The Determinants of Regional Growth in Europe: Assessing The Roles of Spatial Spillovers and Agglomeration

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Abstract

The aim of this study was to revisit and assess the role of spatial agglomerations and spillovers on regional economic growth using spatial econometric techniques and novel geo-data sources to construct measures of agglomeration and travel time, together with other conventional socio-economic data, all at NUTS-3 level. The results obtained indicate that spatial spillovers occur within 150 minutes of travel time between regions, and confirm that spatial agglomeration, as well capital metro regions are strong drivers of growth.

Key words: *Spatial Econometrics, Regional growth, European Union, Agglomeration*

JEL codes: C21, O47, R11

1. INTRODUCTION

The determinants of regional economic growth in Europe have been widely investigated by scholars. Generally, the focus has been put not only on classical variables coming from economic growth theory, but also on further explanatory factors, for example coming from New Economic Geography (NEG) and institutional economics. These factors, among others, rely on soft and hard capital, institutional quality, agglomeration economies, etc.

The objective of this study is to come up with a simple yet robust explanatory model for regional growth in Europe over the period 2000-2011. We are particularly interested in improving the way the spatial dimension of regional economic growth is taken into account, to better assess (i) the strength of spatial spillovers and (ii) the role of spatial agglomerations. We employ a NUTS-3-based dataset that, compared to coarser regional aggregations, is more effective in capturing spatial heterogeneities and relationships. In addition we make use of high-resolution spatial data, the so-called Global Human Settlement Layer (GHSL) that proxies human activity intensity for 300m grid cells. With regards to measuring of spatial spillovers, we resort to spatial econometric techniques using spatial weight matrices derived from a dataset with modelled travel times between NUTS-3 zones. Different decay functions are tested and the most suitable cut-off distances are sought. From a policy perspective, a good representation of the shape and extent of spatial spillovers allows for more sound expectations regarding the actual geographical impact of policies with territorial dimension.

According to NEG, spatial agglomerations are associated with regional growth and inequality. Fujita and Thisse (2002, p. 391) argue that “growth and agglomeration go hand-in-hand”, and more recently Baldwin and Martin (2004, p. 2672) highlight that, through localized spillovers, “spatial agglomeration is conducive to growth”. Spatial agglomeration, in fact, can be a vehicle of knowledge externalities and can contribute to the local accumulation of technological knowledge. The types of externalities identified by Glaeser et al (1992) are three: the Marshall-Arrow-Romer (MAR) externalities, the Jacobs externalities and the Porter externalities. The first are derived from the concentration of firms within a single industry; the second are due to the diversity of firms and industries within a given region; and the third to local competition among firms that are concentrated in the same industry. Previous empirical estimations, however, show rather mixed results. Ciccone (2002), for example, found that agglomeration, measured as the dispersion of GDP per capita of the NUTS-3 within NUTS-1, has a similarly positive effect on economic growth across five Western European countries: Spain, Italy, France, the UK and Germany. Castells-Quintana and Royuela (2014), using country data from 1970-2007, observe that the positive effects of increasing agglomeration is stronger in low-inequality countries, regardless of their initial income. In contrast, David et al. (2013) suggest that European cities with more than 200,000 inhabitants behave differently depending on the stage of development of the countries to which they belong. These different results could be due to insufficient data availability at detailed spatial scales, making it challenging to measure spatial agglomeration in an efficient manner or, as Gardiner et al. (2011) suggest, due to differences in the measure of agglomeration and the spatial scale at which the analysis is conducted.

In this study we try to overcome this limitation by using an innovative measure of agglomeration at the NUTS-3 level, which we derived from the combination of high-resolution population and built-up areas. All the data and methods employed in this study are elements of the LUISA Territorial Modelling Platform, developed by the European Commission for ex-ante evaluation of regional and local impacts of policies and trends.

The remainder of the paper is organised as follows: first, data and methods are presented (Section 2). Section 3 describes the empirical model followed and, finally, section 4 concludes by summarizing the main findings and needs for further research.

2. METHODS AND DATA

2.1 Methods

The empirical strategy is an augmented growth equation based on the framework of Barro and Sala-i-Martin (1991):

$$\frac{1}{T} ln\left(\frac{y_{i,T}}{yi,0}\right) = \alpha + \beta ln\left(y_{i,0}\right) + \theta ln\left(y_{i,0}\right)^2 + \delta(\text{secondary edu.}_0\ ) + \vartheta(\text{tertiary edu.}_0\ ) + \eta(\text{capital metro region}) + \ \phi ln(\text{agglomeration}_0) + \varepsilon_i \quad (1)$$

where, on the left hand side (LFS) of Eq. (1), we have the average growth of Gross Domestic Product (GDP) per capita between period *0* and *T*, where *0* is year 2000 and *T* is year 2011. On the right hand side (RHS), in addition to constant α and GDP per capita at time 2000, y_{i0}, there is a set of additional explanatory variables for the 1290 NUTS-3 regions. Those variables are educational levels (percentage of people with secondary and tertiary education), a dichotomous variable indicating the capital metro region, and a measure of agglomeration.

