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Agglomeration and human capital: an extended spatial Mankiw-Romer-Weil model for European regions

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Abstract

Over the last two decades a handful of very rich European regions have increased the gap separating them from the European average in terms of labour productivity. In this paper we extend a spatial version of the Mankiw, Romer and Weil model (MRW, 1992) as developed by Fischer (2011) to accommodate human capital spillovers linked to agglomeration. After modelling this specific spillover, we go on to test empirically whether its effect has been to stimulate labour productivity growth in those European regions with the greatest potential to benefit from agglomeration economies. The theoretical model leads to a cross-sectional spatial Durbin model specification. The empirical analysis is carried out for 121 European regions for the period 1995-2014. We find significant conditional β-convergence, positive impacts of investment in physical and human capital, and a negative impact of population growth. Our most notable result involves the specific spillover effect that enhances the impact of investment in human capital in the most highly agglomerated regions. We find this externality significant in explaining labour productivity growth and therefore also in increasing labour productivity disparities across European regions.

Keywords: Human capital, labour productivity, spatial externalities, European regions.

JEL classification: C21, O47, O52, R11.

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1. Introduction

Over recent decades, prosperity in Europe has become concentrated in a handful of very high-income regions. A common characteristic of these successful regions is that they are home of big metropolitan areas, which would indicate the presence of agglomeration economies. However, the evidence for European regions over the period 1995-2014 reveals that not all metropolitan regions in Europe enjoyed the same positive results in terms of productivity growth. Indeed, over the course of this period an increasing number of well-off regions and old industrial centres in Western Europe were caught or at risk of being caught in what has become known as the "regional development trap" (Diemer et al, 2022). This refers to the difficulties some regions have in recovering their past dynamism or improving the income levels of their residents. The question of whether spatial heterogeneity across regions is able to generate different spatial regimes of economic growth or "convergence clubs" is not a new subject in the literature, but it does seem to have gained momentum over the last decade when differences in growth potential has been observed between the richest regions in the European Union and all the others (Annoni et al, 2019; Capello and Lenzi, 2021). Something similar has been observed in the United States (Lim, 2016).

If we look at the most prosperous regions in Europe, most of them present high levels of agglomeration. The literature relates the concentration of economic activity in a few specific locations to a wide range of positive externalities that act as important drivers of economic growth (Marshall, 1890; Jacobs, 1969; Lucas, 1988; Glaeser, 2011). Theoretical works such as Martin and Ottaviano (1999), Fujita and Thisse (2002), Baldwin and Martin (2004), Duranton and Puga (2004) and Rosenthal and Strange (2004) support the idea that agglomeration encourages and strengthens economic growth through the efficiency gains deriving from proximity. There is a wide range of models to explain the impact of agglomeration on economic growth. Depending on their micro-foundations, these models can be classified as being based mainly on *sharing*, *matching* or *learning* mechanisms (Duranton and Puga, 2004). *Sharing* and *matching* refer to the presence of a local pool of skilled workers and local linkages between intermediate and final output suppliers. The term "localization economies" is used for these kinds of externalities between plants in the same industry located in the same area. They do not usually need a high density population to operate. The term "urbanization economies", on the other hand, is more comprehensive and also includes the externalities that arise in more densely populated areas, and which are generated outside the industry. There are many different advantages deriving from urbanization. Some are related to the high endowment of infrastructures, while others are in connection with the ample supply of facilities associated with the acquisition and generation of knowledge. This second set of externalities implies the emergence of some specific kind of urban knowledge spillovers directly related to *learning* mechanisms.

Generally speaking, the learning process requires interaction with other individuals, which is why urban centres provide the best opportunities for learning because they offer a wider range of opportunities for people to interact and therefore learn. In theory, the more likely it is that people who have things to learn from one another will actually come into contact with each other, the more feasible it is that economic growth will occur. Likewise, the supply of knowledge amenities in cities encourages people to acquire new skills and makes it easier for workers to increase their level of knowledge. And due to the higher technology level of the activities that become concentrated in big cities, workers are more likely to acquire static knowledge and/or knowledge through work. All these things together can transform the cities or regions in which they are located into centres of innovation and creativity. The available empirical evidence suggests that cities speed up the accumulation of human capital among workers (Glaeser and Maré, 2001) and that people in big cities usually earn more than those in other areas (Baum-Snow and Pavan, 2012; De la Roca and Puga, 2017).

In addition to this, the high levels of human capital in big cities strengthen the cumulative nature of knowledge generation, extending the frontier of knowledge and thus increasing productivity growth. These are aspects that were mentioned early on by Marshall (1890), who described the importance of cities for knowledge diffusion, and Jacobs (1969), who highlighted their relevance in generating knowledge. The cities' potential to develop *learning* mechanisms suggests that those metropolitan areas that are best endowed with human capital and skills would be the most likely candidates for high productivity growth rates. This does not mean that all cities are equally likely to enjoy such *learning* mechanisms – the potential might not exist in metropolitan areas with lower skill levels, as pointed out by Glaeser and Resseger (2010).

With the rise of the so-called "knowledge-based economy", the complementarity between big cities and skills has become even more central to innovation (Gaspar and Glaeser, 1998). Being around skilled people in densely populated areas has taken over from economies of scale based on plant size. Nowadays, the main motivation for economic activity to be concentrated in big metropolitan areas has more to do with the opportunities that arise from contact with highly skilled workers and knowledge amenities. As a result, cities that are better endowed with skills are becoming hubs of attraction for human capital and powerful engines of economic growth. Big cities (and their corresponding regions) have become increasingly specialized in such activities in recent times, and not only in industrialized countries but in developing countries too (Venables, 2006; Moretti, 2013).

A new pattern in the spatial distribution of economic activity across regions can thus be observed. While the innovative industries cluster together to benefit from knowledge spillovers in the big agglomerated areas, more mature sectors spread out following technology diffusion (Desmet and Rossi-Hansberg, 2009). This does not necessarily mean that areas that are more likely to generate agglomeration economies will specialize in just one or two sectors – the opposite could well be true. According to Duranton and Puga (2001), these areas also tend to act as “nurseries” for firms across a wide range of industries. What this means is that when a company in a particular industry tries to develop new products or processes, it tends to settle in the most diversified regions with the aim of benefitting from processes borrowed from other industries. Later, when the process matures and there is a switch to mass production, the company will likely relocate to regions with lower production costs and more “localization externalities”. One of the most important results of this pattern has been the weakening of income convergence across regions, as observed in the US since 1980 (Glaeser et al., 2014). This dynamic process, in which the *learning* mechanism and the knowledge generation tend to become concentrated in the most innovative industries and companies in regions with denser levels of economic activity while mature industries spread to regions with lighter levels, has therefore come to be considered an important source of regional disparities in economic growth rates.

The aim of this paper is to analyse the economic growth of the European regions. We take as our reference the theoretical model devised by Mankiw, Romer and Weil (1992) and extended by Fischer (2011) to account for the technological interdependence across regions caused by disembodied knowledge diffusion deriving from investment in physical and human capital. We include in the model a specific spillover effect deriving from investment in human capital, which will enable us to capture the *learning* mechanism. The transition from theory to econometrics results in a reduced form of the empirical Durbin model specification. To carry out our analysis we have assembled data for 121 NUTS2 regions belonging to 9 European countries for the period 1995-2014.

One of this paper's main contributions is that it focuses on the role of human capital and the development of knowledge spillovers in productivity growth. Human capital influences productivity growth through two different channels – one of these is its capacity to help the diffusion and adoption of new technologies or to generate innovation, while the other is its ability to speed up growth by increasing or complementing the existing production factors (Sunde, 2011). This is represented by incorporating into the model the idea of technological spillovers linked to human capital. These technological spillovers can cross regional borders and generate technological interdependence across regions. We also test whether the regions best endowed to be home to agglomeration economies benefit more from investment in human capital than other regions through the *learning* mechanism described above.

The paper is structured as follows. Section 2 presents a spatial Mankiw, Romer and Weil model extended to accommodate the spillover effect linked to the *learning* mechanism. Section 3 contains the econometric specification and the main descriptive data. Section 4 discusses the econometric results and Section 5 concludes.

