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Externalities and Absorptive Capacity in a context of Spatial Dependence: The case of European Regions

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Externalities and Absorptive Capacity in a context of Spatial Dependence: The case of European Regions

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Abstract

This paper proposes a theoretical model which incorporates capital accumulation and spatial spillovers across economies, while allowing for differences in absorptive abilities. This model is later estimated for a sample of 215 European NUTS2 regions, before and after the last 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. Total Factor Productivity disparities are studied decoding its sources, and results conclude that after the last enlargement of the European Union, instead of a technological convergence, a twin-peak pattern has emerged. Central and Eastern European regions are lacking the benefits from interaction between physical and human capital, while geography appears to be a limitation for most peripheral regions. In this context, it will be difficult for peripheral regions to catch-up, because geographical distance means that these regions are less exposed to spillovers.

KEYWORDS: Total Factor Productivity, Absorptive Capacity, Externalities, Technological Interdependence

Resumen

El presente trabajo propone un modelo teórico que incorpora externalidades vinculadas a la acumulación de capital y a la dependencia espacial de las economías, al tiempo que permite a las diversas economías presenten diferentes capacidades de absorción de las referidas externalidades. El modelo es estimado para una muestra de 215 regiones Europeas NUTS2, antes y después de la última ampliación del mercado común. Los resultados demuestran la importancia de la capacidad local de absorción para que las economías puedan aprovechar las externalidades. Incluso, las externalidades vinculadas a la acumulación de capital no parecen ser aprovechadas en ausencia de capacidades locales. Asimismo se estudian las disparidades vinculadas a la Productividad Total de los Factores, intentando decodificar la fuente de dichas diferencias. Los resultados sugieren que luego de la última ampliación de la Unión Europea, en lugar de una convergencia tecnológica, ha surgido un esquema bimodal de regiones avanzadas y atrasadas. Las regiones de Europa Central y del Este parecen carecer de los beneficios de la interacción entre el capital físico y humano, mientras que la geografía parece ser una limitación para las regiones más periféricas. En este contexto, será difícil para las regiones periféricas converger hacia las regiones más ricas, debido a la distancia geográfica implica que estén menos expuestos a las externalidades provenientes de las regiones avanzadas.

PALABRAS CLAVE: Productividad Total de los Factores, Capacidad de Absorción, Externalidades, Interdependencia Tecnológica.

JEL: C21, I25, O10, O22

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 (2005), 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 percent 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 (Ertur and Koch, 2006; Mora et al, 2004). 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, 1995; López-Bazo, 2003; López-Bazo et al, 2004; Koch, 2006b; Mora et al, 2005) or through the kernel-density distribution approach (Neven and Gouyette, 1995; Quah, 1996a; 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 (López-Bazo, 2003; Magrini, 2004; Koch, 2006b; Bosker, 2009; among others). The relevance of the spatial patterns in the distribution of wealth and poverty in Europe makes that regional studies should take this characteristic into account.

In the light of the reduction of income disparities which took place in period 1999-2007 (as stated by European Commission, 2010), this analysis will focus 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

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

of making the most of externalities. Over these lines, this paper intends to make a theoretical and empirical contribution.

In this context, the strategy followed by this paper is twofold. On the one hand, a theoretical model will be proposed, mainly based on the framework developed by Koch (2006a, 2006b) and Ertur and Koch (2007); but intending to advance a further step, as it will allow for differentials in local absorptive capacities. In a second step, that model will be empirically estimated for the European regions, as it constitutes a suitable case of study for several reasons.

The openness of CEE economies prompted the inflows of external capital through Foreign Direct Investment (FDI), as stated by Bijsterbosch and Kolasa (2010) 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, 2010). 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. Technological diffusion may also have other kind of sources, as trade (Koch, 2006a) or as transmission of ideas through tacit information, which may prompt innovation (Rodriguez-Pose and Crescenzi, 2008). 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).

2 Theoretical Framework

2.1 Brief literature review

From a theoretical perspective, one of the first contributions has been the Solow (1956) model, which 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 stated that the observed differences in Total Factor Productivity (TFP) across countries 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, Koch (2006a, 2006b) and Ertur and Koch (2007) proposed an augmented Solow model which explicitly accounted for spatial dependence and learning-by-doing externalities from capital accumulation.

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 percent 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, in the sense that disparities were found to be mainly accounted for 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 (2006a) showed that incorporating spatial externalities to the analysis made physical capital to increase dramatically its contribution, accounting in some cases for 90 percent 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. 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, the base model is the proposed by Koch (2006a, 2006b) and Ertur and Koch (2007), in which for each economy a Cobb-Douglas production function exhibits constant returns to scale in labour and physical capital:

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

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

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

where k_i is defined as physical capital per worker. 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. The w_{1ij} and w_{2ij} terms represent measures of interaction between regions i and j.

