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# "Factor Accumulation, Externalities and Absorptive Capacity in Regional Growth: Evidence from Europe"

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## Abstract

This paper proposes a model which incorporates capital accumulation and spatial spillovers across economies, while allowing for regional differences in absorptive abilities. This model is estimated using a sample of 215 European NUTS2 regions, before and after the 2004 enlargement of the single-market area. Results confirm the relevance of local absorptive capacities, as are found to be directly linked with the process of making the most of externalities. More than that, capital accumulation externalities do not seem to take place in absence of local capabilities. The process of capital deepening which took place in the period reduced the role of capital in explaining the productivity gap among regions, but so far has not been enough to help lagging regions to equal the return to human capital investments reached by most advanced regions.



***JEL classification:*** C21, O10, R11

***Keywords:*** Regional Disparities, Absorptive Capacity, Technological Interdependence, Spatial Econometrics



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## 1. Introduction

Over the last decades, literature on growth and development has intended to explain the huge disparities in productivity levels among world economies. This field of study is important, because decoding the sources of disparities will surely provide a useful input which should guide the agenda for research and policy advice. As stated by Caselli (2004), if factors were found to account for most of disparities, then development economics should focus on explaining low rates of factor accumulation. In contrast, if efficiency differences are found to play a large role, the task would consist in explaining why some economies are able to extract more output than others from their inputs. Additionally, following the advances in the literature, adding the role of the local context, and that of spillovers into the equation may produce a more global and realistic perspective, in which decoding the interactions among them will surely provide useful information. For instance, if local conditions produce differences in absorptive capacity, then similar policies may produce different results in diverse regions. As an example, in isolated regions with poor local conditions the investment in physical capital may not yield the expected returns, because of inadequate local social-filter and its geographical location, which may make them low exposed to spillovers. This must be taken into account when designing policies, as for example the European cohesion programs, which are oriented to regions which have in common the fact that are poorer in comparison with the core, but that may have differences in geographical locations and local contexts among them.

The enlargement of the European Union (EU) towards the countries of the Centre and East (hereafter CEE countries) provided a challenge to the regional cohesion policy. With the inclusion of 10 countries[1] in 2004 plus Bulgaria and Romania in 2007, the EU became a 27-country single-market area. As many of the these countries had at that time income levels around 40 per cent of the EU mean, the enlargement increased the inequalities and produced the replacement of the former North/South polarization towards a new North-West/East pattern (Mora et al, 2004; Ertur and Koch, 2006). In that context, it seems worth to study the sources behind the evolution of inequalities of the whole area before and after the 2004 enlargement. Dispersion in Gross Domestic Product (GDP) per head had been reduced since late-nineties to 2008, but despite that, inequalities persist, and have even increased within some CEE countries (European Commission, 2010; Monastiriotis, 2011).

In the past numerous articles have studied regional convergence in Europe, either through beta-convergence growth regressions (see for instance Barro and Sala-i-Martin, 1991; Neven and Gouyette, 1994; Sala-i-Martin, 1996; López-Bazo, 2003; López-Bazo et al, 2004; Mora et al, 2005; Koch, 2010; Monastiriotis, 2011) or through the kernel-density distribution approach (Neven and Gouyette, 1994; Quah, 1996; López-Bazo et al, 1999; Mora et al, 2004; López-Bazo, 2003; Magrini, 2004; Bosker, 2009; among others). Some of them have also incorporated the spatial dimension to their analysis, which was found to play a crucial role. The relevance of the

[1] The 2004 enlargement process included Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia and Slovenia.

[2] Benhabib and Spiegel (1994) estimated several growth accounting regressions considering human capital as a conventional input, which was found to enter insignificantly, and almost always with a negative coefficient.

[3] It should be stressed that the same notation ($h$, $A$ and $\Omega$) used so far to denote human capital, technology and its exogenous component is used from this point on to denote their logarithmic

spatial patterns in the distribution of wealth and poverty in Europe makes that regional studies should take this characteristic into account.

The openness of CEE economies prompted the inflows of external capital through Foreign Direct Investment (FDI), as stated by Bijsterbosch and Kolasa (2009) and European Commission (2010). For that reason, capital deepening and technological catch-up should not be analysed in isolation, as capital accumulation through FDI may also act as vehicle for economic restructuring and technological diffusion (Bijsterbosch and Kolasa, 2009). Because of that, the reference model should consider not only capital accumulation as an engine of growth, but also additional sources, for example a learning-by-doing process (Arrow, 1962). Additionally, according to Klenow and Rodriguez-Clare (2005), FDI flows have a relation with geographical distance, therefore spatial dependence should also be considered. The incidence of geography can take place through other channels. In this sense, trade-related flow of ideas across countries is believed to be another channel of geography incidence in spillovers (Coe and Helpman, 1995; Koch, 2008; Rodriguez-Pose and Crescenzi, 2008). The strength of these spillovers can be seen, for instance, as related to the intensity of trade between economies (Coe and Helpman, 1995). In that sense, geography is again expected to play an important role in the process of technological diffusion. For all those reasons, spatial interactions should be considered as additional sources of spillovers. Finally, these externalities may not always be incorporated automatically by those concerned, as there can be regional differences in the absorptive capacities of regions. This may be reflected through a wide range of social and institutional conditions, constituting a social-filter which may include educational achievements, productive employment of human resources, and demographic structure (Rodriguez-Pose and Crescenzi, 2008).

In the light of the reduction of income disparities which took place in period 1999-2007 (as stated by European Commission, 2010), the analysis in this paper focuses in decoding its sources (capital intensity and/or technological catch-up), and in the role played by the local context (through absorptive capacity) in the process of making the most of externalities. In this context, the strategy followed by this paper is twofold. On the one hand, a theoretical model is proposed, consisting in an extension of the framework developed by Ertur and Koch (2007) and Koch (2008, 2010), but advancing a further step, as it allows for differentials in local absorptive capacities. In a second step, that model is fitted for the European regions in the period 1999-2008. Finally, the estimate of the parameters of the model is used to perform a development accounting exercise, following Easterly and Levine (2001), intending to find how much of the gap between rich and poor EU regions can be attributed to differences in physical capital, and how much can be attributed to technology.

This paper is structured as follows: section 2 reviews the literature and proposes a theoretical model which takes into account externalities across regions and supposes that regions differ in their abilities to make the most of that spillovers; section 3 introduces the data and descriptive analysis; section 4 resumes the estimation results, elasticity analysis and capital decomposition; and finally section 5 briefly concludes.

## 2. Theoretical Framework

### 2.1 Brief literature review

From a theoretical perspective, the Solow (1956) model supposed an exogenous process for technological improvements. In that context, neoclassical theorists tended to assume that the level and growth rate of productivity was roughly the same across economies, hence disparities were mainly explained by differences in saving rates and capital stocks (Klenow and Rodriguez-Clare, 1997). This was later challenged, as it gained momentum the idea that relying only on capital differences was not enough to explain disparities across economies. In particular, this prompted the appearance of endogenous growth theories, which intended to explain disparities by endogenizing technology (see for instance Romer, 1990; or Grossman and Helpman, 1991).

In the following years, externalities started to gain consensus as an important aspect to explain disparities. In particular, Klenow and Rodriguez-Clare (2005) described international knowledge externalities as critical to understand growth and development. More than that, they stated that models without externalities were unable to explain some empirical patterns. Additionally, they indicated that the observed differences across countries in Total Factor Productivity (TFP) did not necessarily imply that factor accumulation was a small part of income differences, because TFP disparities may be explained itself by differences in factor intensity. In other words, capital contributed directly as an input, but also indirectly, by boosting technology adoption. Some growth models that incorporate knowledge externalities were developed by Romer (1986, 1990); Lucas (1988, 2004); and Aghion and Howitt (1992), among others.

In this process, technology diffusion became an important aspect of the growth and development literature, and it began to be linked to local absorptive capacity. For instance, Bernard and Jones (1995) stated the importance of technology progress and its diffusion for the growth process of economies, and that differences in absorptive abilities may be the reason behind the existence of different steady states among economies. Some years before, absorptive capacity differentials were already mentioned by some authors, as Nelson and Phelps (1966), who stated that higher education levels speeds the process of technological diffusion. Their approach assigned an indirect role for human capital (through its incidence in technology), rather than the more conventional consideration of human capital as an input. They also added that the inclusion of human capital as an input may be a misspecification of its role. In the same line, Benhabib and Spiegel (1994) stated that the ability of an economy to adopt and implement external technology depended on its human capital stock.