2. The theoretical basis: a spatial Mankiw-Romer-Weil (MRW) model

Our theoretical framework is based on the Mankiw, Romer and Weil (1992) model, which we have extended to account for physical capital externalities, human capital externalities (including the spillover effect associated with the *learning* mechanism), and technological interdependence between regional economies.[1]

Following Fisher (2011), we consider *N* regional economies with the same production possibilities and all agents identical. These regions have different endowments and allocations but present technological interdependence. We assume that each region is characterized by a Cobb-Douglas production function with Hicks-neutral technological progress and homogeneous of degree one in all its determinants:

[1] Lopez-Bazo et al. (2004) use an MRW model and consider that a region's technology depends on the technology levels of its neighbours, which relates it to the physical and human capital-labour ratios. Ertur and Koch (2007) develop a growth model with Arrow-Romer externalities and spatial interactions because of technological interdependence between countries. Fischer (2011) also introduces the existence of externalities of human capital together with those of physical capital in the MRW model with technological interdependence between regions.

$$Y_{i,t} = A_{i,t}\, K_{i,t}^{\alpha_k}\, H_{i,t}^{\alpha_h}\, L_{i,t}^{1-\alpha_k-\alpha_h} \tag{1}$$

where Y is output, L is labour input, K is physical capital stock, H is human capital and A represents the level of technological knowledge. The output elasticities with respect to physical and human capital are positive and represented by α_k and α_h respectively. In equation (1) the regions are denoted by i and the time index by t.

The initial levels of physical capital, human capital, labour and knowledge are taken as given. Labour in each region grows at a constant and exogenous rate denoted by n_i ($L_{i,t} = L_0\, e^{n_i t}$).

The assumption of constant returns allows us to express the production function – equation (1) – by worker or by unit of labour:

$$y_{i,t} = A_{i,t}\, k_{i,t}^{\alpha_k}\, h_{i,t}^{\alpha_h} \tag{2}$$

where y is output per worker, k is the stock of physical capital per worker, i.e. capital intensity, and h is the stock of human capital per worker.

Following Ertur and Koch (2007) and Fischer (2011), we model the level of technological knowledge as[2]:

$$A_{i,t} = \Gamma_t\, k_{i,t}^{\gamma_k}\, h_{i,t}^{\gamma_h+\tau}\, \prod_{j\neq i}^{N} A_{jt}^{\sigma W_{ij}} \tag{3}$$

where $A_{i,t}$ is modelled considering the following assumptions:

(i) The term Γ_t represents the common stock of knowledge in all the regions, which grows at a constant and exogenous rate, φ, i.e. $\Gamma_t = \Gamma_0\, e^{\varphi t}$.

(ii) We consider that technology is embodied in physical and human capital. We assume that investment in physical capital generates externalities (represented by the γ_k parameter, $0 \leq \gamma_k < 1$), which increases the level of technology in the region due to the knowledge spillovers generated (Arrow, 1962 and Romer, 1986).[3]

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[2] Ertur and Koch (2007) introduced the externalities of physical capital and spatial interactions, the second and last terms in equation (3), whereas Fischer (2011) added the externalities of human capital, the third term in the same equation, but without considering the agglomeration effect.

[3] Following Arrow (1962) and Romer (1986), we consider that investing in physical capital not only increases the stock of physical capital per se, but also the level of technology of all companies through knowledge spillover economies.

(iii) Investment in human capital also generates positive externalities (Lucas, 1988, and Romer, 1990) by raising the region's technology level. We split the externalities deriving from human capital into two categories: a more general externality represented by parameter γ_h, and a specific externality linked to the presence of agglomeration economies (Glaeser et al. 1992, 2014, and Glaeser and Resseger, 2010), represented by parameter τ. We associate this specific externality with the *learning* mechanism and assume that $0 \leq \gamma_h + \tau < 1$.

(iv) The technological progress of other regions ($j \neq i$) is represented by the last term in equation (3), where W_{ij} are spatial weight terms and represent the spatial connectivity between regions i and j, for $j = 1 \dots N$.[4] The more connected a region is with its neighbours, the larger W_{ij} will be and the more this region will benefit from spatial externalities. Parameter σ reflects the degree of regional interdependence $(0 \leq \sigma < 1)$. We should therefore look at regions as an interdependent system that brings about this interdependence in regional technology.

Following Ertur and Koch (2007), we can rewrite function (3) in matrix form as:

$$\boldsymbol{A} = \boldsymbol{\Gamma} + \gamma_k \boldsymbol{k} + (\gamma_h + \tau)\boldsymbol{h} + \sigma \boldsymbol{W}\boldsymbol{A} \tag{4}$$

where A is the $(N \times 1)$ vector of the technology level for the N regions, Γ is the $(N \times 1)$ vector of the exogenous part of technology, k and h are the $(N \times 1)$ vectors of physical and human capital per worker, and W is the $(N \times N)$ matrix of spatial weights with W_{ij} terms. Equation (4) can be resolved for A if $\sigma \neq 0$ and if $1/_{\sigma}$ is not an eigenvalue of W:

$$\boldsymbol{A} = (\boldsymbol{I} - \sigma \boldsymbol{W})^{-1}\boldsymbol{\Gamma} + \gamma_k (\boldsymbol{I} - \sigma \boldsymbol{W})^{-1}\boldsymbol{k} + (\gamma_h + \tau)(\boldsymbol{I} - \sigma \boldsymbol{W})^{-1}\boldsymbol{h} \tag{5}$$

Next, developing equation (5) when $|\sigma| < 1$ and using the Sherman-Morrison formula to develop $(I - \sigma W)^{-1}$ in its Taylor expansion form (see Fisher, 2011, p.423) and regrouping terms, we obtain for region *i*[5]:

[4] We assume that terms are non-negative, non-stochastic and finite. Thus $0 \leq W_{ij} \leq 1$, $W_{ij} = 0$ if $i = j$ and $\sum_{j=1}^{N} W_{ij} = 1$ for $i = 1 \dots N$.

[5] Where $(I - \sigma W)^{\mathbf{-1}} = \sum_{r=0}^{\infty} (\sigma W)^r = \sum_{r=0}^{\infty} \sigma^r W^r$. In addition, $\sum_{r=0}^{\infty} W^r$ is row standardized, so $\sum_{r=0}^{\infty} W^r \, \Gamma = \Gamma$ and $\sum_{r=0}^{\infty} \sigma^r = 1/1 - \sigma$.

$$A_{i,t} = \Gamma_t^{\frac{1}{1-\sigma}} k_{i,t}^{\gamma_k} h_{i,t}^{\gamma_h+\tau} \prod_{j\neq i}^{N} k_{j,t}^{\gamma_k \sum_{r=1}^{\infty}\sigma^r W_{ij}{}^r} h_{j,t}^{(\gamma_h+\tau)\sum_{r=1}^{\infty}\sigma^r W_{ij}{}^r} \quad (6)$$

Equation (6) indicates that the level of technology in region *i* depends on both its own levels of physical and human capital per worker and those of its neighbours.[6]

Substituting equation (6) in equation (2), we obtain the production function with spatial heterogeneity in the parameters expressed as:

$$y_{i,t} = \Gamma_t^{\frac{1}{1-\sigma}} k_{i,t}^{x_{ii}} h_{i,t}^{z_{ii}} \prod_{j\neq i}^{N} k_{j,t}^{x_{ij}} h_{j,t}^{z_{ij}} \quad (7)$$

where $x_{ii} = \alpha_k + \gamma_k[1 + \sum_{r=1}^{\infty}\sigma^r W_{ii}{}^r]$, $z_{ii} = \alpha_h + (\gamma_h + \tau)[1 + \sum_{r=1}^{\infty}\sigma^r W_{ii}{}^r]$, $x_{ij} = \gamma_k \sum_{r=1}^{\infty}\sigma^r W_{ij}{}^r$ and $z_{ij} = (\gamma_h + \tau)\sum_{r=1}^{\infty}\sigma^r W_{ij}{}^r$.

We can see that if there are no physical ($\gamma_k = 0$) or human capital $[(\gamma_h + \tau) = 0]$ externalities, then the model would be that of MRW (1992).