While the effect of human capital has been deeply analysed in literature, we are going to check the possible existence of nonlinearity (Kalaitzidakis et al. 2001). Regarding the effects of agglomeration and spatial spillovers, according to the 2009 World Development Report, large cities or highly urbanized areas contribute to regional economic growth economies due to higher investment returns. Capital metro regions are among the largest cities in Europe. As highlighted by Dijkstra (2013), this is the product of accumulation of centuries of investment. This is coherent with Myrdal's theory of cumulative causation (1957). In Europe, there are cases of much higher public investments in capital cities than in the rest of country (European Commission, 2010). This may be due to beliefs about its intrinsic productivity advantage (Henderson, 2003).

Following endogenous growth theory, spatial concentration of economic activities produces spatial spillovers that benefit innovation and subsequently raise average productivity in an agglomeration, thus causing growth of real output (Gardiner et al., 2011). At the same time, increasing competition within a region can lead to a decline of profits of companies, and raise congestion effects and related negative externalities. These phenomena can reduce regional income inequalities and growth. In this study agglomeration is defined as:

$$\text{agglomeration}_0 = \left(\frac{\text{population}_0}{\text{Residential Built−up Areas}_0}\right) \times \text{population}_0 \tag{2}$$

Compared with Crescenzi et al. (2007), who define agglomeration simply as population density, we conceive both population density and demographic size *sine qua non* elements of agglomeration. In the formula above (Eq. 2), the first part captures the level of geographical concentration of population within each region, while the second element accounts for the demographic size of the region. As such, a small but highly dense region will score a lower agglomeration than an equally dense but more populated region. Conversely, a highly populated region will have a relatively low score of agglomeration unless population density is also high. As a matter of fact, many regions have a large population size simply due to their large geographical size. With the proposed approach we therefore address the Modifiable Areal Unit Problem (MAUP), which is "a problem arising from the imposition of artificial units of spatial reporting on continuous geographical phenomena resulting in the generation of artificial spatial patterns" (Heywood, 1988), and in particular the zonation effect[1].

If β is statistically significant and negative, the convergence hypothesis holds: poorer economies tend to grow faster than richer ones. If δ, ϑ, η, ϕ are not statistically significant we can assume absolute convergence, i.e. all regions converge to the same steady state. Otherwise

[1] The zonal effect is related to the grouping schemes that one uses for data analysis and is often caused by variance in the geographic size of the units of analysis.

we have conditional convergence, i.e. equilibrium differs across regions, and each one approaches its own steady state equilibrium depending on regional characteristics/conditions.

The parameter θ measures the curvature of the coefficient related to convergence. If β is negative and θ is positive the parabola opens upward; vice versa the parabola opens downward. The estimation of different signs for β and θ suggests the presence of two clubs of regions. In the former case regions converge up to the estimated threshold of GDP per capita level, while divergence trends dominate afterwards. In the second scenario, we would have divergence of regions with initial GDP per capita levels below the estimated threshold, followed by slowdown of the wealthiest economies (Petrakos et al., 2011). The turning point is defined as $-\beta/2\theta$.[2]

The estimation of the equation is performed using standard Ordinary Least Squares (OLS) and spatial econometric techniques (Anselin, 1988). The latter, in fact, allows us not only to deal with spatial dependence in the data, but also to account formally for the spatial spillover effects (Anselin, 2003). In the literature, two main approaches are used depending on where spatial structure is found. If spatial structure is in the residuals of an OLS regression model, this will lead to inefficient estimates of the parameters, meaning that the standard errors of the parameters will be too large. This leads to incorrect inference on significant parameter estimates. Otherwise, when spatial structure is in the data, the value of the dependent variable in one spatial unit is affected by the independent variables in nearby units. In this case the assumptions of uncorrelated error terms and/or independent observations are also violated. As a result, parameter estimates are both biased and inefficient. In case of spatially correlated error terms a spatial error model needs to be adopted, and in the case of spatially dependent observations a spatial lag model can be adopted. In the first model, 'error' refers to the spatial autoregressive process for the error term , and in the second the 'lag' refers to the spatially lagged dependent variable.

The main difference between the two models is that in the estimation of the marginal effect of the variables, spatial lag model needs to account for the coefficient of spatial autoregressive dependent variable, which captures the strength and direction of the spatial spillovers. In this framework, the partial derivative is defined as:

$$\frac{\partial \frac{1}{T} ln\left(\frac{y_{i,T}}{y_{i,0}}\right)}{\partial x_i} = (\mathbf{I} - \rho\mathbf{W})^{-1}\beta = (\mathbf{I} + \rho\mathbf{W} + \rho^{\mathbf{2}}\mathbf{W}^{\mathbf{2}} \dots)\mathbf{I}\beta_r \quad (3)$$

[2]The turning point is derived from the partial derivative of the logarithm of GDP per capita at time *0* over the GDP per capita growth: $\frac{\partial \frac{1}{T} ln\left(\frac{y_{i,T}}{y_{i,0}}\right)}{\partial ln(y_{i,0})} = \beta + 2\theta$. Putting the equation equal to zero we obtain: $0 = \beta + 2\theta$ The solution is $-\beta/2\theta$, which corresponds to the point where the curvature from negative turns to positive.

where **I** is the identity matrix, **W** the spatial weight matrix, ρ the spatial autoregressive parameter bounded between highest and lowest eigenvalue extracted from the **W** matrix, β_r a vector of parameters (Anselin, 2003), and x_i is a generic variable of the RSH of equation 1. Apart from the spatial lag and error models, other models are gaining interest in literature, namely spatial lag of x (SLX), spatial Durbin and spatial Durbin Error (SDE). These models offer some advantages related to the inclusion of the spatial lag of the independent variables. They have been checked through a Common factor test (Mur an Angulo, 2016) and, as they do not fit well with our data, we chose to not consider them for the purpose of our study.