Technological diffusion soon became linked with geography: for instance Keller (2002) found that technological spillovers were local, not global, as the benefits from foreign externalities decreased with distance. The idea of spatially bounded spillovers; in addition to the stylized fact of a spatial distribution of wealth and poverty in the world; plus the development of the New Economic Geography literature (see for instance Krugman, 1991); made the spatial dependence patterns almost impossible to ignore in the analysis. In recent years, López-Bazo et al (2004), Fingleton and López-Bazo (2006), Ertur and Koch (2007), and Koch (2008, 2010) proposed growth models which explicitly accounted for spatial dependence and externalities.

From an empirical point of view, there is a diversity of studies which have made important contributions. For instance, some empirical findings suggest that cross country differentials in physical capital accounted for a small part of disparities in income per capita. In particular, Denison (1962, 1967) found that differences in the level of physical capital per capita only accounted for about 25 per cent of the differences in income per capita across a sample of industrialized countries. In the same line, King and Levine (1994) found for a sample of 102 countries that capital accounted for around the half of disparities.

On the other hand, other authors found some empirical evidence which suggested some sort of "neoclassical revival", as disparities were found to be mainly accounted for by factor accumulation. Examples are Mankiw et al (1992), who argued that the Solow model explained an important part of income levels when augmented to incorporate human capital; and Young (1994, 1995), who studied the "miracle" of the eastern Asian countries in the second half of the twentieth century and concluded that it was mainly a case of factor accumulation.

In recent years, the empirical analysis performed by Koch (2008) showed that incorporating spatial externalities to the analysis made physical capital to increase dramatically its contribution, accounting in some cases for 90 per cent of the development gap among a sample of 91 countries in 1995. He concluded that neglecting the spatial interactions may potentially bias the role of physical capital in the development process. His model, however, did not account for differences in local absorptive capacity. It may also be the case that the contribution of factor accumulation and that of technology to disparities across region differ from those across countries. This paper, building upon Koch model, intends to incorporate local absorptive capacity as a relevant issue for explaining the sources of disparities between regions.

### 2.2 A Model with externalities and absorptive capacity differentials

As stated before, we build our model on that proposed by Ertur and Koch (2007) and Koch (2008), in which for each regional economy $i$ a Cobb-Douglas production function exhibits constant returns to scale in labour ($L$) and physical capital ($K$):

$$Y_i = A_i K_i^{\alpha} L_i^{1-\alpha} \tag{1}$$

The aggregate level of technology in $i$, $A_i$, depends on some proportion of exogenous technology, common to every region, ($\Omega$), and also on learning-by-doing physical capital externalities and on technological interdependence between economies:

$$A_i = \Omega k_i^{(\emptyset + \lambda h_i)} \prod_{j \neq i}^{N} A_j^{(\gamma w_{1ij} + \delta h_i w_{2ij})} \tag{2}$$

where $k_i$ is defined as physical capital per worker, since as pointed out by Ertur and Koch (2007), knowledge is supposed to be embodied in physical capital per worker and not in levels, in order to avoid scale effects. $h_i$ represents endowment of human capital per worker, which intends to measure regional differences in the abilities to adopt and implement technological externalities, whereas $w_{1ij}$ and $w_{2ij}$ denote the measures of the amount of interaction between regions $i$ and $j$, that may be similar or different.

The production technology in this paper does not consider thus human capital as a conventional input. Instead, human capital is incorporated as an argument of the aggregate level of technology. There have been some papers which were unable to find a significant impact of human capital as a standard input[2]. On the other hand, Nelson and Phelps (1966) and Benhabib and Spiegel (1994) found evidence of human capital incidence through technology, as it constitutes an important element to be able to incorporate technological advances generated abroad. In this spirit, our model incorporates human capital as a measure of local absorptive capacity. It is understood that part of the learning-by-doing externalities may have an impact on technology regardless of the level of human capital, because even if workers are not highly embodied with education, they may still learn something in the process (this effect is measured through the parameter $\emptyset \geq 0$). At the same time, this learning process will be accelerated the higher the skills of the workers (this is measured through $\lambda \geq 0$). In a similar way, absorptive capacity will play a key role in the technological interdependence across economies. As before, it is assumed that some benefit is obtained from interaction regardless of human capital ($\gamma \geq 0$), but the absorptive capacity will be enhanced with higher levels of skills ($\delta \geq 0$).

Therefore, in contrast with the specification for the aggregate level of technology in Ertur and Koch (2007) and in Koch (2008), we assume that the effect of externalities from capital accumulation in region $i$ on its level of technology depends positively on the existing stock of human capital in that region. The same applies in the case of technical progress generated elsewhere. Its effect on the level of technology in region $i$ is assumed to depend on its absorptive capacity that, in turn, is determined by the endowment of human capital. The model in the above-mentioned papers imposes a similar rate of absorption in all regions regardless of the endowment of human capital. In such a case, $\lambda = \delta = 0$. Instead of imposing such a constraint, in this paper we advocate the existence of differences across regions in the absorptive capacity linked to the availability of human capital in each region.

The interpretation of the parameters in (2) is the key of the model. If $\emptyset = 0$ ($\gamma = 0$), then learning-by-doing (technological spatial interdependence) will not take place in the absence of skilled workers. At the same time, $\lambda = 0$ ($\delta = 0$) will reflect a negligible role of human capital in enhancing learning-by-doing (interregional technological spillovers). On the contrary, if $\lambda > 0$ and/or $\delta > 0$, regions highly endowed with human capital will have higher capacity for technology adoption. Similarly, poor regions will face difficulties in catching-up with the rich areas unless they are endowed with a certain level of human capital. If learning-by-doing externalities were verified, then a capital deepening process will indirectly produce a technology improvement in the economy, making a two-source growth process (for instance, convergence as a result of capital stock and technological catch-up). Finally, if $\emptyset = \lambda = \gamma = \delta = 0$, the specification is the original model proposed by Solow (1956), whereas, as mentioned above, the one in Ertur and Koch (2007) and Koch (2008) results if $\lambda = \delta = 0$. In the former case, capital deepening does not have an impact on technological catch-up, while in the latter it takes place but regardless of the availability of skilled labour in each region.

[2] Benhabib and Spiegel (1994) estimated several growth accounting regressions considering human capital as a conventional input, which was found to enter insignificantly, and almost always with a negative coefficient.

Technological spatial spillovers imply that regions must be analysed as an interdependent system. In doing so, it is convenient to write down the model in matrix terms for a system with $N$ regions, and to express the variables in (1) in units of labour (output and physical capital in per-worker terms), and log-linearized. Thus, hereafter, $y$, $k$, $A$, and $\Omega$ denote the vectors with the logarithms of output per worker, capital per worker, aggregate level of technology, and the common-to-all-regions technology. In turn, $h$ denotes a diagonal matrix whose elements are the regional endowment of human capital[3]. Thus, technology in (2) can be re-written in log matrix terms as:

$$A = \Omega + (\emptyset I + \lambda h)k + (\gamma W_1 + \delta h W_2)A \qquad (3)$$

where:

$$A = \begin{pmatrix} A_1 \\ A_2 \\ \vdots \\ A_N \end{pmatrix} \quad \Omega = \begin{pmatrix} \Omega \\ \Omega \\ \vdots \\ \Omega \end{pmatrix} \quad h = \begin{pmatrix} h_1 & 0 & \dots & 0 \\ 0 & h_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & h_N \end{pmatrix}$$

$$k = \begin{pmatrix} k_1 \\ k_2 \\ \vdots \\ k_N \end{pmatrix} \quad W_s = \begin{pmatrix} 0 & w_{s12} & \dots & w_{s1N} \\ w_{s21} & 0 & \dots & w_{s2N} \\ \vdots & \vdots & \ddots & \vdots \\ w_{sN1} & w_{sN2} & \dots & 0 \end{pmatrix}$$

and $w_{sij}$ (for $s = 1{,}2$) measures frictions between regions $i \neq j$. The reasoning behind the specification of the elements in $W_s$ is that knowledge embodied in one region spills over the others but does so with intensity that diminishes with friction. The more intense is the connection of region $i$ with region $j$, the lower is the friction between the two, and the higher $w_{sij}$. That is to say, the higher is the potential benefit of region $i$ from spillovers generated in $j$.

Equation (3) can be expressed as:

$$A - (\gamma W_1 + \delta h W_2)A = \Omega + (\emptyset I + \lambda h)k \Rightarrow (I - \gamma W_1 - \delta h W_2)A = \Omega + (\emptyset I + \lambda h)k$$

which can be rearranged, provided that $(I - \gamma W_1 - \delta h W_2)$ is invertible, as:

$$A = (I - \gamma W_1 - \delta h W_2)^{-1}\Omega + (I - \gamma W_1 - \delta h W_2)^{-1}(\emptyset I + \lambda h)k \qquad (4)$$

As it can be seen in (4), the level of technology is affected by physical capital externalities and by spatial interactions. Also, it shows that a region's ability to absorb and adopt innovations generated elsewhere affects its level of technology: regions with higher endowments of human capital are expected to make more profit from externalities.