The introduction of human capital in this model marks a departure from the Ertur and Koch specification. In this model, human capital will constitute a measure of local absorptive capacity (Nelson and Phelps, 1966; Benhabib and Spiegel, 1994). It is understood that part of the learning-by-doing externalities may have a positive 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 $\phi \geq 0$). 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 spatial interaction will take place regardless of human capital ($\gamma \geq 0$), but the absorptive capacity will be enhanced with higher levels of skills ($\delta \geq 0$). In these expressions, h_i represents the human capital variable, which intends to measure regional differences in the abilities to adopt and implement technological externalities (either from learning-by-doing or from abroad).

The interpretation of these parameters is the key of the model. If ϕ (γ) was found to be not significant, then learning-by-doing (spatial interdependence) process will not take place in absence of skilled workers. At the same time, a non-significance of λ (δ) will reflect the absence of the role of human capital in enhancing the learning-by-doing (external spillovers) process. In contrary, if λ and/or δ were found to be positive, regions richer in human capital will have higher capacity for technology adoption; and on the other hand, poor regions may face difficulties in the catching-up process if not 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 an economy, making a two-source growth process (for instance, convergence as a result of capital stock and technological catch-up). Finally, if $\phi = \lambda = \gamma = \delta = 0$, then the specification is the original model proposed by Solow (1956). In this latest case, a capital deepening process of an economy will not have an impact on technological catch-up.

The interregional technological interdependence implies that regions must be analysed as an interdependent system. This constitutes a major difference with the original Solow (1956) model, in which each economy was studied as in isolation from the others. For this reason the description of the model will be made in matrix terms for an N region sample. At the same time, income and physical capital will be transformed to per-worker terms, so the endogenous variable will now constitute labour productivity. Finally, to make easier the description (and the estimation), the model will be log-linearized. Hereafter, all terms of A, Ω, k, and y will be expressed in logarithms, but to make easier the follow-up and understanding of the model the *log* expression will be omitted. Considering all this, technology can be expressed, in matrix terms:

$$A = \Omega + (\phi I + \lambda h)k + (\gamma W_1 + \delta h W_2)A \qquad (2)$$

Where, supposing a sample of N regions:

$$A = \begin{pmatrix} A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_N \end{pmatrix} \qquad \Omega = \begin{pmatrix} \Omega \\ \Omega \\ \Omega \\ \vdots \\ \Omega \end{pmatrix} \qquad h = \begin{pmatrix} h_1 & 0 & 0 & \cdots & 0 \\ 0 & h_2 & 0 & \cdots & 0 \\ 0 & 0 & h_3 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & h_N \end{pmatrix}$$

$$k = \begin{pmatrix} k_1 \\ k_2 \\ k_3 \\ \vdots \\ k_N \end{pmatrix} \qquad W_s = \begin{pmatrix} 0 & w_{s12} & w_{s13} & \cdots & w_{s1N} \\ w_{s21} & 0 & w_{s23} & \cdots & w_{s2N} \\ w_{s31} & w_{s32} & 0 & \cdots & w_{s3N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ w_{sN1} & w_{sN2} & w_{sN3} & \cdots & 0 \end{pmatrix}$$

W_s (for $s = 1, 2$) represents a matrix where frictions among every regions $i \neq j$ are represented. The idea behind this is that knowledge embodied in one region extends across its borders but does so with diminished intensity. The more a given region i is connected to its neighbours, the higher w_{sij} is, and the more region i benefits from spillovers. Equation (2) can be expressed as:

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

Which can be rearranged, supposing $(I - \gamma W_1 - \delta h W_2)$ is invertible:

$$A = (I - \gamma W_1 - \delta h W_2)^{-1}\Omega + (I - \gamma W_1 - \delta h W_2)^{-1}(\phi I + \lambda h)k \tag{3}$$

As it can be seen in (3), TFP is affected by physical capital externalities and by the spatial repartition of this factor. Also, a region's ability to adopt and implement the externalities is important: regions with higher human capital are expected to make a better use of them. Consider (1) in logarithms for the whole sample, in matrix terms:

$$y = A + \alpha k \tag{4}$$

Replacing (3) in (4):

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

Pre-multiplying both sides by $(I - \gamma W_1 - \delta h W_2)$:

$$(I - \gamma W_1 - \delta h W_2)y = \Omega + (\phi I + \lambda h)k + \alpha(I - \gamma W_1 - \delta h W_2)k$$