2.2 Data

All the socio-economic data per NUTS-3 were collected from the Eurostat online database. The level of education is based on NUTS-2 because this is the lowest available disaggregation level, and then assigned to the correspondent NUTS-3. The choice for the lowest level of spatial disaggregation is led by evidence in two recent publications. The first, related to the results of Díaz Dapena et al. (2016), proves that, using an OLS framework, the empirical variability of the estimates are substantially lower when estimated from a sample of spatially disaggregated data. The second, following the study of Mendes Resende et al. (2016), is that spatial spillover coefficients vary according to the spatial scale under analysis, and, in general, such coefficients are statistically significant when lower geographical scale is taken as a reference. A possible explanation for the scale sensitivity of spatial effects is given by Arbia (1989) and Jacobs-Crisioni et al. (2014).

The capital metro regions indicate national capitals and those NUTS-3 regions in which at least 50% of the regional population lives inside a given Functional urban area (FUA). Such FUAs are spatial delineations that contain major cities and their surrounding commuting zones. Apart from the capital city regions, two other classes of metro regions exist: second-tier metro regions and smaller metro regions.[3] We do not account for these additional metro regions because it would overlap with the agglomeration measure.

The accounting of residential built-up areas per NUTS-3 was done by aggregating high-resolution residential built-up areas derived from the combination of two datasets: the European Commission's Joint Research Centre Global Human Settlement Layer (GHSL) (Pesaresi et al.,

[3] According with the Eurostat definition metro regions are NUTS-3 regions or groupings of NUTS-3 regions representing all urban agglomerations of more than 250 000 inhabitants. Second-tier metro regions are the group of largest cities in the country excluding the capital. Instead of a fixed population threshold, a natural break served the purpose of distinguishing the second tier from the smaller metro regions. The distinction between second tier and smaller metro regions is an adaptable concept.

2016) and a recently refined version of the European Environment Agency's CORINE Land Cover (Batista e Silva and Rosina 2016). Built-up area is based on built-up densities derived from the GHSL for 2000, with 300m grid cells as units of analysis. The variable is continuous (min = 0 = no built-up, max = 255 = fully built-up).

The variable residential built up area has been constructed in the following steps:

First, the GHSL time series was pre-processed according with the following stages:

1. GHSL built-up areas in a selected set of land use/land cover classes from the CORINE Land Cover 2012 – Refined map (CLC-R) were filtered out to mitigate misclassification in bare ground areas and to remove non-residential built-up.
2. The resulting GHSL residential built-up layer was then converted from its original continuous values to absolute values of built-up surface in hectares: RBU_ha = [(300 * 300) / 10000] * (RBU_0_255 / 255).

Second, and final, the variable RBU_ha at the level of 300m grid cells was aggregated at NUTS3 level.

Resident population per NUTS3 for the year 2000 was obtained from a time series of population at municipality level procured by the European Commission's DG REGIO (European Commission 2013). Based on an analysis of the distribution of population density values per NUTS3, nine regions were considered outliers, all of which are cases of significant underestimation of residential built-up land, leading to extremely high population densities. These outlier regions are located in Northern Scotland (4), Finland (3), Sweden (1) and Greece (1).