Now we can characterize the behaviour of each regional economy by describing the dynamics of physical and human capital per worker as:

$$\dot{k}_{i,t} = s_i^k y_{i,t} - (n_i + \delta)k_{i,t} \quad (8)$$

$$\dot{h}_{i,t} = s_i^h y_{i,t} - (n_i + \delta)h_{i,t} \quad (9)$$

Output is divided between consumption of and investment in both types of capital, with s^k and s^h being the fractions of output invested in physical and human capital respectively, both of which are exogenous and constant. Parameter δ represents the depreciation rate, which we assume to be the same for both types of capital. We also assume that the same production function applies to physical capital, human capital, and consumption (MRW, 1992). The dot over a variable indicates its derivate with respect to time.

The production function (7) has diminishing returns to physical and human capital per worker and, as in the Solow model, this implies that each region *i* converges to the balanced growth path[7], a situation in which each variable grows at a constant rate ($\dot{k}_{i,t} =$

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[6] Note that $W_{ij}{}^r$ are the (i, j)-th elements of the matrix W^r.

[7] Our model predicts conditional convergence if the hypotheses for physical capital $\alpha_k + \gamma_k \frac{1}{1-\sigma} < 1$ and human capital $\alpha_h + (\gamma_h + \tau)\frac{1}{1-\sigma} < 1$ are confirmed.

$\dot{h}_{i,t} = g$). Thus equations (8) and (9) imply that the regional economy converges to a steady state defined by:

$$\frac{k^*_{i,t}}{y^*_{i,t}} = \frac{s_i^k}{(n_i+g+\delta)} \quad (10)$$

$$\frac{h^*_{i,t}}{y^*_{i,t}} = \frac{s_i^h}{(n_i+g+\delta)} \quad (11)$$

where $g = \frac{\varphi}{(1-\alpha_k-\alpha_h)(1-\sigma)-\gamma_k-(\gamma_h+\tau)}$.

Next we can obtain the income per worker of region *i* at steady state as follows. First, by rewriting the production function (2) in matrix form, whereby we substitute A by its expression in (4), and pre-multiplying by $(I-\sigma W)$ on both sides and rearranging terms, we can obtain:

$$\boldsymbol{y} = \boldsymbol{\Gamma} + (\alpha_k+\gamma_k)\boldsymbol{k} + (\alpha_h+\gamma_h+\tau)\boldsymbol{h} - \alpha_k\sigma\boldsymbol{Wk} - \alpha_h\sigma\boldsymbol{Wh} + \sigma\boldsymbol{Wy} \quad (12)$$

Secondly, by taking logarithms of equations (10) and (11), substituting in (12) and reordering terms, we can obtain income per labour unit at steady state for region *i* as follows:

$$\begin{aligned} lny^*_{i,t} = {} & \frac{1}{1-u}\ln\Gamma_t + \frac{\alpha_k+\gamma_k}{1-u}lns_i^k + \frac{\alpha_h+\gamma_h+\tau}{1-u}lns_i^h - \frac{u}{1-u}ln(n_i+g+\delta) \\ & - \frac{\sigma\,\alpha_k}{1-u}\sum_{j\neq i}^{N} W_{ij}lns_j^k \\ & - \frac{\sigma\,\alpha_h}{1-u}\sum_{j\neq i}^{N} W_{ij}lns_j^h \\ & + \frac{\sigma(\alpha_k+\alpha_h)}{1-u}\sum_{j\neq i}^{N} W_{ij}ln\left(n_j+g+\delta\right) + \frac{\sigma(1-\alpha_k-\alpha_h)}{1-u}\sum_{j\neq i}^{N} W_{ij}lny^*_{j,t} \end{aligned} \quad (13)$$

where $u = \alpha_k + \alpha_h + \gamma_k + \gamma_h + \tau$.

Our model predicts that regions reach different steady states. As we can see in equation (13), differences in the accumulation of physical and human capital and in the population growth of each region and its neighbouring regions – along with the level of income per worker of the neighbouring regions – determine different regional stationary states.

The dynamics of the transition to the steady state can be analysed by means of the log-linearization of equations (8) and (9) around their steady states. Following Ertur and Koch (2007) and postulating as they do that the gap of region *i* relative to its own steady state is proportional to the corresponding gap for region *j*, the solution for $lny_{i,t}$, subtracting $lny_{i,0}$ from both sides, is:

$$lny_{i,t} - lny_{i,0} = gt - \left(1 - e^{-\lambda_i t}\right)\frac{\varphi}{1-\sigma}\frac{1}{\lambda_i} - \left(1 - e^{-\lambda_i t}\right)lny_{i,0} + \left(1 - e^{-\lambda_i t}\right)lny_i^* \qquad (14)$$

where λ_i is the speed of convergence.

Now we use equations (13) and (14) in matrix form by substituting the first into the second. Next we pre-multiply both sides by $D^{-1}\,(I - \rho W)$ and rearrange the terms to obtain:

$$\boldsymbol{G} = gt\boldsymbol{\zeta}_{(\boldsymbol{N},\boldsymbol{1})} + \frac{1}{1-u}\boldsymbol{D\Gamma} - gt\rho\boldsymbol{DWD^{-1}}\boldsymbol{\zeta}_{(\boldsymbol{N},\boldsymbol{1})} - \boldsymbol{D}y_0 + \frac{\alpha_k+\gamma_k}{1-u}\boldsymbol{DS^k} + \frac{\alpha_h+\gamma_h+\tau}{1-u}\boldsymbol{DS^h} + \rho\boldsymbol{DWy_0} - \frac{\sigma\alpha_k}{1-u}\boldsymbol{DWS^k} - \frac{\sigma\alpha_h}{1-u}\boldsymbol{DWS^h} + \rho\boldsymbol{DWD^{-1}G} \qquad (15)$$

where G is the $(N \times 1)$ vector of growth rates of output per worker; $\zeta_{(N,1)}$ is the $(N \times 1)$ vector of 1; D is the $(N \times N)$ diagonal matrix with $\left(1 - e^{-\lambda_i t}\right)$ terms on the main diagonal; y_0 is the $(N \times 1)$ vector of the initial level of output per worker in logarithms; S^k is the $(N \times 1)$ vector of the saving rates of physical capital divided by $(n + g + \delta)$ in logarithms; S^h is the $(N \times 1)$ vector of saving rates of human capital divided by $(n + g + \delta)$ in logarithms; and $\rho = \frac{\sigma(1-\alpha_k-\alpha_h)}{1-u}$.

Finally, we can rewrite the growth of income per worker equation for region *i* as:

$$
\begin{aligned}
lny_{i,t} - lny_{i,0} = {} & \Omega_i - \left(1 - e^{-\lambda_i t}\right) lny_{i,0} + \left(1 - e^{-\lambda_i t}\right) \frac{\alpha_k + \gamma_k}{1-u} lns_i^k \\
& + \left(1 - e^{-\lambda_i t}\right) \frac{\alpha_h + \gamma_h + \tau}{1-u} lns_i^h - \left(1 - e^{-\lambda_i t}\right) \frac{u}{1-u} ln(n_i + g + \delta) \\
& + \left(1 - e^{-\lambda_i t}\right) \frac{\sigma(1 - \alpha_k - \alpha_h)}{1-u} \sum_{j \neq i}^{N} W_{ij} lny_{j,0} \\
& - \left(1 - e^{-\lambda_i t}\right) \frac{\sigma\, \alpha_k}{1-u} \sum_{j \neq i}^{N} W_{ij} lns_j^k \\
& - \left(1 - e^{-\lambda_i t}\right) \frac{\sigma\, \alpha_h}{1-u} \sum_{j \neq i}^{N} W_{ij} lns_j^h \\
& + \left(1 - e^{-\lambda_i t}\right) \frac{\sigma(\alpha_k + \alpha_h)}{1-u} \sum_{j \neq i}^{N} W_{ij} ln\left(n_j + g + \delta\right) \\
& + \left(1 - e^{-\lambda_i t}\right) \frac{\sigma(1 - \alpha_k - \alpha_h)}{1-u} \sum_{j \neq i}^{N} \frac{1}{1 - e^{-\lambda_j t}} W_{ij} \left(lny_{j,t} - lny_{j,0}\right)
\end{aligned}
\tag{16}
$$

where $\Omega_i = gt + \frac{\left(1-e^{-\lambda_i t}\right)}{1-u} ln\Gamma_t - \frac{\sigma(1-\alpha_k-\alpha_h)}{1-u} gt\left(1 - e^{-\lambda_i t}\right) \sum_{j\neq i}^{N} \frac{W_{ij}}{\left(1-e^{-\lambda_j t}\right)}$

