities. Operationally, we will end up with a block-matrix, as in the right panel of Figure 6. Additionally, since it is conceivable that, as pointed by Tobler (1970), 'everything is related to everything else, but near things are more related than distant things' (p. 234), we used the inverse distance function to assign the spatial weights to all neighbours within the specified distance band, so that nearer municipalities have more influence in estimating the local set of regression parameters than do the municipalities farther away (Ma *et al.*, 2012). Thus

$$w_{ij} = \begin{cases} 1/d_{ij} & if\ d_{ij} \leq d_{max} \\ 0 & if\ d_{ij} > d_{max} \end{cases}$$

where d_{max} is the maximum distance between municipality i and the medium-sized city, while d_{ij} is the Euclidean distance between municipalities.

Finally, as the key point of our approach is to find the exact threshold beyond which a medium-sized city has no effects on the surrounding municipalities, we specified a 'search neighbourhood' strategy (Li *et al.*, 2014). The optimal search neighbourhood was determined using the Akaike Information Criterion (AIC) approach, and was found to be 57,754.4 m (d_{max}). Therefore, a municipality is neighbour to a medium-sized city if it is within a radius of 57,754.4 m from it. Figure 7 shows in dark red the municipalities considered as neighbours of medium-sized cities.



$$W = \begin{array}{c|cccccc}
 & A & B & C & D & E & F \\
\hline
A & 0 & \frac{1}{d_{AB}} & \frac{1}{d_{AC}} & \frac{1}{d_{AD}} & 0 & 0 \\
B & \frac{1}{d_{BA}} & 0 & \frac{1}{d_{BC}} & \frac{1}{d_{BD}} & 0 & 0 \\
C & \frac{1}{d_{CA}} & \frac{1}{d_{CB}} & 0 & \frac{1}{d_{CD}} & 0 & 0 \\
D & \frac{1}{d_{DA}} & \frac{1}{d_{DB}} & \frac{1}{d_{DC}} & 0 & 0 & 0 \\
E & 0 & 0 & 0 & 0 & 0 & 0 \\
F & 0 & 0 & 0 & 0 & 0 & 0
\end{array}$$

Figure 6. Spatial weights matrix based on distance from medium-sized cities.
Note. Point A represents a medium-sized city, while B, C, D, E, and F represent smaller cities.

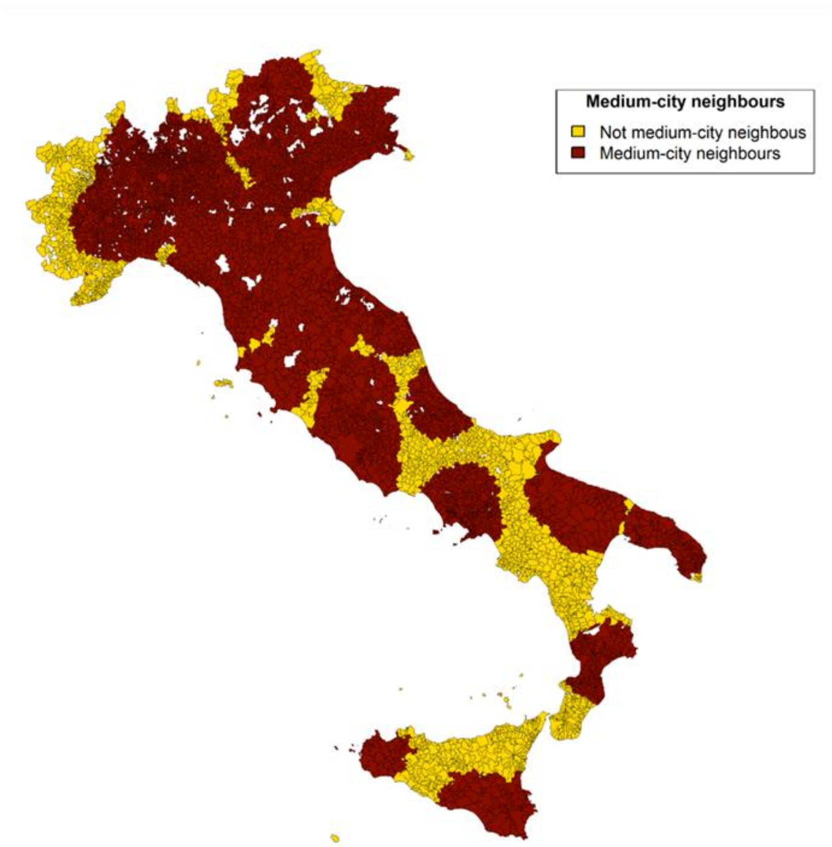


Figure 7. Map of neighbouring and non- neighbouring municipalities of medium-sized cities.