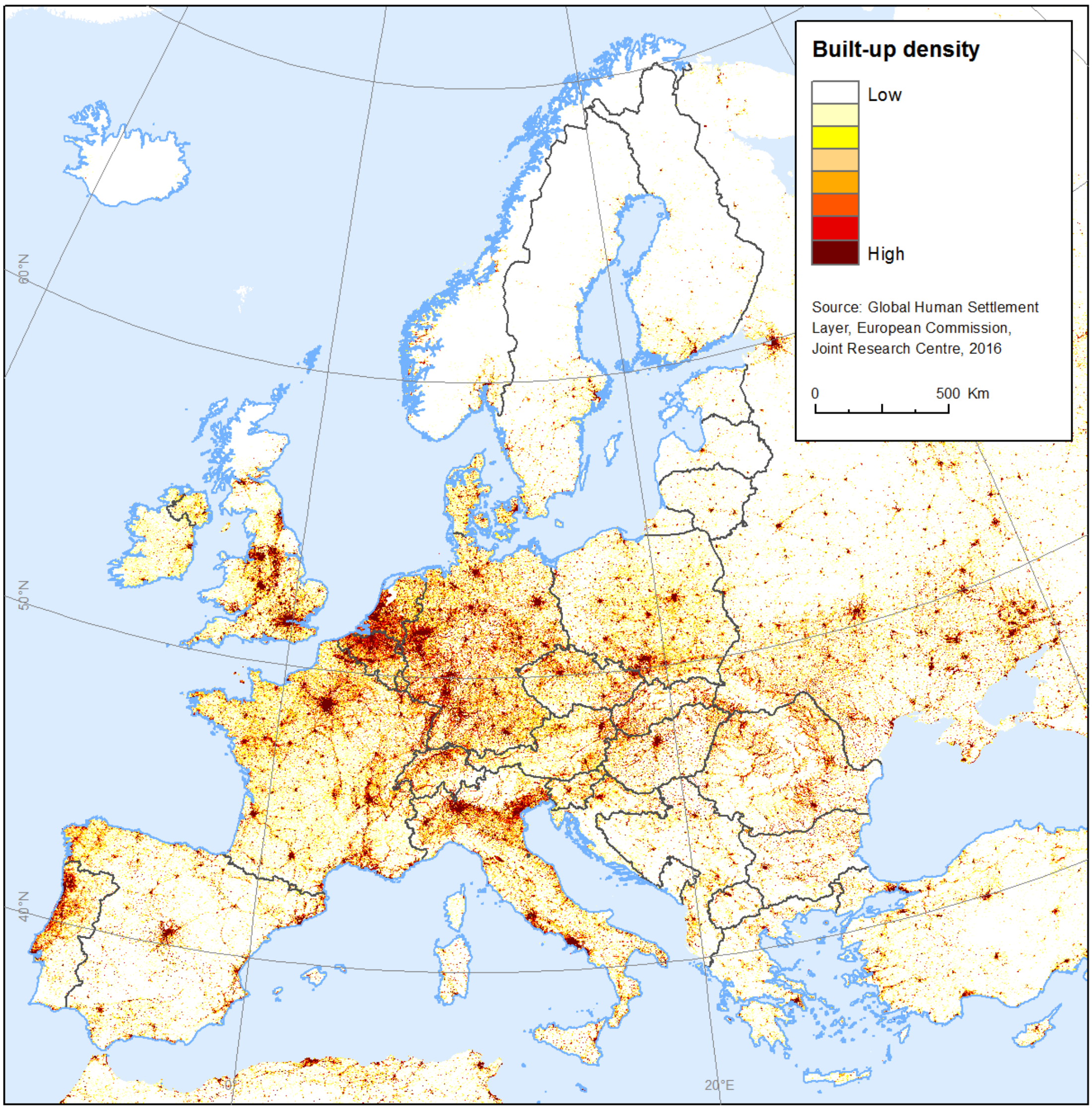


Figure 1: residential built-up density

Source: own elaboration of the Global Human Settlement Layer.

Travel times between NUTS-3 population-weighted centroids are used to construct the **W** matrices necessary for the spatial econometric specifications (see section 3). Population-weighted centroids, whose construction relied on a high-resolution population grid map (Batista e Silva et al. 2013), are used here because, as recently shown (Stepniak and Jacobs-Crisioni, 2017), such centroids are less affected by inaccurate measurements of travel time due to aggregation. Finally, travel times are based on the road network used in the TRANS-TOOLS European transport model (Rich et al., 2009) and computed using shortest-path routines in the GeoDMS software (ObjectVision, 2014).

Table 1 shows the descriptive statistics for the variables included in the model. The average growth between 2000 and 2011 was around 2.7% with a standard deviation of 1.8%, that shows a quite high variability and a huge gap between the regions with the highest and lowest value, 11% and -1.8% respectively. The level of GDP per capita in 2000, as well as the variables related to educational attainment show a big gap between the most and less performant region. The average regional secondary educational attainment, furthermore, is more than the double of tertiary educational attainment: 47% against less than 20%. Finally, the spatial autocorrelation measured by Moran's I is positive and significant in all cases. The strongest value is for secondary education and the lowest is for agglomeration.

Table 1: descriptive statistics

Variable	Min.	Max.	Mean	Std. dev.	Moran's I
GDP/pop growth	-0.0177	0.1102	0.0274	0.0176	0.7310***
GDP/pop$_{2000}$	2262	123300	17930	8721.43	0.7262***
Secondary edu.	0.0850	0.7780	0.4748	0.1496	0.9248***
Tertiary edu.	0.0540	0.4890	0.1961	0.0788	0.7957***
Agglomeration	$1.114*10^6$	$757.8*10^6$	$33.42*10^6$	$52.3*10^6$	0.4813***
Capital metro regions	0	1	0.0620	0.2413	

3. RESULTS

When using spatial econometric tools, a first, fundamental step is the choice of the spatial weight matrix **W**, as it determines the shape, strength and direction of spatial spillovers. According to Arbia and Fingleton (2008), the spatial weight is a non-stochastic matrix describing a hypothesis of the nature of the spatial interactions, and its arbitrary creation is often subject to criticism. Hence, scholars (e.g. Postiglione et al. 2017) have suggested forms of sensitivity analysis and theoretical justification to support the choice of weight matrix structures.