Replacing (4) in the log-linear version of (1) with the variables in units of labour results in:

$$y = (I - \gamma W_1 - \delta h W_2)^{-1}\Omega + (I - \gamma W_1 - \delta h W_2)^{-1}(\emptyset I + \lambda h)k + \alpha k \qquad (5)$$

[3] It should be stressed that the same notation (*h*, *A* and *Ω*) used so far to denote human capital, technology and its exogenous component is used from this point on to denote their logarithmic transformation. We took this option to prevent complicating the notation.

Pre-multiplying both sides by $(I-\gamma W_1-\delta hW_2)$:

$$(I-\gamma W_1-\delta hW_2)\,y=\Omega+(\emptyset I+\lambda h)k+\alpha(I-\gamma W_1-\delta hW_2)k$$

After some rearrangements, this yields:

$$y=\Omega+(\emptyset+\alpha)k+\lambda hk-\alpha\gamma W_1k-\alpha\delta hW_2k+\gamma W_1y+\delta hW_2y \tag{6}$$

This expression shows that under the assumption of interregional externalities whose strength is a function of the absorptive capacity of each region, local productivity depends on local physical capital, on the productivity and physical capital of other regions, and also on all these variables in interaction with local human capital. As a result, the change in local productivity induced by capital deepening in a region is affected by externalities within the region and from other regions, and by its endowment of human capital. Interestingly, local productivity is also expected to vary with capital deepening in the other regions as a result of technological diffusion that cross regional borders. Formally speaking, output-physical capital elasticities from (5) are defined as:

$$\xi_k\equiv\frac{\partial y}{\partial k}=\alpha I+(I-\gamma W_1-\delta hW_2)^{-1}(\emptyset I+\lambda h) \tag{7}$$

where $I$ denotes the $NxN$ identity matrix.

$\xi_k$ is an $NxN$ matrix with the elasticity of output per worker in each region with respect to its own level of physical capital per worker and with the elasticities with respect to physical capital per worker in all the other regions. These elasticities depend on the capital share in income, on the learning-by-doing process, and on spatial interactions, through the spatial multiplier $(I-\gamma W_1-\delta hW_2)^{-1}$. Also, from (7) it is clear that elasticities will be higher in those regions endowed with higher levels of human capital, *ceteris paribus*. All in all, in comparison to the Solow model, the existence of externalities across regions increases the effect of capital on productivity. And with respect to Ertur and Koch (2007) and Koch (2008), differences in absorptive capacity, through the availability of skilled individuals, make some regions more prone to incorporate innovations originated elsewhere and thus to improve their level of technology.

As for the effect of changes in the endowment of human capital on productivity, the corresponding elasticities are defined as:

$$\xi_h\equiv h\left(\frac{\partial y}{\partial h}\right)=h((I-\gamma W_1-\delta hW_2)^{-1}(\delta W_2)(I-\gamma W_1-\delta hW_2)^{-1}\Omega$$
$$+(I-\gamma W_1-\delta hW_2)^{-1}(\delta W_2)\,(I-\gamma W_1-\delta hW_2)^{-1}(\emptyset I+\lambda h)k$$
$$+(\delta W_2)(I-\gamma W_1-\delta hW_2)^{-1}\lambda k \tag{8}$$

$\xi_h$ is an $Nx1$ vector whose elements are the elasticities of output per worker in each region with respect to the own level of human capital. These elasticities depend not only on the human capital stock, but also on the physical capital stock and on the spatial interactions, through the spatial multiplier.

Finally, it needs to be mentioned that the inclusion of the mechanism of absorptive capacity modifies the decomposition of the gap in the level of output per worker suggested by Easterly and Levine (2001), and adapted to the case of the existence of spillovers across economies by Koch (2008). Defining $\kappa$ as the log of the capital-output ratio, and $y^*, \kappa^*, and\ h^*$ as $y, \kappa\ and\ h$ in relative terms with respect to a reference region, equation (5) can be expressed as:

$$y^* = (I - \gamma W_1 - \delta h^* W_2)^{-1}\Omega + (\alpha I + (I - \gamma W_1 - \delta h^* W_2)^{-1}(\emptyset I + \lambda h^*))(\kappa^* + y^*)$$

Defining a diagonal matrix $D$ whose elements are the output per worker in each region in relative terms with respect to the reference region, and pre-multiplying both sides of the previous equation by the inverse of $D$ results in:

$$D^{-1}y^* = D^{-1}(I - \gamma W_1 - \delta h^* W_2)^{-1}\Omega + (\alpha D^{-1} + D^{-1}(I - \gamma W_1 - \delta h^* W_2)^{-1}(\emptyset I + \lambda h^*))\kappa^* + \alpha 1 + (D^{-1}(I - \gamma W_1 - \delta h^* W_2)^{-1}(\emptyset I + \lambda h^*))y^*$$

where $\alpha 1$ is a column vector of with all elements equal to $\alpha$. After some arrangements, the contribution of capital to the gap in the level of development is obtained as:

$$\Upsilon_k = \alpha 1 + (\alpha D^{-1} + D^{-1}(I - \gamma W_1 - \delta h^* W_2)^{-1}(\emptyset I + \lambda h^*))\kappa^* + (D^{-1}(I - \gamma W_1 - \delta h^* W_2)^{-1}(\emptyset I + \lambda h^*))y^* \quad (9)$$

As in Koch (2008), the contribution of physical capital depends on three terms: the capital share in the income, the capital-output ratio, and finally the spatial distribution of productivity. However, in the second and third terms in (9), the region's ability to adopt technology enhances the influence of capital, as it strengths the externalities.

In order to easier comparisons, the percentage gap in output for each region $i$ relative to a reference region $r$ is calculated:

$$GAP_i = 100 \times \frac{(Y/L)_i - (Y/L)_r}{(Y/L)_r} \quad (10)$$

Then, for a given region $i$, the contribution of capital to accounting for disparities with respect to the reference region is $\Upsilon_{ki} \times GAP_i$.

### 3. Data and Descriptive Analysis

Our empirical exercise aims at providing evidence on the effect of spatial spillovers and differences in absorptive capacity in the level of productivity of the EU regions. To estimate the coefficients in equation (6) we used data on Gross Value Added (GVA) per worker and on the physical capital stock per worker for all sectors (both measured in constant 2000 Euros), from the Cambridge Econometrics database. As for the absorptive capacity, it was proxied by a measure of human capital. In particular, following the previous literature which indicates that high skills are a requisite to assimilate new technology (Manca, 2011; Leiponen, 2005) we opted for using data on the percentage of workers with tertiary-level education over the whole workforce. The source of the data for this variable is the Eurostat Regio database. However, the lack of available data for the share of high skilled workers imposed some constraints in terms of the sample of regions included in the analysis as well as for the time period under consideration. Among the first 15-entry countries, regional data on the share of workers with tertiary education is not available for Denmark, Sweden, and Luxembourg. In turn, such information is only available for 4 of the CEE countries that acceded the EU in 2004: the Czech Republic, Hungary, Poland, and Slovakia. Finally, no regional data on educational attainment is available yet for a long-enough period for Bulgaria and Romania, the two countries that joined the EU in 2007. Still, the lack of data for some regions before 1999 forced us to define the period under analysis from this year to 2008, that is the last year covered so far by the Regio database.

**Table 1: Variables description**

| Variable | 1999 | | | | 2008 | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Standard Deviation | Maximum | Minimum | Mean | Standard Deviation | Maximum | Minimum |
| Log of GVA per worker | 3.513 | 0.594 | 4.249 (Inner London) | 1.887 (Podkarpackie) | 3.636 | 0.522 | 4.504 (Inner London) | 2.202 (Lubelskie) |
| Log of Physical capital per worker | 4.819 | 0.490 | 5.480 (Oberbayern) | 3,206 (Podkarpackie) | 4.996 | 0.477 | 5.743 (Flevoland) | 3.434 (Lubelskie) |
| Human Capital | 0.204 | 0.091 | 0.460 (Inner London) | 0.021 (Provincia Autonoma Bolzano / Bozen) | 0.275 | 0.086 | 0.564 (Inner London) | 0.084 (Severozápad) |

All in all, the sample included 215 NUTS2[4] regions from 16 EU countries for the period between 1999 and 2008 (the complete list of regions is detailed in the appendix). Some simple summary statistics of the variables under analysis are provided in Table 1 for the beginning and the end of the period under analysis, whereas Figures 1 and 2 plot the corresponding estimates of the density functions, as a way of summarising the characteristics of the entire regional distribution of these variables. As already reported by the previous literature, our descriptive results confirm the existence of sizeable disparities in labour productivity that persist over the period under analysis. The gap, in log terms, between the most and the less productive regions in the sample (Inner London and Podkarpackie) was 2.36 in 1999, similar to that observed in 2008 between Inner London and Lubelskie (the region with the lowest level of productivity that year), which was 2.30. Interestingly, the gap in capital per worker was of a similar order of magnitude: 2.27 between Oberbayern and Podkarpackie in 1999, and 2.31 between Flevoland and Lubelskie in 2008[5]. The comparison of the measure of absorptive capacity also reveals marked regional differences, with Inner London as the region that all over the period made the most intensive use of high skilled labour.