The estimation results presented in Table 3 show that, in all cases, the spatial lag parameter (ρ) is positive and significant, which means that proximity to a medium-sized city has a positive impact on the productivity growth of neighbouring municipalities. The coefficient on the initial level of productivity, i.e. β, is always negative and statistically significant, indicating the existence of β-convergence: low-productive municipalities have grown faster than high-productive ones, and are catching up on them.

The minimum distance from the closest tollgate has a positive coefficient, meaning that being close to a highway access has a positive impact on productivity growth. As expected, even the share of employment in the secondary sector has a positive and significant effect on growth.

The coefficient on the Moran index is negative and statistically significant. This means that the more municipalities exhibit a spatial clustering of similar values, i.e. the more monocentric they are, the lower their productivity growth. However, the coefficient loses its significance when either the coefficient of variation or population density is introduced into the model. All a-spatial concentration indices, except the Gini index, have negative coefficients, but none of them is statistically significant. Therefore, the fact that the population is equally or unequally distributed in the study area does not seem to have an impact on its productivity growth.

With regard to population density-related measures, while the coefficient on population weighted density is negative but not significant, that on standard population density is negative and significant. This suggests a negative link between high density areas and productivity growth. In relation to this, it is important to remember that standard population density measures the density experienced by the average unit of land and it can be strongly influenced by the size of the geographical units (Kompil *et al.*, 2015).

Table 3

Spatial model estimation results using the maximum likelihood estimation method

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.049***	0.047***	0.055***	0.052***	0.051***	0.053***
	(0.013)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)
Ln(redditi/ empl.)$_{12}$	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Access to tollgates	0.003*	0.003*	0.002	0.002*	0.003*	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
%empl second. sec.$_{12}$	0.012***	0.012***	0.011***	0.011***	0.012***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Moran coeff.	-0.008**	-0.003	-0.010**	-0.009***	-0.008**	-0.005
	(0.004)	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)
Gini	0.002					
	(0.009)					
Coeff. of variation		-0.000				
		(0.000)				

Gen. Entropy			-0.001			
			(0.001)			
Herfindahl				-1.501		
				(1.357)		
log(PWD)					0.00000	
					(0.001)	
Pop. dens						-1.686***
						(0.575)
Spatial lag	0.3452***	0.3462***	0.3300***	0.3366***	0.3424***	0.3364***
	(0.0485)	(0.0462)	(0.0497)	(0.0470)	(0.0466)	(0.0466)
N. obs.	7,272	7,272	7,272	7,272	7,272	7,272
Loglik	15,153.0	15,154.2	15,153.3	15,153.6	15,153.0	15,157.3
AIC	-30,290	-30,292	-30,291	-30,291	-30,290	-30,298

Note: *** p < 0.01, ** p < 0.05, * p < 0.10. Standard errors in brackets.

Table B1 in the Appendix section also reports the results obtained with the instrumental variable estimation (GS2SLS) method, which are very similar to those found using the maximum likelihood estimation method. Once again, the spatial lag parameter is positive and significant.

6. Conclusions

Although the importance of agglomeration economies has been recognized by many empirical studies, most of them have treated cities as points in space without considering the way they are spatially organized, thus disregarding whether they are neighbours or distant. Nevertheless, the importance of the spatial dimension has been confirmed by numerous studies (e.g. Arbia, 2001; Guillain & Le Gallo, 2006; Arbia & Piras, 2009; Panzera & Postiglione, 2020), and there is evidence that ignoring this dimension can lead to incorrect agglomeration estimates.

Throughout this study, we have tried to examine the possible relationship between the urban spatial structure and the productivity growth of 7,272 Italian municipalities for the years 2012-2018. We focused our attention on medium-sized cities, and, in particular, on whether proximity to them has an impact on the growth of neighbouring municipalities. Thus, to capture their influence, we used a spatial lag model, and we constructed the spatial weight matrix considering municipalities within a certain distance from them as neighbours. Moreover, in order to evaluate whether agglomeration effects have an impact on growth, we included in our model a-spatial concentration measures as well as spatial autocorrelation measures. Indeed, as Arbia (2001) suggests, these measures provide different but complementary information on spatial concentration. On the one hand, a-spatial concentration measures, like the Gini index, reveal the degree to which population is concentrated in a few parts of the study area, however these measures are invariant to spatial permutations. On the other hand, measures of spatial autocorrelation, like the Moran coefficient, are able to estimate the degree to which sub-areas with similar values are clustered or randomly distributed, but are insensitive to the general variability of the phenomenon.