3. The empirical model and data

Assuming $\lambda_i = \lambda$ for all *i,* from equation (16) we can express the empirical model for any region *i* at a given time as,

$$\hat{y}_i = \beta_0 + \beta_1 \ln y_{i,0} + \beta_2 \ln s_i^k + \beta_3 \ln s_i^h + \beta_4 \ln(n_i + g + \delta) +$$

$$+ \theta_1 \sum_{j \neq i}^{N} W_{ij} \ln y_{j,0} + \theta_2 \sum_{j \neq i}^{N} W_{ij} \ln s_j^k + \theta_3 \sum_{j \neq i}^{N} W_{ij} \ln s_j^h +$$

$$+ \theta_4 \sum_{j \neq i}^{N} W_{ij} \ln\left(n_j + g + \delta\right) + \rho \sum_{j \neq i}^{N} W_{ij} \hat{y}_j + \varepsilon_i \tag{17}$$

where $\beta_0 = cte = g + \frac{(1-e^{-\lambda T})}{T(1-u)} ln\Gamma - \frac{\sigma(1-\alpha_k-\alpha_h)}{1-u} g\left(1 - e^{-\lambda T}\right) \sum_{j \neq i}^{N} \frac{1}{1-e^{-\lambda T}} W_{ij}$; $\beta_1 = -\frac{1-e^{-\lambda T}}{T}$; $\beta_2 = \frac{(1-e^{-\lambda T})}{T} \frac{\alpha_k+\gamma_k}{1-u}$; $\beta_3 = \frac{(1-e^{-\lambda T})}{T} \frac{\alpha_h+\gamma_h+\tau}{1-u}$; $\beta_4 = -\frac{(1-e^{-\lambda T})}{T} \frac{u}{1-u}$; $\theta_1 = \frac{(1-e^{-\lambda T})}{T} \frac{\sigma(1-\alpha_k-\alpha_h)}{1-u}$; $\theta_2 = -\frac{(1-e^{-\lambda T})}{T} \frac{\sigma\alpha_k}{1-u}$; $\theta_3 = -\frac{(1-e^{-\lambda T})}{T} \frac{\sigma\alpha_h}{1-u}$; $\theta_4 = \frac{(1-e^{-\lambda T})}{T} \frac{\sigma(\alpha_k+\alpha_h)}{1-u}$; $\rho = \frac{\sigma(1-\alpha_k-\alpha_h)}{1-u}$; ε_i is an error term distributed as $N(0, \sigma^2)$; and *T* denotes the number of periods under consideration (T=19). The circumflex over a variable denotes its growth rate.

Equation (17) contains a spatial lag on the dependent variable and on all the explanatory variables. This kind of specification is known in the literature as a spatial Durbin model (SDM) (LeSage and Pace, 2009) and is supported by the theoretical model developed in Section 2. To carry out a robustness check, this specification is compared with the spatial lag and the spatial error specifications. Table A.1 in the Appendix presents the results of the Lagrange multiplier (LM) tests on spatial dependence and spatial error autocorrelation. Additionally, a common factor test using the likelihood ratios is presented. The results confirm that the SDM specification is preferable to the other alternatives.

The estimation will be carried out for a sample of 121 European regions over the period 1995-2014 using cross-section analysis. The units of observation are NUTS-2 regions located in the following 9 EU countries: Germany, Austria, Belgium, Spain, France, the Netherlands, Italy, Portugal and Sweden. The data for our study are taken from the BD.EURS (NACE Rev.2) regional database (gross value added, employment and investment on physical capital) and from EUROSTAT's regional statistics database (population, education level and education level in S&T)[8]. The endogenous variable is the growth rate of gross value added (GVA) per worker. Table 1 shows the explanatory variables used in the regional growth regressions together with their definitions and data sources. All variables are expressed in logarithms. The initial level of GVA per worker is set in 1995 and captures the convergence through the expected negative sign. Investment in physical capital per worker is proxied by gross fixed capital formation per worker.[9] We take two measures provided by EUROSTAT to proxy investment in human capital: the percentage of population aged 25-64 with tertiary education attainment (high level of education) and the percentage of the labour force with tertiary education employed in science and technology (high level of education employed in science and technology). This second variable more specifically represents the human capital devoted to innovation and is therefore more closely related to the innovative potential of a region (Siller et al., 2021). To proxy the steady-state level we take the average of n_i, s_i^k and s_i^h. The n_i is the logarithm of the average growth rate of the working population over the period 1995-2014 and, as usual in the economic growth literature, we assume that $\delta + g = 0.05$ (MRW, 1992; Ertur and Koch, 2007; Fisher, 2011; Panzera and Postiglione, 2022). We take the average for the period 1995-2014 for investment in physical capital per worker, s_i^k, and the average for the period 2000-2014 for s_i^h due to limited data availability. Table 2 summarizes the main descriptive statistics of the variables. The pairwise correlations can be found in Table A.2 in the Appendix.

[8]The BD.EURS (NACE Rev.2) database is available at https://www.sepg.pap.hacienda.gob.es/sitios/sepg/es-ES/Presupuestos/DocumentacionEstadisticas/Documentacion/Paginas/BasededatosBDEURS.aspx and the EUROSTAT database at https://ec.europa.eu/eurostat/data/database.

[9] Panzera and Postiglione (2022) use the similar extension of the MRW model devised by Fischer (2011), but they take within-region inequality as a proxy for physical capital investment. They assume that a higher level of inequality encourages investment while a redistribution of resources from rich to poor regions has a negative effect on the savings rate and thus the investment rate.

Table 1. Explanatory variables.

	Variable name (in regression)	Definition and sources	Reason for inclusion	Expected sign
Initial GVA per worker	Initial GVA per worker $\ln y_{i,0}$	Level of wealth/development in 1995 BD.EURS	Initial level of income per worker, capturing convergence	Negative would imply conditional convergence/ Positive would imply divergence
Investment in physical capital	Investment share $\ln s_i^k$	Gross fixed capital formation per worker BD.EURS	Proxy for investment in physical capital to represent the steady state	Positive
Investment in human capital	High education level $\ln s_i^h$	Share of population aged 25-64 whose highest education level is tertiary education (ISCED 5_8, PC_1 25-64) EUROSTAT	Proxy for investment in human capital to represent the steady state	Positive
	High education level in S&T $\ln s_i^h$	Share of population aged 25-64 with tertiary education (ISCED 5_8) and employed in science and technology EUROSTAT		Positive
Population growth	n_i	Growth rate of working population BD.EURS	Variable that determines the steady state	Negative
Depreciation rate (K and H)	δ	Effective rate of depreciation $\delta + g = 0.05$		
Balanced growth rate	g			
Matrix of spatial dependence	W_{ij}	Standardized contiguity matrix	$W_{ij} \neq 0$, common borders $W_{ij} = 0$, otherwise	

Table 2. Main descriptive statistics

Variable	Obs.	Mean	Std. dev.	Min.	Max.
GVA per worker growth	121	0.0064	0.0055	-0.0098	0.0223
$\ln y_{,0}$	121	10.8515	0.1953	9.9271	11.2833
$\ln s^k$	121	9.5543	0.1988	8.6881	9.9728
$\ln s^h$ (high level of education)	121	3.0266	0.3719	2.2784	3.7591
$\ln s^h$ (high level of education in S&T)	121	2.7172	0.2960	2.1349	3.3677
ln (population growth (n) + 0.05)	121	-2.8592	0.0965	-3.1112	-2.5459

Returning to the theoretical model developed in Section 2, investment in human capital generates positive externalities by raising the technology level of the regions. In the theoretical model we distinguish between a more general externality represented by parameter γ_h and a specific externality represented by parameter τ. This latter parameter refers to the *learning* mechanism that we assume is more likely to activate in the presence of agglomeration economies. In the economic hubs where these externalities arise, individuals will have more opportunity to interact with other people and therefore to learn and generate new ideas. The potential to develop such a *learning* mechanism makes those metropolitan areas best endowed with human capital and skills the most likely to enjoy higher productivity growth rates.