In this study we run *spatial lag* and *spatial error* models using different decay functions and different distance cut-offs to determine **W**. The distance is defined in minutes of travel time between NUTS-3 population-weighted centroids. The optimal cut-off for each decay function was determined by analyzing improvements to the Akaike Information Criterion (AIC) (Arbia et al. 2009; Postiglione et al. 2017). The decay functions used are as follows:

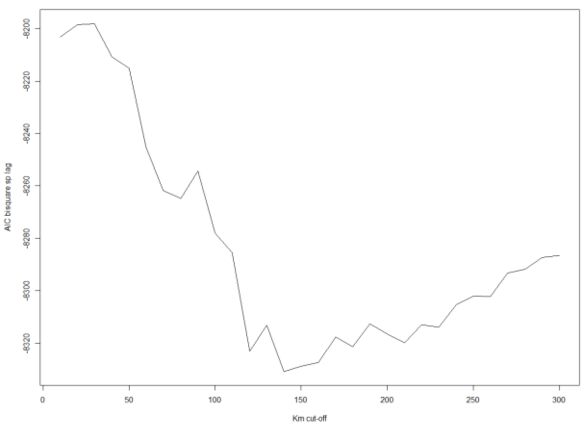
- Gaussian: $exp(-\,dist/cutoff)$
- Gravity: $1/dist^2$

Our results are given in Figure 2, which shows the relation between the travel time in minutes, on the x-axis, and the AIC, on the y-axis. We expect that an optimal cut-off value is where the

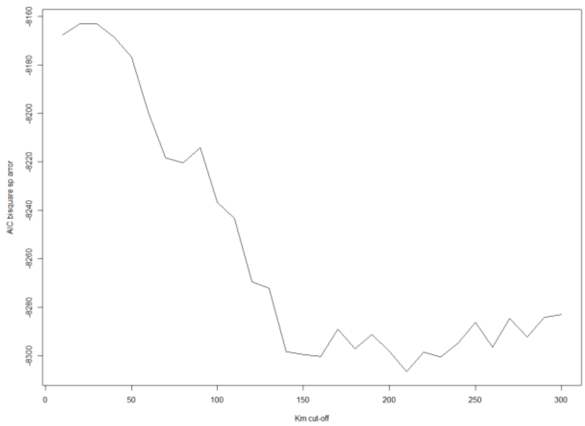
AIC stops to decrease substantially, which with both distance decay specifications is the case at roughly 150 minutes.

Gauss decay function

Spatial lag

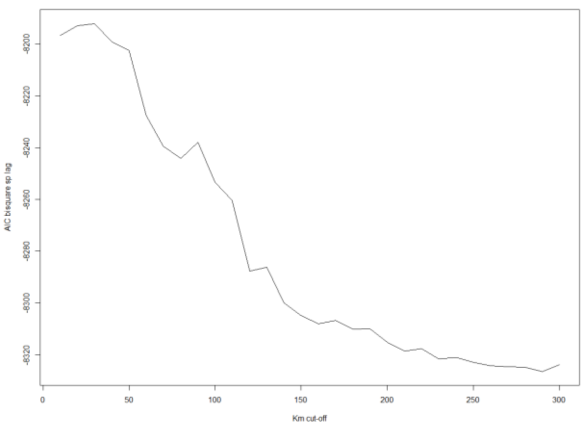


Spatial Error

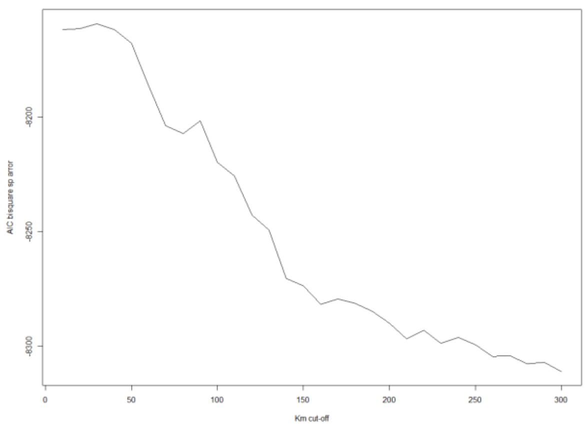


Gravity decay function

Spatial lag



Spatial Error



Source: own elaboration.

Figure 2: decay functions and AIC as a function of distance cut-off values in minutes

In function of these outcomes we estimate our models, whose results are reported in Table 2. Coherent with growth theory, the coefficient of GDP per capita at the base year is negative and significant. In addition we find a concave curvature that is significantly different from zero. Secondary education has a slighly concave shape too, while tertiary education has a strong positive and significant sign. The result related to capital metro regions shows a positive and significant coefficient.

Thus, agglomeration economies have a strong and positive effect on growth, confirming predictions from the NEG theory (see Baldwin and Martin, 2004 and Petrakos et al., 2011).

Moran's I and Lagrange Multiplier (LM) tests are very significant, indicating the presence of spatial dependence in OLS, and clearly justifying the use of spatial econometric models.

LM and Robust LM tests were done to check whether lag or error spatial dependence could be at work. If only one is significant, lag or error, we choose the correspondent model. If both are significant, then we have to check the Robust LM tests. As before, if only one is significant, we choose the correspondent model, otherwise, if they are both significant, we choose the test with the largest value. In this case the results suggest the use of the spatial lag model.