We also included in the analysis additional explanatory variables, such as the initial level of productivity, an accessibility index, the share of employment in the secondary sector, and population density.

One of the main findings that emerged from our analysis is that the 'sphere of influence' of medium-sized cities is 57,754.4 m and that there exists a positive relationship between proximity to medium-sized cities and productivity growth. This preliminary finding was robust to the various specifications and estimation methodologies. Thus, returning to the concepts of 'borrowed size' and 'agglomeration shadow' presented in Section 2.3, our results suggest that it is more likely that small municipalities borrow size from their larger neighbours, rather than medium-sized cities casting a shadow over their smaller neighbours.

Moreover, from a policymaking perspective, these findings shed light on the importance of giving due attention and resources to medium-sized cities, as they play a key role in the growth of surrounding municipalities. In fact, there is evidence that decentralising responsibilities, powers, resources, as well as spreading investments across multiple cities rather than over-concentrating them in large cities, generates economic benefits (Parkinson *et al.*, 2015; ESPON, 2012).

Our analysis also showed that in the period 2012-2018 a convergence process occurred between low-productive municipalities and high-productive ones, and that being close to highway accesses has a positive effect on productivity growth. This latter finding highlights the importance of strengthening and developing the transportation network. This is of particular relevance in Southern Italy, where the inadequate endowment of efficient transport infrastructure is evident, and is one of the reasons that deter the business community from investing in this area (Musolino, 2018).

As far as agglomeration is concerned, our results suggest that urban spatial structure matters for productivity growth, but only with respect to the degree of spatial clustering. Again, what emerged from our analysis is that the more monocentric an area, the lower its productivity growth. On the other hand, the degree of equal distribution of the population does not seem to have an effect on productivity growth, at least in the short-run.

Nevertheless, it is important to note that given the limited time period and the scarcity of data at the municipal level, any conclusion must be treated with caution. Notwithstanding these limitations, the findings of this study provide a starting point for further investigations on this topic.

Finally, possible future extensions of this work could, for instance, analyse if the effect of spatial concentration measures is mediated by a-spatial concentration measures. Another option is the inclusion of a variable identifying urban and rural municipalities, eventually distinguishing between those close to medium-sized cities. Moreover, it would also be interesting to consider the effect that accessibility to other types of transport infrastructures, like railways and harbours, has on economic and productivity growth.

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APPENDIX

APPENDIX A. Descriptive statistics

Table A1

Descriptive statistics

Statistic	Mean	St. Dev.	Min	Max
Ln(redditi/empl.)$_{12}$	10.63194	0.50633	8.14896	13.06863
Growth (redditi/ empl.)$_{12\text{-}18}$	0.01290	0.03052	-0.14857	0.14966
Gini	0.92318	0.05035	0.79232	0.99961
Coeff. of var.	3,090.43	2,990.04	0.16052	11,364.67
Entropy	2.61093	0.44022	1.65632	3.89607
Herfindahl	0.00016	0.00027	0.00003	0.01520
PWD	882.41	590.67	32.4394	9,208.39
Moran Coeff.	0.66925	0.11999	0.22837	0.93242
%empl. second. sec.$_{12}$	0.41790	0.17402	0.00000	1.00000
Access to tollgates	0.50879	0.28221	0.000002	1.00000

APPENDIX B. Generalized spatial two-stage least squares estimation method

Table B1

Spatial model estimation results using the GS2SLS method

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.048***	0.049***	0.052***	0.051***	0.048***	0.052***
	(0.013)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)
Ln(redditi/ empl.)$_{12}$	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Access to tollgates	-0.001	-0.001	-0.001	-0.001	-0.001	-0.0001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
%empl second. sec.$_{12}$	0.008***	0.009***	0.009***	0.009***	0.009***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Moran Coeff.	-0.004	-0.002	-0.005	-0.005	-0.005	-0.003
	(0.004)	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)
Gini	0.002					
	(0.009)					
Coeff. of var.		-0.0000				
		(0.0000)				

Gen. Entropy			-0.0004			
			(0.001)			
Herfindahl				-1.107		
				(1.357)		
log(PWD)					0.0004	
					(0.001)	
Pop. dens						-1.125*
						(0.581)
Spatial lag	0.643***	0.604***	0.598***	0.589***	0.607***	0.598***
	(0.073)	(0.073)	(0.077)	(0.074)	(0.073)	(0.072)
N. obs.	7,272	7,272	7,272	7,272	7,272	7,272
R^2	0.034	0.034	0.034	0.034	0.034	0.035
Adjusted R^2	0.033	0.033	0.033	0.033	0.033	0.034

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors in brackets.