We are aware that econometrically isolating the *learning* mechanism spillover effect represented by parameter τ is not a straightforward task. This effect is encapsulated within β_3, jointly with the other parameters associated with the impact of human capital on growth, α_h and γ_h. We have therefore devised an econometric strategy to find evidence that such a mechanism may be at work in the European regions and could be giving rise to differences in the economic growth rates of the most densely populated regions compared to the average European region. As we suggested in Section 2, these are places where individuals find more opportunities to be in contact with people with higher skills, thus enabling them to upgrade their own. This is assumed to generate knowledge spillovers that will more effectively increase the technology level of the host regions compared to other regions.

In order to prove the potential of some regions to benefit more than others in terms of economic growth from their investment in human capital, we have constructed a synthetic index that brings together various dimensions associated with agglomeration economies through the use of the following indicators: employment density, total population in metropolitan areas and specialization or location indexes. The first, employment density, is very common in the literature. It enables us to identify areas with a high concentration of economic activity, which represents not only plentiful job opportunities but also a better chance of labour connectivity (Ciccone, 2002). The second, total population in metropolitan areas, aims to capture the spread of urban efficiency gains over the entire region in which the metropolitan area is located. The "efficiency premium" of this urban area tends to spill over into the surrounding area, which "borrows" the benefits of the city but escapes its congestion costs (Alonso, 1973). Following Capello and Cerisola (2020), we take those metropolitan regions (metro-regions) defined by EUROSTAT as NUTS-3 regions that represent all agglomerations of at least 250,000 inhabitants[10] and aggregate them at NUTS-2 level. In our sample, 86 NUTS-2 regions have at least one metro-region, while 35 have none.[11] The third is the specialization or location index (*LQ*), which measures the extent to which a region specializes in

[10] For further information go to https://ec.europa.eu/eurostat/web/metropolitan-regions/background.

[11] If a particular metro-region is shared by more than one NUTS-2 region, the population is assigned to all the NUTS-2 regions involved since all of them benefit from the related agglomeration economies (Capello and Cerisola, 2020).

innovative services compared to the European average. We break specialization down into the three branches of the services sector most associated with the implementation of new technologies: information and communication services (IC), financial services (F) and professional services (P).[12] Of our sample, 27 regions specialize in IC services, 27 in financial services and 45 in professional services.

To build our synthetic index we first need to normalize each of the five indicators (x) using a re-scaling method that ranges them between 0-1.[13] We then aggregate them to obtain the agglomeration index, $I_i^{ag} = \frac{1}{5}\sum_{x=1}^{5} I_i^x$. The values of the I_i^{ag} thus allow us to rank the 121 regions according to a combination of different dimensions related to agglomeration.

The main advantage of our index is that it can consider five criteria simultaneously when selecting the regions where agglomeration benefits are more likely to arise, whereas other classifications usually rely exclusively on just one. Table 3 shows the P75 regions in descending order according to the following criteria: metropolitan region (column 1), employment density (column 2), specialization in IC services (column 3), specialization in financial services (column 4), and specialization in professional services (column 5). The sixth column shows the P75 regions as ordered by the synthetic agglomeration index. The index's multidimensional character gives consistency to our classification and enables us to reconcile the disparities observed when using different selection criteria. For example, as can be seen in Table 3, some of the metropolitan regions in the P75 group such as Andalucia (Spain), Sicilia (Italy), Brandenburg (Germany) and Burgenland (Austria) appear in the metropolitan region (column 1) but not in any of the other four dimensions, and therefore they do not appear in the P75 of our synthetic index. Conversely, a number of Dutch regions including Utrecht, Groningen and Flevoland, which are not included in the P75 metro-region classification, do in fact belong in the P75 of our synthetic index because they score highly in most of the other dimensions. The

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[12] The index is computed as follows: $LQ_{i,j} = \frac{GVA_{i,j}/GVA_{i,s}}{GVA_{EU9,j}/GVA_{EU9,s}}$, where $LQ_{i,j}$ is the location quotient in service industry *j* for region *i*; $GVA_{i,j}$ is the level of gross value added in service industry *j* for region *i*; and $GVA_{i,s}$ is the total gross value added for private services in region *i*. The reference EU9 refers to the total 121 European regions.

[13] We normalize indicator *x* as $I_i^x = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}$, where x_i is the value of indicator *x* for region *i*, and max(x_i) and min(x_i) are the maximum and minimum values for the *x* variable across all regions.

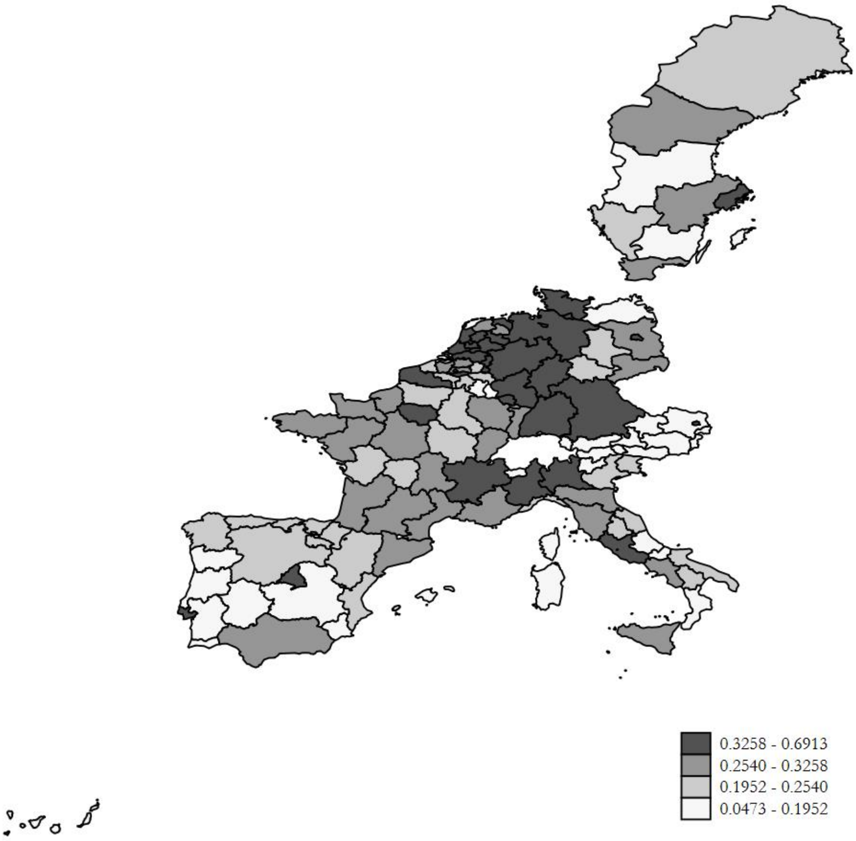
great disparities observed across classifications raise concerns as to the risk of excluding regions with interesting agglomeration economies when using a single criterion.

As can be observed in the last column of Table 3 (I^{ag} ranking), the regions that are home to their country's capital – BE10 (Brussels), DE3 (Berlin), FR10 (Paris), AT13 (Vienna), SE11 (Stockholm), ITI4 (Rome), NL32 (Amsterdam), ES30 (Madrid) and PT17 (Lisbon) – are included in this ranking. The top four regions in the synthetic index simultaneously satisfy all five criteria: Région de Bruxelles, Berlin, Île de France and Hamburg. With the exception of Berlin, these regions tend to be in or around the top ten in terms of labour productivity over the period analysed. There are seven regions with at least four criteria (Nordrhein-Westfalen, Hessen, Baden-Württemberg, Utrecht, Bayern, A. Metro-Lisboa and Lazio), each of which includes large agglomerations comprising important economic, technological and financial centres such as Düsseldorf, Frankfurt, Stuttgart, Utrecht and Munich. Most of the regions that appear in this index include vital logistical and transportation centres like Rotterdam and political centres like The Hague (both NL33), financial centres like Milan (ITC4) and technological hubs like Eindhoven (NL41). In short, 71% of the regions with the highest potential to benefit from agglomeration economies (P75) have high employment density and/or specialize in financial services, 61% host metropolitan regions, and 51% specialize in IC or professional services.