[4] French acronym for Nomenclature for Territorial Statistical Units used by Eurostat

[5] Due to its particular industrial mix, specialized in highly productive services that do not make extensive use of physical capital, Inner London was not the region with the highest capital-labour ratio despite being that with the highest level of labour productivity.

The estimated density functions in Figures 1 and 2 reveal that disparities went beyond those for the regions with the highest and lowest values for the variables under analysis. The one corresponding to labour productivity reveals a bimodal distribution, with an important amount of regions near the core, and a less numerous but distant group at the left which constitutes a periphery (mainly of CEE regions). The distance between the two modes is rather high and remained stable over the period under analysis. In turn, the density of capital per worker has a long left-tail but without a clear mode in that area, which indicates larger dispersion for values below the average than in the case of productivity. In fact, the comparison of the densities for the two variables suggests that polarisation in the distribution of productivity was not just caused by the distribution of the capital-labour ratio. In agreement with our hypothesis in this paper, differences in the level of technology and in the absorption capacity might well have played a role. The density for the measure of absorptive capacity, the share of workers highly endowed with human capital, provides preliminary support to this hypothesis, since it reveals a substantial mass of probability at the left of the distribution, corresponding to regions with much lower endowments of human capital. It is worthwhile noting that the increase in the endowment of education in the entire EU over the period under analysis caused a shift to the right in the distribution which, in any case, did not prevent the presence of strong regional disparities in the share of workers with tertiary education in 2008.

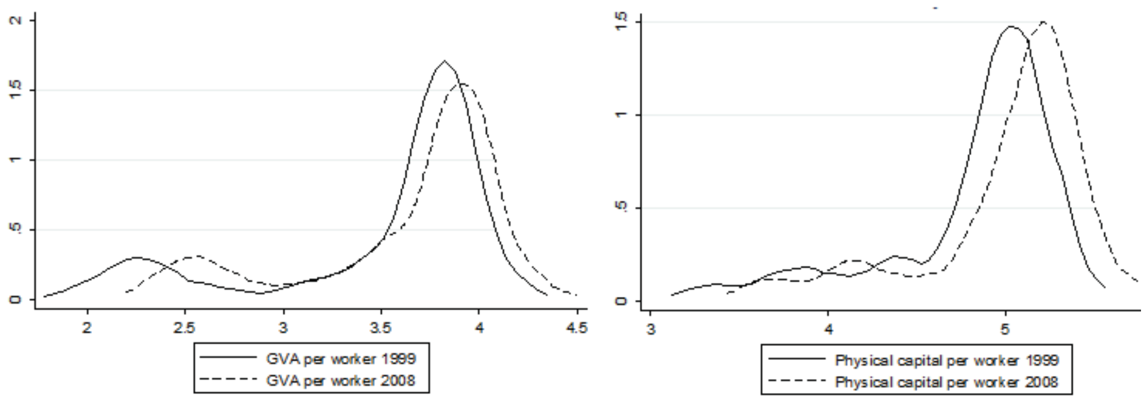


**Figure 1: Kernel density distribution of GVA per worker (left) and physical capital per worker (right)**

As an additional element of the simple descriptive analysis in this section, we want to mention that the distribution of the variables under analysis is characterised by a clear geographical or spatial pattern.

The representation in maps of labour productivity, capital per worker, and the measure of human capital (not included here to save space but available from the authors) provides the well-known core-periphery pattern commonly reported for the EU.

Broadly speaking, the lowest levels of productivity, physical capital, and human capital are found in the south and CEE regions, while the highest levels are seen in the traditional core.

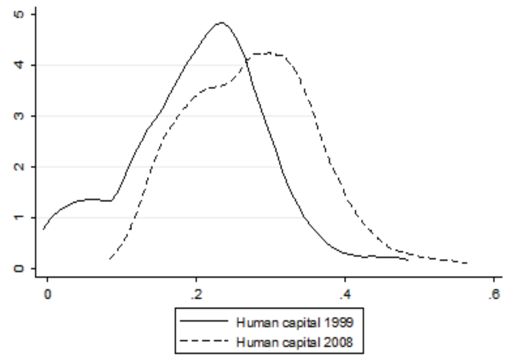


**Figure 2: Kernel density distribution of human capital**

This results in a distribution of the variables that is characterised by strong spatial dependence. Using the Moran's I and Geary's C statistics to measure the strength of the spatial association, and a square-distance inverse weight matrix (row-normalized)[6], the figures in Table 2 clearly confirm the positive spatial correlation for all variables for 1999 and 2008.

**Table 2: Spatial Autocorrelation Statistics**

| Year | Statistic | Log GVA (per worker) | Log Capital (per worker) | Human capital |
|---|---|---|---|---|
| 1999 | Moran's I | 0.618*** | 0.523*** | 0.505*** |
| | Geary's C | 0.384*** | 0.451*** | 0.550*** |
| 2008 | Moran's I | 0.600*** | 0.550*** | 0.499*** |
| | Geary's C | 0.387*** | 0.427*** | 0.580*** |

Note: (***) represents significance at 1 per cent

## 4. Results

Equation 6 includes spatial lags of both endogenous and exogenous variables. For that reason, Ordinary Least Squares (OLS) estimations will not be consistent. An alternative method is Maximum Likelihood, which can ensure the desired properties of the estimations. As the empirical equation has non-linear restrictions, the estimation procedure must take this fact into account. For that reason, the estimation process will incorporate the transformation to four pseudo-regressors, allowing the incorporation of the nonlinear constraints (the complete explanation of the estimation procedure is detailed in the appendix). These complexities

[6] Similar results were reached in all cases using first-order contiguity and 250 kilometers cut-off weight matrices (not shown here to save space).

required of manual programming for the estimation, which meant that the calculation was performed on cross-section basis rather than panel data estimations.

Estimation of equation (6) requires a few previous definitions. In particular, as stated by LeSage and Pace (2009), $W_1$ and $hW_2$ are required to be not functionally related. That technical limitation prevents using the same weights matrix for $W_1$ and $W_2$. As a result, it will be supposed that for spatial externalities that do not rely on local absorptive capacity, interaction will take place with its closest neighbours. For that reason, $W_1$ will be represented by a first-order contiguity matrix. For technological externalities that are dependent on local human capital levels, it will be assumed that interactions have a higher scope, taking place among regions within a radius of 250 kilometres, following Moreno et al (2005) and Rodriguez-Pose and Crescenzi (2008)[7]. As a result, $W_2$ will be represented by a 250km cut-off matrix. Matrices $W_1$ and $W_2$ may still share some overlapping data, but this is not believed to be a problem, as $W_2$ is pre-multiplied by $h$, and the resulting matrix $hW_2$ appears to be sufficiently differentiated with $W_1$ to avoid identification problems[8].

Another important definition is the normalization procedure for the referred matrices, considering the required stability condition of $|I - \gamma W_1 - \delta h W_2| > 0$. In similar cases of two-weight matrices affecting the endogenous variable, a common approach is to row-normalize each matrix (Lacombe, 2004; LeSage and Pace, 2009). In this case that is not desirable, because to row-normalize $hW_2$ means to get rid of the term $h$, as the same values multiply every element of each row. A solution in this case is to follow Beck et al (2006), and to joint-normalize both matrices, so that the rows of both matrices $w_{1i}$ and $h_i w_{2i}$ sum to one.

The estimation results are exposed in Table 3, for years 1999, 2002, 2005 and 2008. Lagrange multiplier contrasts to detect remaining spatial dependence cannot be applied in this case due to the model non-linearity, therefore a Moran's I analysis was performed to the residuals after each regression, with results suggesting no further spatial dependence in any case. Additionally, the Breusch-Pagan (Koenker modified) contrast suggested some heteroskedasticity problems for the 1999 estimation, so the results from that year must be taken with caution[9]. No major heteroskedasticity problems were found for the rest of estimations (for 2002 equation rejection of the null hypothesis is obtained only at 10 per cent).

A first look at the results confirms a high value for $\alpha$, averaging 0.78 for the four years of analysis. This is higher than the typical capital share in income in national accounts, usually one-third (as found by Koch, 2010), but closer to Koch (2008) results of 0.46-0.52 for a Spatial Durbin Model, and 0.68-0.70 for a Spatial Error Model (although Koch works with a different sample, consisting of 91 countries).