After some rearrangements, this yields:

$$y = \Omega + (\phi + \alpha)k + \lambda hk - \alpha\gamma W_1 k - \alpha\delta h W_2 k + \gamma W_1 y + \delta h W_2 y \tag{6}$$

As a result, local productivity will depend on local physical capital, on the productivity and physical capital of neighbours, and also on all those variables in interaction with local human capital. Recall equation (5). As this expression is double-logarithmic, output-physical capital elasticity is simple computed as $\xi_k = \frac{\partial y}{\partial k}$. This yields the following expression:

$$\xi_k = \alpha I + (I - \gamma W_1 - \delta h W_2)^{-1}(\phi I + \lambda h) \tag{7}$$

ξ_k constitutes an NxN matrix which expresses the elasticity of output per worker in a region in respect to its own level of physical capital and in respect to the level of physical capital per worker in foreign regions. This elasticity expression will depend on the capital share in the income, on the learning-by-doing process and on the spatial interactions, expressed through the spatial multiplier $(I - \gamma W_1 - \delta h W_2)^{-1}$. Also, from (7) it is clear that returns will be higher in those regions endowed with higher levels of human capital, *ceteris paribus*. As a result, the externalities increase the effect of capital on productivity, in comparison to the original Solow model.

With respect to output - human capital, as human capital is not measured through logarithms, then elasticity equals: $\xi_h = h(\frac{\partial y}{\partial h})$. As a result:

$$\xi_h = h((I - \gamma W_1 - \delta h W_2)^{-1}(\delta W_2)(I - \gamma W_1 - \delta h W_2)^{-1}\Omega$$

$$+(I - \gamma W_1 - \delta h W_2)^{-1}(\delta W_2)(I - \gamma W_1 - \delta h W_2)^{-1}(\phi I + \lambda h)k$$

$$+(\delta W_2)(I-\gamma W_1-\delta h W_2)^{-1}\lambda k) \qquad (8)$$

ξ_h constitutes an Nx1 matrix which expresses for every region the elasticity of output per worker in respect to its own level of human capital. This expression of elasticity will depend not only on the human capital stock, but also on the physical capital stock and on the spatial interactions, expressed through the spatial multiplier.

3 Empirical Analysis

3.1 Descriptive Analysis

As it was mentioned before, disparities in European regions have an important spatial component. In this section, a set of techniques of Exploratory Spatial Data Analysis (ESDA) will be applied, intending to study the spatial distribution of the key variables. This descriptive analysis is important to understand the necessity of including the spatial dimension in the analysis. As a starting point, the analysis will be centred in the logarithms of Gross Value Added per worker (GVA) and physical capital stock per worker (in both cases measured in 2000 Euros), data extracted from the Cambridge Econometrics database[2]. The sample includes 215 NUTS2[3] regions from 16 countries for years 1999 and 2008.

In first place, Figure 1 presents the average growth rate of GVA (left) and physical capital (right) for period 1999-2008. A first look to the GVA growth rates suggest a convergence process, as peripheral CEE regions (plus Finland and Ireland) are the fastest growing. In the case of physical capital per worker, a deepening

[2]The physical capital variable has been refined by the Institute for Prospective Technological Studies of the European Commission

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

process appears to be the driving force behind convergence to some peripheral regions, as Polish, Portuguese, Irish and Greek regions. At the same time, some core regions also register important capital growth, as some French and British regions. In Spain, capital grew as well as labour, and as a result a capital intensity process was not verified. If only FDI is considered, clearly CEE regions registered a capital intensity process[4].

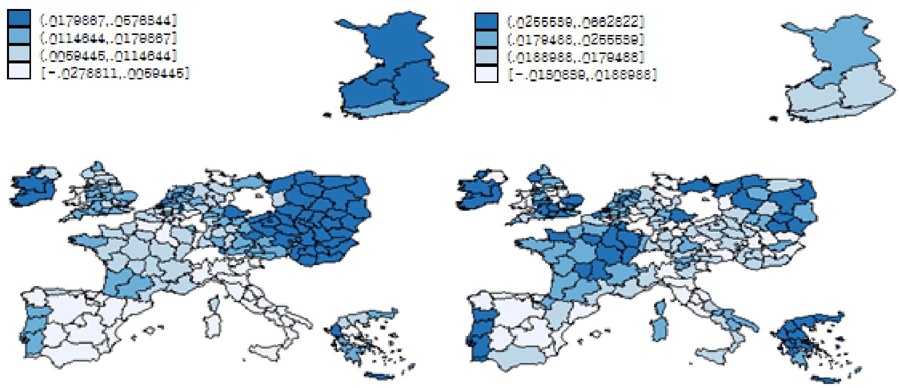

Figure 1: Average growth of GVA (left) and capital (right) 1999-2008

Despite that evidence of productivity catch-up, a closer analysis suggests a different picture. In Figures 2A and 2B the GVA variable is plotted through the EU map for 1999 and 2008, respectively. These figures show that the spatial correlation is clear, with a core (regions of Germany, Netherlands, Belgium, north-France, north-Italy) and a periphery at the regions of CEE (Poland, Slovakia, Hungary, Czech Republic) and at the south (Portugal, Greece, south-Spain, south-Italy). Another clear pattern is persistence: the picture is almost unchanged between 1999 and 2008, despite regional growing rates suggesting a convergence process.