In the spatial lag model, the key parameter through which spatial spillovers effects are transmitted to the whole economy (i.e. global externalities) is ρ. It enters in the spatial multiplier $(\boldsymbol{I} - \rho\mathbf{W})^{-1}$ that defines the strength of the linkage between the productivity growths of the neighbouring regions. An estimated positive value for the parameter ρ means that the spatial multiplier amplifies the effects of a change in surrounding provinces with respect to the productivity growth of the original province. On the contrary, an estimated negative value for ρ implies that a province does not fully exploit, in terms of productivity growth, the variation of a variable in neighbouring provinces.

The spatial multiplier associated to this model is equal to $(1\text{-}0.5810)^{-1}$=2.38. Thus almost 3/2 of the impact of growth is reflected in neighborhood growth through indirect reaction effects from neighbors.

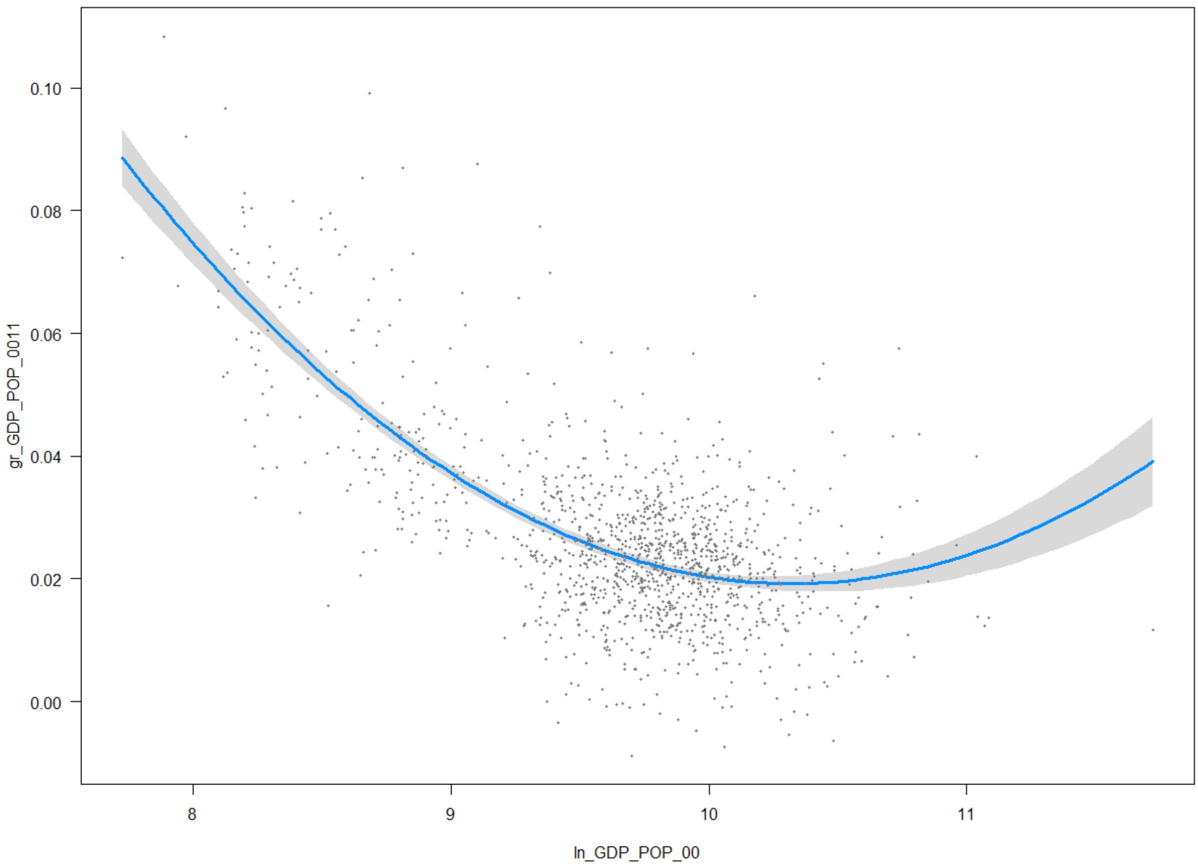
Failure to account for redundancy in shocks by muting indirect effects (OLS model) would lead to a rise of the estimated marginal impacts, which are biased upwards in magnitude, because the model is misspecified by omission of spatial spillover effects (Mobley et al., 2009). Taking the example of agglomeration, we have that the parameter of OLS is equal to 0.0010, while in the spatial lag model it is 0.0007. This means that the OLS overestimates the direct effect on growth by 43%. Accounting for spatial multiplier effects, we have 0.0007×2.38=0.0017.This is higher than the OLS estimate because it accounts for the feedback effects coming from the surrounding regions.