[7] Rodriguez-Pose and Crescenzi (2008) suggest a threshold of a 3-hour drive for innovation spillovers.

[8] To check the robustness of the results, the inverse combination for $W_1$ and $W_2$ was also tested, but reported lower likelihood.

[9] This situation is not believed to be a problem, because standard deviations are similar to the other estimations, as well as the coefficient values which look reasonable in the comparison.

**Table 3: Maximum Likelihood Estimation Results**

| | 1999 | 2002 | 2005 | 2008 |
|---|---|---|---|---|
| Constant | -0.215** | -0.217* | -0.193* | -0.186* |
| | [0.104] | [0.122] | [0.115] | [0.111] |
| $\emptyset$ | 0.032 | 0.017 | 0.007 | 0.000 |
| | [0.093] | [0.103] | [0.105] | [0.108] |
| $\lambda$ | 0.036 | 0.075*** | 0.081*** | 0.084*** |
| | [0.025] | [0.026] | [0.023] | [0.022] |
| $\alpha$ | 0.772*** | 0.782*** | 0.782*** | 0.783*** |
| | [0.060] | [0.071] | [0.073] | [0.078] |
| $\gamma$ | 0.918*** | 0.902*** | 0.888*** | 0.895*** |
| | [0.029] | [0.039] | [0.042] | [0.052] |
| $\delta$ | 0.753*** | 0.609*** | 0.622*** | 0.482*** |
| | [0.023] | [0.026] | [0.027] | [0.028] |
| Log Likelihood | 137.32 | 134.76 | 145.38 | 149.64 |
| Moran's I | 0.019 | 0.013 | 0.012 | 0.014 |
| Breusch-Pagan | 16.81*** | 8.25* | 4.99 | 1.30 |

Note: Standard deviations in brackets. Standard deviation for the implied parameter $\emptyset$ computed using the delta method. Moran's I is computed over the residuals. (*), (**) and (***) mean significant at 10 percent, 5 percent and 1 percent.

Another important confirmation is the presence of both kinds of externalities affecting the TFP: learning-by-doing and spatial interaction. In the first year of analysis, 1999, learning-by-doing externalities are not significant; but that must be considered with caution, because that regression reported some heteroskedasticiy problems, as stated before. Despite that setback, the pattern is clear: $\emptyset$ is never significant, while $\lambda$ is significant at 1 per cent in all the following estimations. This means that human capital seems to have a direct role in the absorption of spillovers from capital accumulation. This may explain why in Koch's articles the parameter $\emptyset$ is not significant in its estimations[10], because in absence of interaction with local conditions these externalities do not seem to have an incidence on technological levels. This result appears to suggest that high skilled workforce is essential to obtain a high return on physical capital investment. This means that two economies which have made a similar investment in physical capital may have a different return depending of its human capital endowment. Significance of $\lambda$ implies a higher return for physical capital investment for those regions with highest skilled workforce. This means that both types of capital are complementary. This may have some important consequences for regional development, as regions with poor human capital endowment (especially from the periphery) will have little technological benefit from capital accumulation spillovers and as a result will face difficulties to catch-up. As stated before

[10] Koch (2010) found $\emptyset$ to be not significant in European regions, while Koch (2008) estimated six regressions for 91 countries, varying weight matrices and depreciation rates, and only in one case $\emptyset$ was significant, at a 10 percent level (p-value of 0.094).

some peripheral regions received important amount of FDI during the period. It can be supposed that these capital flows were mostly endowed with advanced technology (in contrast to local stocks), and in the light of this results, possibly only the relatively good human capital-endowed regions have been able to make the most of that advances.

With respect to spatial spillovers, both measures ($\gamma$ and $\delta$) are significant at 1 per cent in all estimations, showing the spatial dependence present among European regions. The direct measure $\gamma$ averages stable values of 0.9, while the measure which incorporates absorptive capacity through human capital $\delta$ descends from 0.75 in 1999, to 0.48 in 2008[11]. This trend should not be seen as a decreasing role of local abilities, because average levels of human capital increase during the period. In any case, it seems that there is a more intense transmission of technology not related to local capabilities. These results confirm that not all regions are able to incorporate to the same degree the externalities, as differences in absorptive capacity exist and seem to play a crucial role.

### a. Elasticity Analysis

The calculation of physical and human capital elasticity, through respectively equations (7) and (8), is an effective way to consider the degree of different returns among regions. This is important to analyse how local conditions and geographic location can have an incidence in the returns to investment in physical and human capital. Additionally, human capital investment returns in a region will also be conditioned to its endowment of physical capital per worker, something which will constitute a limitation to overcome for lagging regions.

As a result, each region has its own individual elasticity level. For that reason, the elasticity results will be exposed as regional averages for three groups: Core, South and CEE regions[12]. Equation (7) gives an indication of the elasticity after an increase in physical capital in a local specific region (the diagonal elements of the resulting matrix) or after an increase in physical capital in other regions (after which can be computed the overall elasticity of an increase in physical capital in each other region). This latest overall elasticity measure reflects the interregional spillovers generated as a result of the spatial interaction among regions.

Physical capital measures exposed at Table 4 reflect that CEE regions reach similar levels of elasticity as the core or the south. Another interesting fact is that in 1999 there were overall social increasing returns to capital for all groups, although that was later reversed and in 2008 results were in the order of 0.86-0.88, which can still be considered as high levels. This suggests that externalities help to counteract in some degree the effect of decreasing returns.

As seen in equation (8), human capital elasticity depends on both measures of capital, and as a result the disparities in physical capital endowment among regions have an incidence in the returns to investments in human capital. The higher levels are reached by the core, followed respectively by southern and CEE regions. As stated before, low levels of human capital

[11] These values ensure stability as the required condition of $|I - \gamma W_1 - \delta h W_2| > 0$ is verified

[12] Core: regions from Belgium, Germany, France, Netherlands, Austria, Finland, Ireland, United Kingdom; South: regions from Greece, Spain, Italy and Portugal; CEE: regions from Czech Republic, Hungary, Poland and Slovakia.

elasticity for peripheral regions (especially CEE regions) seem to be explained by low endowment of physical capital per worker. In the case of southern regions, geographic distance may also constitute a limitation for having lower returns to human capital investment than the core.

**Table 4: Average Productivity Elasticities**

| Elasticity | Group of Regions | 1999 | 2002 | 2005 | 2008 |
|---|---|---|---|---|---|
| $\xi_k$ (local) | Core | 0.825 | 0.827 | 0.819 | 0.814 |
| $\xi_k$ (local) | South | 0.834 | 0.828 | 0.817 | 0.810 |
| $\xi_k$ (local) | CEE | 0.823 | 0.819 | 0.810 | 0.805 |
| $\xi_k$ (all regions) | Core | 1.042 | 0.945 | 0.911 | 0.871 |
| $\xi_k$ (all regions) | South | 1.123 | 0.987 | 0.929 | 0.887 |
| $\xi_k$ (all regions) | CEE | 1.079 | 0.952 | 0.903 | 0.862 |
| $\xi_h$ (local) | Core | 0.072 | 0.260 | 0.313 | 0.322 |
| $\xi_h$ (local) | South | -0.020 | 0.173 | 0.229 | 0.292 |
| $\xi_h$ (local) | CEE | -0.450 | -0.152 | -0.096 | 0.036 |

Note: Local refers to the percentage of productivity variation after a 1 per cent increase in an average local region of the respective group. Overall refers to the percentage of productivity variation in an average region after a 1 per cent increase in every region.

An interesting pattern is the increasing trend of human capital elasticity levels through the years, which is more pronounced in the southern and especially in CEE regions. The important increase in human capital elasticity reached by CEE regions may reflect that in 1999, these economies were still in the early stages of the transition from communism, and as a result human capital improvements were unable to make a significant contribution. In the following years, after the openness process which prompted important FDI inflows, an increase in physical capital endowment and with a more suitable institutional framework, these regions were able to start extracting positive returns to human capital. This may reflect a case of skilled biased technical change, which is a shift in the technology that favours skilled labour by increasing its relative productivity. This interpretation goes in the same direction as the conclusions reached in some other studies, as for example Esposito and Stehrer (2007), who found evidence of this process in Hungary and Poland between 1995 and 2003[13]. In a lesser degree, southern regions may still have undergone through a similar process, reaching higher returns to human capital while its development increased through the years.

Figure 3 represents the kernel density of physical capital elasticity. Local elasticity distribution (Figure 3, left) seems to be less concentrated in 2008, and the right tail of regions with high returns appears to have been reduced. Overall elasticity distribution (Figure 3, right) seems to be much more concentrated in 2008, although persist a group of regions with higher returns.

[13] This process happened previously in developed countries. In particular, Berman et al (1997) found evidence of skilled-biased technical change for OECD countries after 1979.