Map 1 represents the regional values for the agglomeration index classified by quartile. The darker the colour, the higher the quartile. The aim of the econometric exercise is to explore the significance of the potential *learning mechanism* in those regions most likely to exhibit agglomeration economies. To this end, we introduce a dummy variable that represents those regions placed in the top quartile (P75) of the distribution of the synthetic index. On the map these particular regions are the most heavily shaded.

Table 3. Regional (NUTS-2) ranking according to individual and synthetic indicators. Percentile P75

Metropolitan region		Employment density		LQ (IC services)		LQ (F services)		LQ (P services)		I^{ag} **ranking**	
DEA	Nordrhein-Westfalen	BE10	Région de Bruxelles	SE11	Stockholm	BE10	Région de Bruxelles	FR10	Île de France	BE10	Région de Bruxelles
FR10	Île de France	AT13	Wien	AT13	Wien	DE7	Hessen	NL23	Flevoland	DE3	Berlin
DE9	Niedersachsen	DE3	Berlin	BE10	Région de Bruxelles	NL12	Friesland (NL)	NL33	Zuid-Holland	FR10	Île de France
DE1	Baden-Württemberg	DE6	Hamburg	NL11	Groningen	DE3	Berlin	DE7	Hessen	DEA	Nordrhein-Westfalen
DE2	Bayern	DE5	Bremen	NL31	Utrecht	DE9	Niedersachsen	DE3	Berlin	DE6	Hamburg
ITC4	Lombardia	FR10	Île de France	FR10	Île de France	DE1	Baden-Württemberg	NL31	Utrecht	DE7	Hessen
ES61	Andalucía	NL33	Zuid-Holland	DE3	Berlin	DE2	Bayern	DE6	Hamburg	DE1	Baden-Württemberg
DE7	Hessen	PT17	A.Metro. Lisboa	SE32	Mellersta Norrland	DE6	Hamburg	DE1	Baden-Württemberg	NL31	Utrecht
ES30	Madrid Com.	NL31	Utrecht	PT17	A.Metro. Lisboa	NL31	Utrecht	FRF1	Alsace	DE2	Bayern
DE3	Berlin	NL32	Noord-Holland	ES30	Com. Madrid	DEC	Saarland	FRC2	Franche-Comté	AT13	Wien
DE4	Brandenburg	ES30	Com. Madrid	DEB	Rheinland-Pfalz	NL32	Noord-Holland	FRK2	Rhône-Alpes	SE11	Stockholm
ES51	Cataluña	DEA	Nordrhein-Westfalen	ITI4	Lazio	DEB	Rheinland-Pfalz	FRE1	Nord–Pas de Calais	DE9	Niedersachsen
DEF	Schleswig-Holstein	NL42	Limburg (NL)	DEA	Nordrhein-Westfalen	DEF	Schleswig-Holstein	NL21	Overijssel	ITC4	Lombardia
FRK2	Rhône-Alpes	BE21	Prov. Antwerpen	ES22	Com. Foral Navarra	NL22	Gelderland	BE31	Prov. Brabant Wallon	NL11	Groningen
FRL0	Alpes-Côte d'Azur	NL41	Noord-Brabant	SE22	Sydsverige	DEA	Nordrhein-Westfalen	NL13	Drenthe	NL33	Zuid-Holland
ITI4	Lazio	DEC	Saarland	DE6	Hamburg	SE11	Stockholm	FRB0	Centre (FR)	ITI4	Lazio
ES52	Com. Valenciana	BE24	Vlaams-Brabant	ITC1	Piemonte	DED	Sachsen	NL11	Groningen	NL23	Flevoland
ITF3	Campania	NL22	Gelderland	DE2	Bayern	DE5	Bremen	FRF3	Lorraine	NL32	Noord-Holland
DE6	Hamburg	ITC4	Lombardia	SE33	Övre Norrland	NL23	Flevoland	NL41	Noord-Brabant	DEB	Rheinland-Pfalz
ITG1	Sicilia	BE23	Oost-Vlaanderen	ES51	Cataluña	NL42	Limburg (NL)	FRD2	Haute-Normandie	ES30	Com. Madrid
BE23	Oost-Vlaanderen	NL21	Overijssel	ITF3	Campania	NL21	Overijssel	FRG0	Pays de la Loire	DEF	Schleswig-Holstein
PT17	A.Metro. Lisboa	SE11	Stockholm	NL32	Noord-Holland	NL33	Zuid-Holland	DE2	Bayern	PT17	A.Metro de Lisboa
DEB	Rheinland-Pfalz	DE1	Baden-Württemberg	ES24	Aragón	ITC4	Lombardia	FRE2	Picardie	NL41	Noord-Brabant
FRE1	Nord–Pas de Calais	BE25	West-Vlaanderen	BE31	Prov. Brabant Wallon	DEG	Thüringen	NL42	Limburg (NL)	ITC1	Piemonte
ITH3	Veneto	DE7	Hessen	FRK1	Auvergne	NL13	Drenthe	FRD1	Basse-Normandie	FRK2	Rhône-Alpes
FRG0	Pays de la Loire	ITF3	Campania	ES21	País Vasco	FR10	Île de France	FRJ2	Midi-Pyrénées	BE31	Brabant Wallon
AT11	Burgenland (AT)	ES21	Com. Valenciana	FRJ2	Midi-Pyrénées	ITI4	Lazio	FRI1	Aquitaine	DEC	Saarland
AT12	Niederösterreich	ITI4	Lazio	SE12	Östra Mellansverige	NL34	Zeeland	DEA	Nordrhein-Westfalen	FRE1	Nord–Pas de Calais
AT13	Wien	BE22	Prov. Limburg (BE)	ES11	Galicia	PT17	A.Metro. Lisboa	BE22	Prov. Limburg (BE)	NL21	Overijssel
ITC1	Piemonte	FRE1	Nord–Pas de Calais	SE23	Västsverige	ITH4	Friuli-Venezia Giulia	BE25	West-Vlaanderen	NL42	Limburg (NL)
BE10	Région de Bruxelles	ITC3	Liguria	BE24	Vlaams-Brabant	ITI1	Toscana	BE24	Vlaams-Brabant	NL22	Gelderland



Map 1. Synthetic agglomeration index (I_i^{ag}). NUTS-2 European regions (EU-9).
Source: Own elaboration

4. Estimation results

Tables 4 and 5 present the estimation results taking into account spatial dependence across the 121 European regions for the period 1995-2014. We take a standardized contiguity matrix to represent the spatial weights W, with $w_{ij} \neq 0$ if two spatial units share a common border and 0 otherwise. The ordinary least squares (OLS) estimation results and the diagnostic tests for normality and heteroskedasticity, and also for spatial dependence, can all be found in Table A.1 in the Appendix.

Table 4 shows the parameter estimates and standard deviations of the SDM specification for 1995-2014.[14] The dependent variable is average labour productivity growth over the period 1995-2014 and the explanatory variables are the initial level of

[14] The estimates have also been carried out using the robust variance estimator, which provides standard errors that are robust to violations of normality, and the results do not change.

labour productivity, average investment in physical capital per worker, investment in human capital and population growth. The estimation of the baseline model (equation 17) uses high education level (column 1) or high education level in science and technology (column 2) to proxy human capital. In the next two columns an interaction is added to each regression. The two proxies of human capital interact with a dummy that represents the P75 regions of our synthetic index I_i^{ag}. The dummy variable will be equal to 1 if the regions are in the P75 percentile and zero otherwise.

We find that the estimated coefficients of almost all the variables included in the two specifications of the baseline model are statistically significant and present the correct signs. The negative sign for the coefficient for the initial level of productivity ($\ln y_{i,0}$) suggests some evidence of conditional β-convergence, i.e. each region converges to its own steady state. The implied value for the speed of convergence (λ) is shown towards the bottom of the table, reaching a rate of around 2%, a normal figure for developed economies. The coefficients of the logarithm of investment in physical and human capital have positive signs and the ln $(n + g + \delta)$ has a negative sign, as predicted by the model.