Table 2: estimation results

Sp. Weight matrix		**Gravity, cut-off = 150 min**		**Gauss, cut-off = 150 min**	
Model	**OLS**	**Spatial lag**	**Spatial error**	**Spatial lag**	**Spatial error**
Intercept	1.0904***	0.4878***	0.7158***	0.4069***	0.5453***
	(0.0671)	(0.0628)	(0.0705)	(0.0631)	(0.0752)
ln(GDP/pop 2000)	-0.2115***	-0.0944***	-0.1398***	-0.0786***	-0.1042***
	(0.0137)	(0.0128)	(0.0143)	(0.0128)	(0.0152)
ln(GDP/pop 2000)^2	0.0102***	0.0045***	0.0067***	0.0037***	0.0049***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)
Secondary edu. 2000	-0.0783***	-0.0416***	-0.0567**	-0.0372***	-0.0501**
	(0.0109)	(0.0095)	(0.0176)	(0.0095)	(0.0198)
Secondary edu. 2000^2	0.1403***	0.0739***	0.1150***	0.0660***	0.1085***
	(0.0123)	(0.0111)	(0.0195)	(0.0111)	(0.0217)
Tertiary edu. 2000	0.0354***	0.0193***	0.0276***	0.0172***	0.0248***
	(0.0044)	(0.0039)	(0.0066)	(0.0039)	(0.0069)
ln(agglomeration)	0.0010***	0.0007**	0.0017**	0.0007**	0.0014**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Capital regions	0.0034***	0.0023***	0.0043***	0.0028***	0.0049***
	(0.0013)	(0.0011)	(0.0015)	(0.0011)	(0.0013)
Rho (spatial lag)		0.51401***		0.5810***	
Lambda (spatial error)			0.5735***		0.6783***
AIC	-8004.625	-8304.8	-8276.3	-8327.5	-8300.2
R^2	0.6253	0.7209	0.7195	0.7238	0.7246
Moran's I	0.3254***	-0.0242	-0.0438	-0.0083	-0.0254
LM error	318.918***				
LM lag	342.879***				
Robust LM error	16.442***				
Robust LM lag	40.403***				
Breusch-Pagan test	109.41***	80.689***	39.506***	83.207***	39.958***
	(df = 7)	(df = 7)	(df = 7)	(df = 7)	(df = 7)

*Significant at 1%, ** significant at 5%, *** significant at 10%. Standard error in brackets.

The nonlinear effect of initial levels of GDP per capita (on the x-axis) on growth (on the y-axis) is shown in Figure 3. However, only about 21 NUTS-3 regions with GDP per capita higher than exp(0.0786×2.38)/(2×0.0037×2.38) = ~ 41k € are diverging upwards. This is coherent with the J-shaped pattern of regional per-capita GDP growth found by Petrakos et al. (2011), indicating that, above some threshold level of development, regional convergence trends vanish and regional divergence starts to emerge.

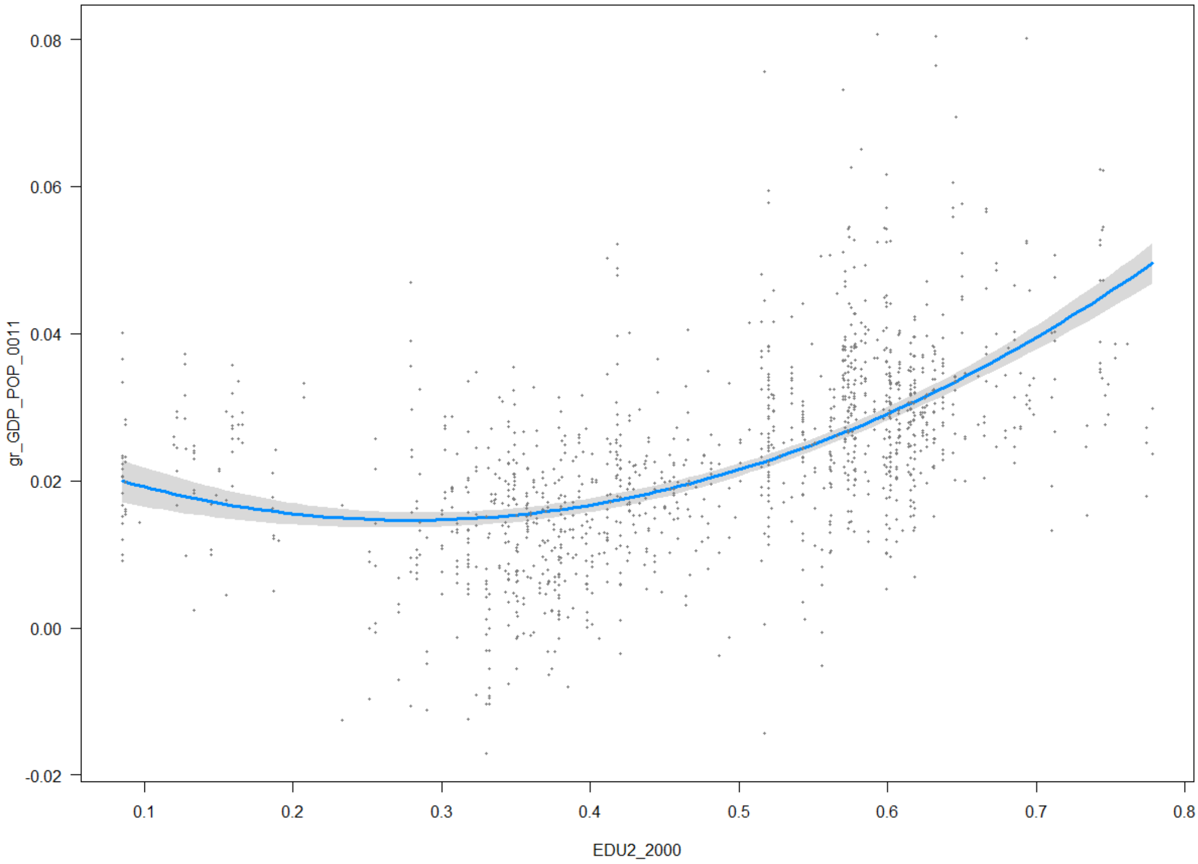


Source: own elaboration.