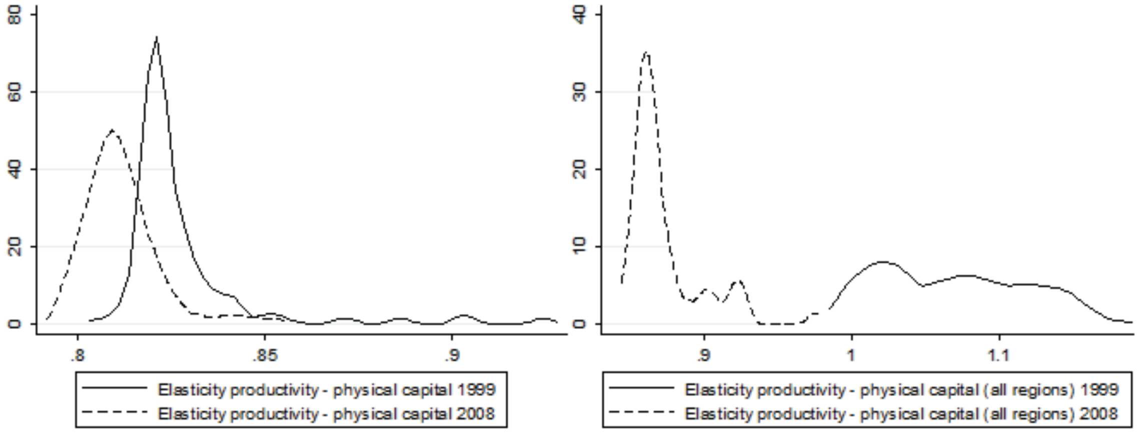


**Figure 3: Kernel densities for elasticities: local (left) and overall (right) physical capital**

Human capital elasticity seems to have been increased on average between 1999 and 2008 (Figure 4). Especially the left tail which was registered in 1999 seems to have been hugely reduced in 2008.

This may me the result of some lagging regions reaching improvements in its physical capital endowment, which may had an incidence in human capital elasticity. Despite the capital intensity process, CEE regions remain with considerable lower returns to human capital in comparison with richer regions, as seen in Table 4.

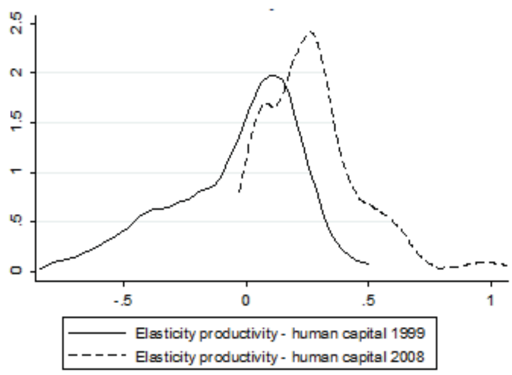


**Figure 4: Kernel density for human capital elasticity**

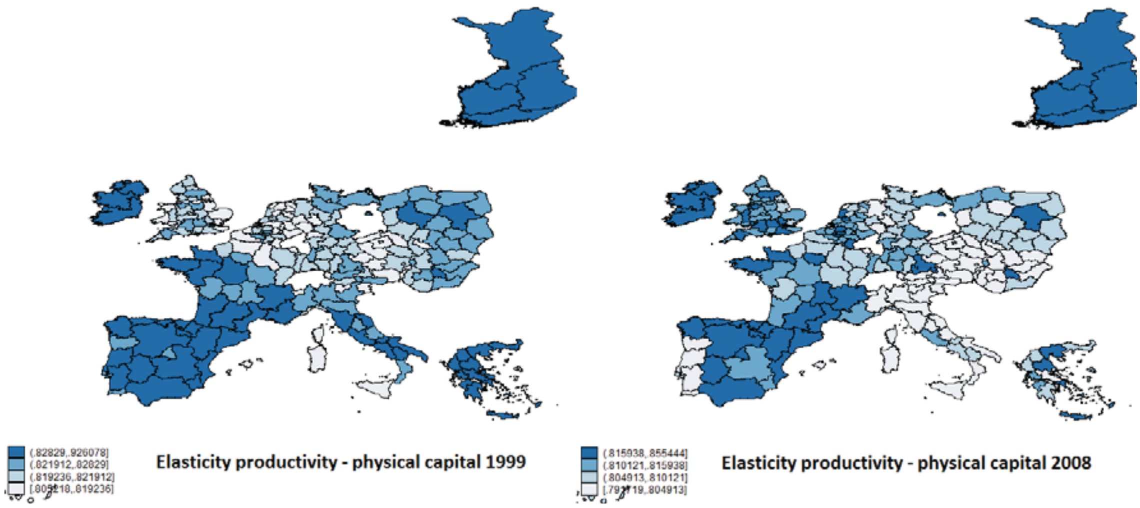


**Figure 5: Productivity – physical capital elasticity 1999 (left) and 2008 (right)**

Figure 5 resumes physical capital elasticity levels for each region. It is clearly seen that in 1999 highest returns were reached in peripheral regions (Portugal, Spain, southern France, southern Italy, Greece, CEE regions), in contrast to lower levels reached in northern France, Germany, Netherlands or UK. This fact, which clearly suggested the role of diminishing returns, was later relativized in 2008, as some lagging regions (Portugal, Italy, CEE) reached on average lower returns to the core.

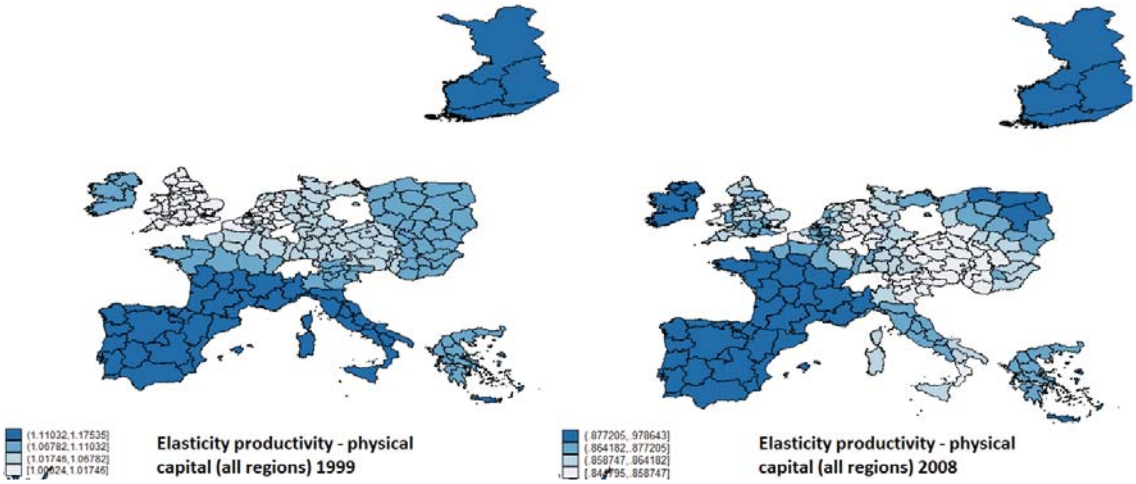


**Figure 6: Productivity – physical capital elasticity (all regions) 1999 (left) and 2008 (right)**

Figure 6 reflects overall levels of elasticity considering an increase in physical capital levels in every region. Evidence suggests higher returns for some peripheral regions. In the case of CEE regions, returns seem to be slightly lower than in some southern regions, perhaps as a result of lower human capital endowment.

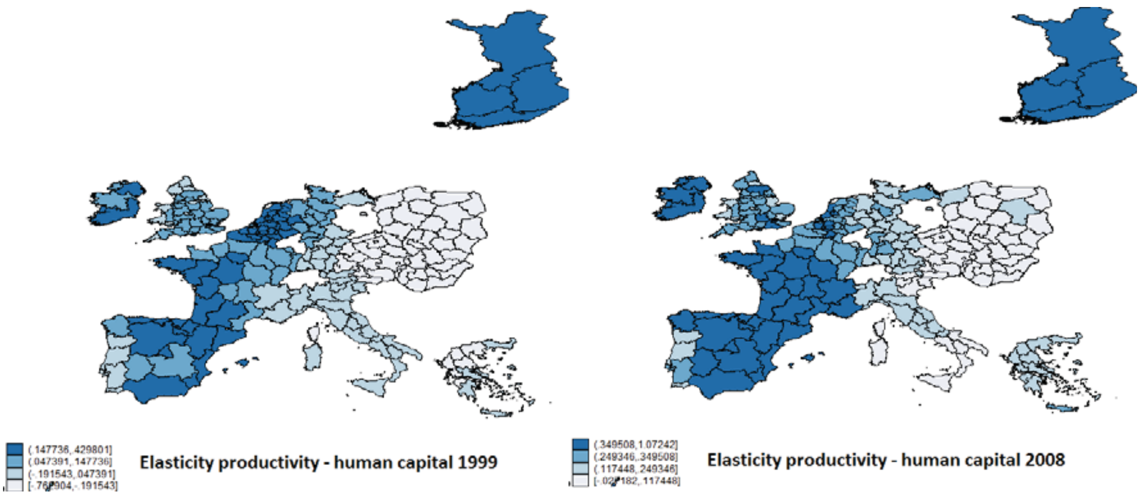


**Figure 7: Productivity – human capital elasticity 1999 (left) and 2008 (right)**

Figure 7 resumes results for human capital elasticity. Clearly physical capital endowment has an important incidence on human capital elasticity, something which can be seen in the case of CEE regions. The incidence of physical capital endowment in the returns to investments in human capital constitutes a limitation to some lagging regions, mainly from CEE but also to Portuguese, Greek and southern Italian regions.