The interactions of the dummy variable with human capital are introduced to pick up the impact of the *learning* spillover effect, represented by parameter τ in the theoretical model. Columns 3 and 4 show the results of the corresponding regressions. The interaction terms have positive and significant estimated coefficients. This means that investment in human capital in regions with agglomeration economies (P75) has a higher impact on labour productivity growth than in the average region. This positive premium of investment in human capital is observed whenever high education level or high education level in S&T are considered. The same interactions are considered for the central part of the distribution (P25-P75) of index I_i^{ag}. In this case the estimated coefficients are negative and not significantly different from zero.[15] In other words, investment in human capital overperforms only in those regions most likely to develop agglomeration economies, while its impact on the economic growth of the P25-P75 regions does not differ significantly from that observed for the sample as a whole. These results are in line with Capello and Cerisola (2021) and Panzera and Postiglione (2022). The former find that the less developed regions of Europe exhibit a less efficient use of

[15] See Table A.3 in the Appendix. The interaction is also not significant when the regions belonging to the P50-P75 percentile are considered.

human capital than the average region, while the latter find that investment in human capital impacts positively on the economic growth of regions not eligible for the convergence objective, but is not significant for less developed regions that are.

As for the SDM specification, according to the theoretical model all the coefficients of the independent variables have the expected sign except for those associated with initial labour productivity and investment in physical capital, neither of which are significant in any of the four specifications. With regard to the spatial lag of the dependent variable, the parameter estimated presents a significant positive sign in all columns, indicating that a region's labour productivity growth is positively related to that of its neighbouring regions. Consequently, the coefficients estimated from the SDM specification and shown in Table 4 are not as straightforwardly interpretable as in a linear regression. We therefore present the direct, indirect and total impacts of each explanatory variable on labour productivity in Table 5.

Following LeSage and Pace (2009), the direct impact is defined as the average impact of a change in the explanatory variable in a particular region on the dependent variable in that same region. This effect includes not only the magnitude of the change within the region but also the accumulation of feedback influences stemming from its impact on the labour productivity growth of neighbouring regions through positive spatial dependence. The indirect effects represent all potential spatial spillovers arising from changes in the explanatory variables of the neighbouring regions. In our model the investment in physical and human capital unleashes a stream of spillover effects that generates technological dependence across regions.

In Table 5 the estimates of the direct, indirect and total effects are presented along with their respective statistics. Focusing on the initial level of labour productivity, the direct, indirect and total effects all have the negative sign and are statistically significant in all of the specifications. The negative sign is evidence of conditional convergence in each region. Population growth in all four specifications has a significant negative direct effect on labour productivity growth, but a non-significant indirect effect. The latter shows that there is no room for spatial population growth spillovers in any of the specifications and we find that the average total impact is not significantly different from zero.

In the case of investment in physical capital, the average direct and indirect impacts are positive and significant. Thus the average total impacts are also positive and significant, i.e. investment in physical capital has a higher positive effect on growth when the effect of physical capital externalities and spatial technological dependence is taken into account. As for human capital, the direct impact is positive and significant whatever the proxy used in the regression. Increased investment in human capital will bring about an increase in labour productivity growth within the same region. This positive direct impact is very slightly offset by a non-significant negative indirect effect from the other regions, resulting in a positive and significant total impact, although with values lower than those of the direct effect.

In Table 4 the signs and significance of the coefficients of the baseline model (columns 1 and 2) remain largely unaffected by the introduction of the interaction terms in the last two columns. This is not the case with the magnitude of the coefficients for human capital. In columns 3 and 4 the term for the interaction between human capital and the P75 regions lowers the value of the coefficient for human capital compared to the baseline model. It falls from 0.7% (column 1) to 0.5% (column 3) and from 0.9% (column 2) to 0.7% (column 4). This means that the term for the interaction in the P75 regions now captures the greater impact of human capital on labour productivity, and thus the impact on an average region is made smaller. The 0.44% and 0.47% values of the estimated coefficients for the interaction terms should be added to the now lower estimates for the average region, 0.55% and 0.70% respectively. These results indicate the potential of those European regions that are home to large concentrations of population, many of them capital cities, with important business and financial centres, technology hubs, and specializing in services involving more advanced technology, to benefit most from investment in human capital. And, thus with higher potential to generate productivity growth.

Table 4. Regional labour productivity convergence estimates. Period 1995-2014.

	[1]	[2]	[3]	[4]
Initial GVA per worker ($\ln y_{i,0}$)	-0.0158***	-0.0186***	-0.0179***	-0.0200***
	(0.0027)	(0.0028)	(0.0028)	(0.0029)
Investment share ($\ln s_i^k$)	0.0109***	0.0121***	0.0124***	0.0132***
	(0.0025)	(0.0024)	(0.0025)	(0.0025)
High education level ($\ln s_i^h$)	0.0070***		0.0055***	
	(0.0018)		(0.0018)	
High ed. level in S&T ($\ln s_i^h$)		0.0090***		0.0070***
		(0.0020)		(0.0021)
$\ln(n_i + g + \delta)$	-0.0133***	-0.0124***	-0.0153***	-0.0142***
	(0.0046)	(0.0044)	(0.0045)	(0.0043)
Constant	0.0424*	0.0697**	0.0430*	0.0655**
	(0.0254)	(0.0269)	(0.0250)	(0.0263)
P75_I_i^{ag} * High ed. level			0.0044**	
			(0.0020)	
P75_I_i^{ag} * High ed. level in S&T				0.0047*
				(0.0026)
P75_I_i^{ag}			0.0079**	0.0098**
			(0.0031)	(0.0047)
$W_{ij} \ln y_{j,0}$	-0.0026	-0.0016	-0.0013	-0.0004
	(0.0049)	(0.0050)	(0.0048)	(0.0049)
$W_{ij} \ln s_j^k$	0.0063	0.0054	0.0051	0.0042
	(0.0053)	(0.0053)	(0.0051)	(0.0052)
$W_{ij} \ln s_j^h$	-0.0034	-0.0037	-0.0030	-0.0027
	(0.0022)	(0.0024)	(0.0021)	(0.0024)
$W_{ij} \ln(n_j + g + \delta)$	0.0125*	0.0137**	0.0135**	0.0139**
	(0.0069)	(0.0068)	(0.0067)	(0.0067)
$W_{ij}\hat{y}_j$	0.3557***	0.3429***	0.3631***	0.3472***
	(0.1192)	(0.1181)	(0.1169)	(0.1166)
Speed of convergence λ	*0.0188*	*0.0229*	*0.0219*	*0.0252*
Country FE	Yes	Yes	Yes	Yes
N	121	121	121	121
Log-likelihood/N	4.2743	4.2963	4.3092	4.3226

Notes: Maximum likelihood estimates. Standard errors are in parentheses. Coefficients are statistically significant at * p<0.1, ** p<0.05, and *** p<0.01. All variables are in log form. Dependent variable: $\hat{y}_i$, average growth of gross value added per worker (1995-2014). A row-standardized contiguity matrix is used.

Table 5. Direct, indirect and total impact estimates.

Spatial Durbin model	[1]	[2]	[3]	[4]
Average direct impact				
$\ln y_0$	-0.0166***	-0.0193***	-0.0187***	-0.0206***
$\ln s^k$	0.0118***	0.0130***	0.0133***	0.0140***
$\ln s^h$	0.0069***	0.0090***	0.0054***	0.0069***
$\ln(n \quad + g + \delta)$	-0.0126***	-0.0115***	-0.0145***	-0.0134***
Average indirect impact				
$\ln y_0$	-0.0115**	-0.0110**	-0.0110**	-0.0102**
$\ln s^k$	0.0142**	0.0131**	0.0136**	0.0122**
$\ln s^h$	-0.0013	-0.0008	-0.0015	-0.0004
$\ln(n \quad + g + \delta)$	0.0108	0.0130	0.0112	0.0123
Average total impact				
$\ln y_0$	-0.0282***	-0.0304***	-0.0297***	-0.0309***
$\ln s^k$	0.0261***	0.0262***	0.0269***	0.0262***
$\ln s^h$	0.0056***	0.0081***	0.0039**	0.0065***
$\ln(n \quad + g + \delta)$	-0.0017	0.0014	-0.0033	-0.0010

Coefficients are statistically significant at * p<0.1, ** p<0.05, and *** p<0.01.