Figure 3: nonlinear convergence effect on growth

Education also shows a nonlinear effect on growth (figure 4). It has a flex point at $(0.0372\times2.38)/(2\times0.0660\times2.38) = \sim 28\%$. This means that there are decreasing marginal returns until the share of people with secondary education over total population is equal to 28%, and then the marginal returns start to rise exponentially.

Finally, we must underline that, contrary to the OLS specification, the spatial models do not present autocorrelation in the residuals (randomized Moran's I are not significant). However, despite the much higher variance explained by the spatial models in respect to the OLS (about 10% more), problems of heteroskedasticity still persist (see Breusch-Pagan test) possibly due to misspecification.



Source: own elaboration.

Figure 4: nonlinear effect of secondary education on growth

The choice of the spatial lag model introduces a dependence among regions' economic systems in form of global externalities: a shock in province *i* is transmitted to its neighbours by parameter ρ that, in turn, is transmitted again to region *i* through **W**, reinitiating the process until the effect becomes negligible for *N* tending to infinite (LeSage and Fischer, 2008). This is due to the presence of the spatial autoregressive parameter ρ and the parameter associated with the spatial lags of the independent variables as shown in equation (3).

LeSage and Pace (2009a, 2009b) define the average direct effect as the average of the diagonal elements of equation (3), and the average indirect effect as the average of the off-diagonal elements, where the off-diagonal row elements are first summed up, and then an average of these sums is taken. Finally, the sum of the direct and indirect effects gives the average total effect. Specifically, the direct effect captures the effect on growth in region *i* caused by a unit change in an exogenous variable in *i*. Indirect effects can be interpreted as the effect of a change of a variable in all other regions, $j \neq i$, on the economic growth rate in *i*. It has been noted that direct effect estimates include feedback effects. This is shown in table 3, where the direct, indirect, total and feedback effects are reported.

These are the result of impacts passing through neighboring regions and back to the region where the change was originated. On average, feedback effects increase the coefficient estimate by 6-7%. The variability is quite low. Larger feedback effects emerge from the agglomeration, which has double the effect of the other variables. Finally, the indirect effects show the same sign of the indirect effects, a similar magnitude and a strong significance, which reinforces the idea that spatial spillovers have an important role in regional growth.

Table 3: direct, indirect and total effects results

	Gravity, cut-off = 150 min				**Gauss, cut-off = 150 min**			
Variable	*direct*	*indirect*	*total*	*Feedb.*	*direct*	*indirect*	*total*	*Feedb.*
ln(GDP/pop 2000)	-0.0830***	-0.1043***	-0.1873***	0.072	-0.1012***	-0.0932***	-0.1944***	0.056
ln(GDP/pop 2000)^2	0.0039***	0.0049***	0.0089***	0.076	0.0048***	0.0045***	0.0093***	0.065
Secondary edu. 2000	-0.0394***	-0.0495***	-0.0890***	0.071	-0.0446***	-0.0411***	-0.0856***	0.060
Secondary edu. 2000^2	0.0699***	0.0877***	0.1576***	0.070	0.0791***	0.0729***	0.1519***	0.059
Tertiary edu. 2000	0.0183***	0.0229***	0.0412***	0.073	0.0207***	0.0191***	0.0398***	0.061
ln(agglomeration)	0.0008***	0.0010***	0.0018***	0.133	0.0008***	0.0007***	0.0015***	0.118

*Significant at 1%, ** significant at 5%, *** significant at 10%.

3. PRELIMINARY CONCLUSIONS AND WAY FORWARD

The aim of this study was to assess the role of spatial agglomerations and spillovers on regional economic growth. We used spatial econometric techniques and new geo-data sources to construct a dataset of socio-economic and transport data at NUTS-3 level. Our first results, based on novel data able to properly capture agglomeration and spatial spillovers, are in line with NEG, confirm that both these factors have a strong role. It is worth mentioning that spatial spillovers have a limited extent and occur within 150 minutes of travel time between regions. The positive effect of spatial agglomeration, as well capital metro regions might be related to their economy of scale and localized spillovers that generate knowledge externalities that can contribute to the local accumulation of technological knowledge.

These initial results leave some open questions that need to be addressed in forthcoming research. These are mainly related to the necessity of testing alternative measures of agglomeration (Gardiner et al. 2011) as well as their 'life cycle' (Potter and Watts, 2010), i.e. how the incentives to agglomerate and disperse evolve over time, and the relationship between Marshall's agglomeration economies, which predicts that increased concentration of firms of the same industry within a region facilitates knowledge spillovers, and firms' capacity to remain innovative and performant.

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