In the case of CEE, many of its regions registered a capital intensity process between 1999 and 2008, but that accumulation does not appear to have been so far enough to allow them reach the returns from richer regions.

### b. Capital decomposition

With the estimation results exposed in section 4, the capital decomposition referred in equation (9) can be performed. The main objective of this analysis is to find out how much of the gap between rich and poor regions can be attributed to differences in physical capital. Average levels for the richest decile were taken as the "reference region", and the analysis was performed by different groups of regions. Average results by deciles are exposed in Figure 8; while averages by CEE, south and core groups of regions are exposed in Figure 9.

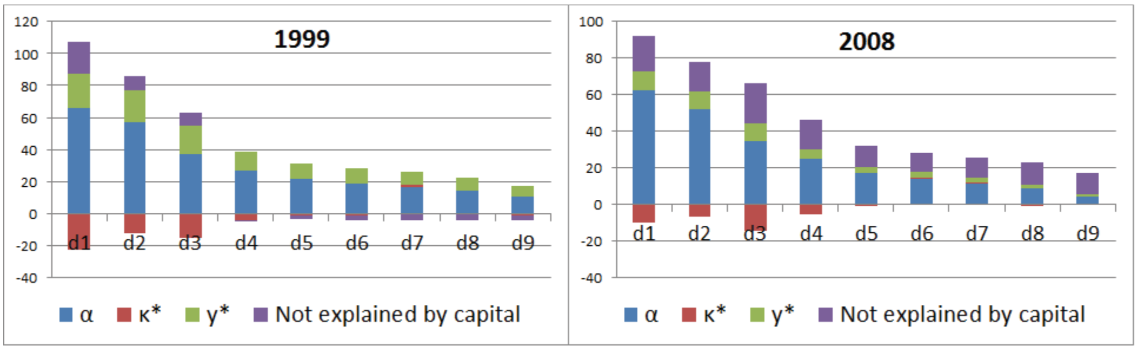


**Figure 8: Capital contribution 1999 (left) and 2008 (right) – averages by decile**

Figure 8 suggest that for poorer regions (deciles 1, 2 and 3), an important amount of the gap to the richer decile is explained by capital, but there is also a considerable portion explained by efficiency differentials, especially in 2008. On average, in 2008 the amount of the gap explained by capital differentials it's slightly reduced in comparison with 1999; instead there is an increasing portion of the gap not explained by capital. This may be the result of the economic integration process, which registered a capital intensity process for some lagging regions. For middle income and richer regions (deciles 5 and onwards), almost all of the gap to the richest decile was explained by capital in 1999, while in 2008 efficiency disparities have a much bigger role, sometimes accounting for half of the gap. Negative contribution of capital-output ratio in some regions may be the result of lesser physical capital requirements for highest value-added activities in the richest regions. Capital-output ratio seems to be lower for high value added industrial activities and highly productive services. Negative contribution of capital-output ratio for the poorest deciles may be related to lesser industrialization in those regions. Capital share in income ($\alpha$) contribution appears to be very important in all cases, while the $y^*$ component contribution is lower and seems to decrease between 1999 and 2008.

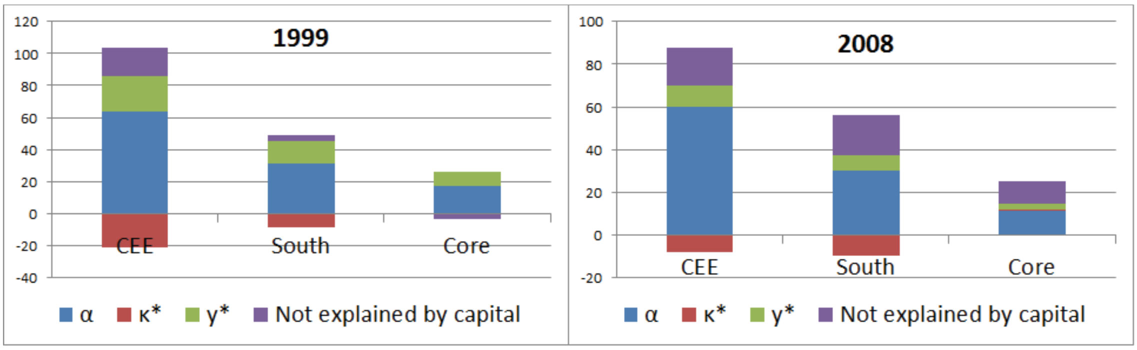


**Figure 9: Capital contribution 1999 (left) and 2008 (right) – averages by groups of regions**

Figure 9 indicates differences among groups of regions. Biggest gap with respect to the richest decile is clearly seen for CEE regions, and in this case physical capital contribution seems to have been slightly reduced between 1999 and 2008. In the case of southern and core regions, in 1999 the gap was mainly explained by physical capital differentials, but in 2008 seem to appear some considerable efficiency differentials as well. As in the analysis by decile, capital share in income $(\alpha)$ contribution appears to be very important in all cases, while the $y^*$ component contribution is lower and seems to decrease between 1999 and 2008.

To sum up, EU regions are not homogeneous in their relative contribution of physical capital/efficiency to the gap with the richest decile. The capital intensity process appears to be related to the fact that disparities are more explained by efficiency differentials in 2008 than in 1999.

## 5. Conclusions

In this paper a theoretical model was presented, which combined externalities and differences in local absorptive capacities. The idea behind was that externalities have a crucial role in development, but not all economies are able to make the most of those spillovers, as local absorptive capacity is relevant. Estimation results for a sample of 215 European NUTS2 regions confirmed the important role of local absorptive capacities, as well as the relevance of externalities in explaining cross-sectional differences. Physical capital contributes to explain productivity disparities, not only through the capital share in the economy, but also because of the capital-income ratio and externalities. As a result, capital has a bigger role than in some previous studies, but in this case there are important regional efficiency differentials as well.

In the case of regions of CEE, despite the recent capital intensity process and economic integration, these regions will need to be better endowed in physical capital to be able to reach higher returns to human capital investments and to be able to achieve some technological catch-up. Regardless of that, an increase of factor endowment at the periphery may contribute to reduce disparities, but this will be slow because of geography: most of peripheral regions are far from the spillover influence of the core.

These conclusions may derive in some policy implications. In first place, peripheral regions seem to have different necessities, given the geographic locations and the heterogeneous distribution of physical and human capital. As a result, EU policies towards lagging regions should be designed taking into account the specific necessities of each region. As an example, Ertur and Koch (2006) stated the necessity to assign different treatment to lagging regions depending on its geographical location. In that sense, regions situated farther away should be specially considered. Finally, as stated by López-Bazo et al (2004), regional or national policy-makers should also take into account the fact that some initiatives may spill-over to other regions. In this context, coordinated actions (instead of individual efforts) may help to counteract the poverty trap generated by geographical location of lagging regions.

As a final remark, some extensions can be proposed for future research. In first place, the model developed allows the analysis of some further counterfactual scenarios. As an example, a simulation can be performed intending to analyse what would have happened to TFP and productivity distribution if southern and/or central regions can reach similar levels of physical and/or human capital as the core. Additionally, given the fact that only the better positioned regions of the south and CEE appear to be benefiting from integration, another interesting simulation will be to study what would have happen if lagging regions from peripheral areas had physical and human capital levels of the richest regions of those countries. In that case, the disparities emerging from that counterfactual scenario will reflect mainly the incidence of geographic location.

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**Appendix**

**Sample of Regions**

Belgium: Région de Bruxelles-Capitale / Brussels Hoofdstedelijk Gewest; Prov. Antwerpen; Prov. Limburg (BE); Prov. Oost-Vlaanderen; Prov. Vlaams-Brabant; Prov. West-Vlaanderen; Prov. Brabant Wallon; Prov. Hainaut; Prov. Liège; Prov. Luxembourg (BE); Prov. Namur.