6. Conclusions

The pattern of economic growth in Europe over the last three decades is characterized by increasing disparities across regions, driven mainly by the high productivity growth found in a handful of very rich regions. In this paper we have extrapolated the idea of the positive relationship between skills and productivity growth in big cities in order to explain the differences in regional labour productivity growth in European regions. To that end we used a spatial version of the MRW model developed by Fischer (2011) to analyse labour productivity growth in the period 1995-2014 in a set of 121 NUTS-2 European regions. We focused especially on introducing the *learning* spillover effect so we could explore the productivity growth of these regions over the period. This effect involves the ability of the most highly agglomerated regions to obtain higher productivity growth from similar levels of investment in human capital as other regions. In the literature this effect is associated with spillovers deriving from connectivity between highly-skilled individuals in the big cities and their interaction with local knowledge amenities. When it applies to a region with high levels of agglomeration, this *learning* spillover effect is thought to increase the region's productivity growth by fostering higher levels of innovation and creativity.

In addition, the theoretical growth model we employ enables us to consider spatial interdependencies among European regions. The results show that the rate of labour productivity growth in a given region is influenced not only by traditional determinants like investment effort, initial productivity and population growth, but also by effects originating from relationships with neighbouring regions.

Our spatial MRW model is estimated using an SDM specification in which labour productivity growth is explained by a set of independent variables and their corresponding spatial lags (initial productivity level, population growth and investment in physical and human capital) plus the growth in labour productivity in neighbouring regions. We find that almost all the coefficients associated with the explanatory variables are statistically significant and present the correct sign. The negative sign of the coefficient for the initial level of labour productivity implies some evidence of conditional β-convergence and reaches a value for the speed of convergence of around 2%. The coefficients of the logarithm of investment in physical and human capital exhibit positive signs, while that for population growth has a negative sign, as predicted by the model. The estimated direct effects of each explanatory variable are significant and have the expected sign, while only the indirect effects of the initial productivity level and physical capital investment are significant. In fact, consistent with Fisher (2011), we observe spatial spillovers from investment in physical capital, while spatial externalities from human capital are absent.

To capture the impact of the spillover effect associated with the *learning* mechanism, which is represented by the parameter τ in the theoretical model, we introduce interactions between the human capital variable and a dummy variable that represents the P75 regions on the basis of a synthetic agglomeration index. The interactions of the dummy variable with human capital always throw up positive and significant values, which means that investment in human capital in the most agglomerated regions generates a positive premium in terms of labour productivity growth. A comparison with regions in the central part of the distribution (P25-P75), for which the interaction is not significantly different from zero, provides additional support for our results.

The econometric specification of the extended version of the MRW, which includes technological interdependence and externalities from investment in physical and human capital, therefore enables us to test the forces behind labour productivity growth in the European regions in the period 1995-2014. The robustness of the coefficient estimates, including the value for the speed of β-convergence and the correct and significant signs of the other explanatory variables, help strengthen and give relevance to the main hypothesis set out at the beginning of the paper, i.e. that agglomerated regions provide a privileged environment in which the *learning* mechanism can operate. This makes them grow faster than the European average by obtaining higher returns from investment in human capital. These results combined with the absence of spatial spillovers from human capital enable us to conclude that human capital today is an important source of divergence across European regions to be considered by economic policy makers.

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APPENDIX

Table A.1. Regional labour productivity convergence, 1995-2014. OLS estimations

Variable	(1)	(2)
$\ln y_{i,0}$ (Initial GVA per worker)	-0.0196***	-0.0231***
	(0.0026)	(0.0025)
$\ln s_i^k$ (Investment share)	0.0156***	0.0168***
	(0.0027)	(0.0026)
$\ln s_i^h$ (High education level)	0.0076***	
	(0.0010)	
$\ln s_i^h$ (High education level in S&T)		0.0099***
		(0.0012)
$\ln(n_i + g + \delta)$	-0.0120***	-0.0097*
	(0.0040)	(0.0038)
Constant	0.0464*	0.0868***
	(0.0273)	(0.0282)
Country FE	Yes	Yes
Observations	121	121
R^2	0.5223	0.5392
Normality tests		
Shapiro –Wilk	1.377*	1.860**
Shapiro –Francia	1.507*	1.988**
Skewness and kurtosis	2.51	7.26**
Heteroskedasticity test		
Breusch-Pagan	1.30	11.84***
Tests for spatial dependence		
Moran's *I* test	4.314	4.549
p-value	[0.000]	[0.000]
LM_{error}	11.902	13.471
p-value	[0.001]	[0.000]
LM_{lag}	19.912	20.930
p-value	[0.000]	[0.000]

Notes: OLS estimation. Standard errors are in parentheses. Coefficients are statistically significant at * p<0.1, ** p<0.05, and *** p<0.01. Dependent variable: $\hat{y}_i$, average growth of gross value added per worker (1995-2014). LM tests are obtained using a row-standardized contiguity matrix with a dimension 121x121.

Following Elhorst (2010) and using the residuals of the OLS estimation, if the LM tests indicate that the spatial error model or the spatial lag model or both are preferable to the OLS model, the SDM model should be estimated. As can be seen towards the bottom of Table A.1, the LM tests are significant and indicate a preference for both spatial specifications.

A spatial error model (SEM) and an SDM model have also been estimated, and the likelihood ratio (LR) test has been used to verify whether the SDM model can be simplified by an SEM model, also known as the common factor hypothesis (LeSage and Pace, 2009). The results for the LR test for baseline specifications (columns 1 and 2 in Table 3) are 11.38 (p-value 0.0226) and 10.85 (p-value 0.0283) respectively. These indicate that the common factor hypothesis ($\theta = -\rho\beta$) should be rejected.

Table A.2. Pairwise correlations

	$\ln y_{,0}$	$\ln s^k$	$\ln s^h$ (high ed. level)	$\ln s^h$ (high ed. level in S&T)	ln(n+ 0.05)
$\ln y_{,0}$	1.0000				
$\ln s^k$	0.7221*** (0.0000)	1.0000			
$\ln s^h$(high ed. level)	0.2528** (0.0052)	0.3800*** (0.0000)	1.0000		
$\ln s^h$ (high ed. level in S&T)	0.3759*** (0.0000)	0.4013*** (0.0000)	0.9320*** (0.0000)	1.0000	
ln (n + 0.05)	0.2827** (0.0017)	0.3573*** (0.0006)	0.3076*** (0.0006)	0.2314** (0.0107)	1.0000

Table A.3. Regional labour productivity convergence estimates. Period 1995-2014.

	[1] SDM	[2] SDM
Initial GVA per worker ($\ln y_{i,0}$)	-0.0167***	-0.0190***
	(0.0028)	(0.0029)
Investment share ($\ln s_i^k$)	0.0114***	0.0122***
	(0.0025)	(0.0025)
High education level ($\ln s_i^h$)	0.0077***	
	(0.0019)	
High ed. level in S&T ($\ln s_i^h$)		0.0095***
		(0.0020)
$\ln(n_i + g + \delta)$	-0.0144***	-0.0137***
	(0.0046)	(0.0044)
Constant	0.0450*	0.0709***
	(0.0261)	(0.0269)
P25/75_I_i^{ag} * high ed. level	-0.0015	
	(0.0018)	
P25/75_I_i^{ag} * high ed. level in S&T		-0.0002
		(0.0024)
P25/75_I_i^{ag}	-0.0033	-0.0015
	(0.0028)	(0.0045)
$W_{ij} \ln y_{j,0}$	-0.0016	-0.0004
	(0.0049)	(0.0050)
$W_{ij} \ln s_j^k$	0.0053	0.0042
	(0.0053)	(0.0053)
$W_{ij} \ln s_j^h$	-0.0030	-0.0033
	(0.0022)	(0.0024)
$W_{ij} \ln(n_j + g + \delta)$	0.0126*	0.0140**
	(0.0069)	(0.0068)
$W_{ij} \hat{y}_{j,t}$	0.3532***	0.3381***
	(0.1187)	(0.1181)
Country FE	Yes	Yes
N	121	121
Log-likelihood/N	4.2868	4.3088

Maximum likelihood estimates. Standard errors are in parentheses. Coefficients are statistically significant at * p<0.1, ** p<0.05 and *** p<0.01. All variables are in log form. Dependent variable: $\hat{y}_i$, average growth of gross value added per worker (1995-2014). A row-standardized contiguity matrix is used.