Czech Republic: Praha; Strední Cechy; Jihozápad; Severozápad; Severovýchod; Jihovýchod; Strední Morava; Moravskoslezsko.

Germany: Stuttgart; Karlsruhe; Freiburg; Tübingen; Oberbayern; Niederbayern; Oberpfalz; Oberfranken; Mittelfranken; Unterfranken; Schwaben; Berlin; Bremen; Hamburg; Darmstadt; Gieben; Kassel; Mecklenburg-Vorpommern; Braunschweig; Hannover; Lüneburg; Weser-Ems; Düsseldorf; Köln; Münster; Detmold; Arnsberg; Saarland; Schleswig-Holstein; Thüringen.

Ireland: Border; Midland and Western; Southern and Eastern.

Greece: Anatoliki Makedonia, Thraki; Kentriki Makedonia; Dytiki Makedonia; Thessalia; Ipeiros; Ionia Nisia; Dytiki Ellada; Sterea Ellada; Peloponnisos; Attiki; Voreio Aigaio; Notio Aigaio; Kriti.

Spain: Galicia; Principado de Asturias; Cantabria; País Vasco; Comunidad Foral de Navarra; La Rioja; Aragón; Comunidad de Madrid; Castilla y León; Castilla-la Mancha; Extremadura; Cataluña; Comunidad Valenciana; Illes Balears; Andalucía; Región de Murcia; Canarias (ES).

France: Île de France; Champagne-Ardenne; Picardie; Haute-Normandie; Centre (FR); Basse-Normandie; Bourgogne; Nord - Pas-de-Calais; Lorraine; Alsace; Franche-Comté; Pays de la Loire; Bretagne; Poitou-Charentes; Aquitaine; Midi-Pyrénées; Limousin; Rhône-Alpes; Auvergne; Languedoc-Roussillon; Provence-Alpes-Côte d'Azur; Corse.

Italy: Piemonte; Valle d'Aosta/Vallée d'Aoste; Liguria; Lombardia; Provincia Autonoma Bolzano/Bozen; Provincia Autonoma Trento; Veneto; Friuli-Venezia Giulia; Emilia-Romagna; Toscana; Umbria; Marche; Lazio; Abruzzo; Molise; Campania; Puglia; Basilicata; Calabria; Sicilia; Sardegna.

Hungary: Közép-Magyarország; Közép-Dunántúl; Nyugat-Dunántúl; Dél-Dunántúl; Észak-Magyarország; Észak-Alföld; Dél-Alföld.

Netherlands: Groningen; Friesland (NL); Drenthe; Overijssel; Gelderland; Flevoland; Utrecht; Noord-Holland; Zuid-Holland; Zeeland; Noord-Brabant; Limburg (NL).

Austria: Burgenland (AT); Niederösterreich; Wien; Kärnten; Steiermark; Oberösterreich; Salzburg; Tirol; Vorarlberg.

Poland: Lódzkie; Mazowieckie; Malopolskie; Slaskie; Lubelskie; Podkarpackie; Swietokrzyskie; Podlaskie; Wielkopolskie; Zachodniopomorskie; Lubuskie; Dolnoslaskie; Opolskie; Kujawsko-Pomorskie; Warminsko-Mazurskie; Pomorskie.

Portugal: Norte; Algarve; Centro (PT); Lisboa; Alentejo.

Slovakia: Bratislavský kraj; Západné Slovensko; Stredné Slovensko; Východné Slovensko.

Finland: Itä-Suomi; Etelä-Suomi; Länsi-Suomi; Pohjois-Suomi; Aland.

United Kingdom: Tees Valley and Durham; Northumberland and Tyne and Wear; Cumbria; Cheshire; Greater Manchester; Lancashire; Merseyside; East Yorkshire and Northern Lincolnshire; North Yorkshire; South Yorkshire; West Yorkshire; Derbyshire and Nottinghamshire; Leicestershire, Rutland and Northamptonshire; Lincolnshire; Herefordshire, Worcestershire and Warwickshire; Shropshire and Staffordshire; West Midlands; East Anglia; Bedfordshire and Hertfordshire; Essex; Inner London; Outer London; Berkshire, Buckinghamshire and Oxfordshire; Surrey, East and West Sussex; Hampshire and Isle of Wight; Kent; Gloucestershire, Wiltshire and Bristol/Bath area; Dorset and Somerset; Cornwall and Isles of Scilly; Devon; West Wales and The Valleys; East Wales; Northern Ireland (UK).

**Empirical specification and estimation procedure**

It can be assumed that for every region, the exogenous component of the TFP can be decomposed into a constant term, and a region-specific shock. As a result, (6) can be expressed as:

$$y = \mu + (\emptyset + \alpha)k + \lambda hk - \alpha\gamma W_1 k - \alpha\delta h W_2 k + \gamma W_1 y + \delta h W_2 y + \varepsilon$$

where $\varepsilon$ constitutes the $Nx1$ vector of perturbations. The model to be estimated is close to a spatial-Durbin model, as it includes spatial lags of both endogenous and exogenous variables. For that reason, Ordinary Least Squares (OLS) estimations will not be consistent. An alternative method is Maximum Likelihood, which under the compliance of some conditions[14] ensures the desirable properties of consistency, efficiency and asymptotic normality (Anselin, 1988).

As the empirical equation has non-linear restrictions, the estimation procedure must take this fact into account. For that reason, the estimation process will be similar to the proposed by Vayá et al (2004). With some rearrangement, the empirical equation can also be expressed as:

$$(I - \gamma W_1 - \delta h W_2)y = \mu + (\emptyset + \alpha)k + \lambda hk - \alpha(\gamma W_1 + \delta h W_2)k + \varepsilon$$

For different combination of values of $\gamma \geq 0$ and $\delta \geq 0$, the Nx4 matrix of pseudo-regressors $X_0$ is computed:

[14] It is required the existence of the log-likelihood for the parameter values under consideration, continuous differentiability of the log-likelihood, boundedness of various partial derivatives, the existence of positive definiteness and/or non-singularity of covariance matrices, and the finiteness of various quadratic forms (Anselin, 1988). According to Lee (2004), the quasi-maximum likelihood estimators of the Spatial Autoregressive Model can also be considered if disturbances are not truly normally distributed.

$$X_0 = \begin{pmatrix} 1 & k_1 & h_1 k_1 & \gamma \sum_{j=1}^{N} w_{11j} k_j + \delta h_1 \sum_{j=1}^{N} w_{21j} k_j \\ \vdots & \vdots & \vdots & \vdots \\ 1 & k_N & h_N k_N & \gamma \sum_{j=1}^{N} w_{1Nj} k_j + \delta h_N \sum_{j=1}^{N} w_{2Nj} k_j \end{pmatrix}$$

This transformation to four pseudo-regressors allows the incorporation of the nonlinear constraints. As a result, the logarithm of the likelihood function is:

$$\ln L = \ln|I - \gamma W_1 - \delta h W_2| - \frac{N}{2} \ln \sigma^2$$
$$- \frac{1}{2\sigma^2} [(I - \gamma W_1 - \delta h W_2) y - X_0 \beta]' [(I - \gamma W_1 - \delta h W_2) y - X_0 \beta]$$

where $\beta$ is a vector of parameters. Then, OLS is applied to the following equations: (i) $X_0$ on $y$, (ii) $X_0$ on $W_1 y$, and (iii) $X_0$ on $hW_2 y$, obtaining the 4x1 parameters vectors $\beta_0$, $\beta_{L1}$, $\beta_{L2}$. From those regressions the following residuals are obtained: $e_0$, $e_{L1}$ and $e_{L2}$. With those residuals, the logarithm of the concentrated likelihood function can be expressed as:

$$\ln L_C = \mathrm{C} + \ln|I - \gamma W_1 - \delta h W_2| - \frac{N}{2} \ln \left\langle \frac{(e_0 - \gamma e_{L1} - \delta e_{L2})'(e_0 - \gamma e_{L1} - \delta e_{L2})}{N} \right\rangle$$

where C is a constant. This process is performed for each combination of $\gamma$ and $\delta$. These parameters $\gamma$ and $\delta$ are chosen in order to maximize the concentrated likelihood function. Then, the remaining parameters are obtained following the next expression:

$$\beta_{ML} = \beta_0 - \gamma \beta_{L1} - \delta \beta_{L2}$$

$\beta_{ML}$ represents a 4x1 vector of parameters. With those estimations, the structural parameters $(\mu, \emptyset, \lambda, \alpha)$ can be easily recovered and all restrictions are fulfilled. Asymptotic variances for the estimated parameters are obtained by computing the inverse of the information matrix. The variance of the implied parameter $\emptyset$ is computed through the delta method.

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