[4]FDI flows from the core to CEE between 2004 and 2008 amounted on average 4.5 percent of its GDP. In particular, the centre countries included in this sample (Hungary, Poland, Slovakia and Czech Republic) were net recipients of FDI during 2004-2008, in contrast to the majority of core regions(European Commission, 2010).

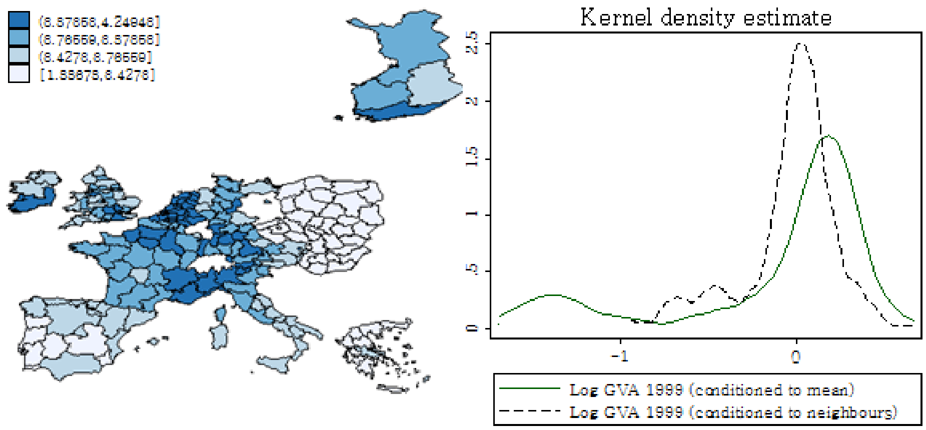

Figure 2A: Log of GVA per worker 1999

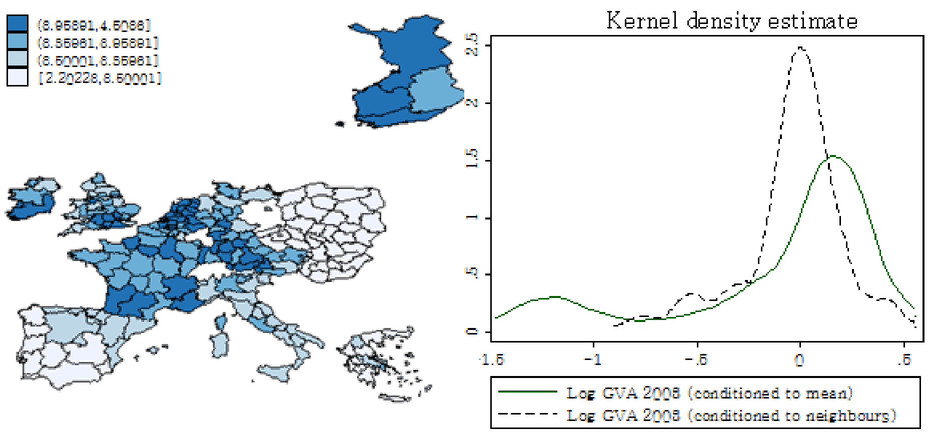

Figure 2B: Log of GVA per worker 2008

Disparities are clearly seen at the kernel density functions, at the right of figures 2A and 2B. It is clear that there is a bipolar situation in the productivity distribution, with an important amount of regions near the core, and a small but distant group at the left which constitutes a periphery (mainly CEE regions). Despite reduction of disparities, the bipolar situation is similar in both years, 1999 and 2008, which suggests a polarization scheme. This situation reflects that analysis based only on standard deviations or regressions towards the mean are unable to detect bimodal or twin-peak distributions[5]. The spatial incidence is clearly seen for

[5]See for instance Quah (1993, 1996b) for a detailed explanation.

both years when comparing the original density function with the dashed figure, which represents the distribution of productivity conditioned to that of neighbour regions. This representation is mainly unimodal for both years, which confirms that spatial dependence is the main reason behind the bipolar pattern.

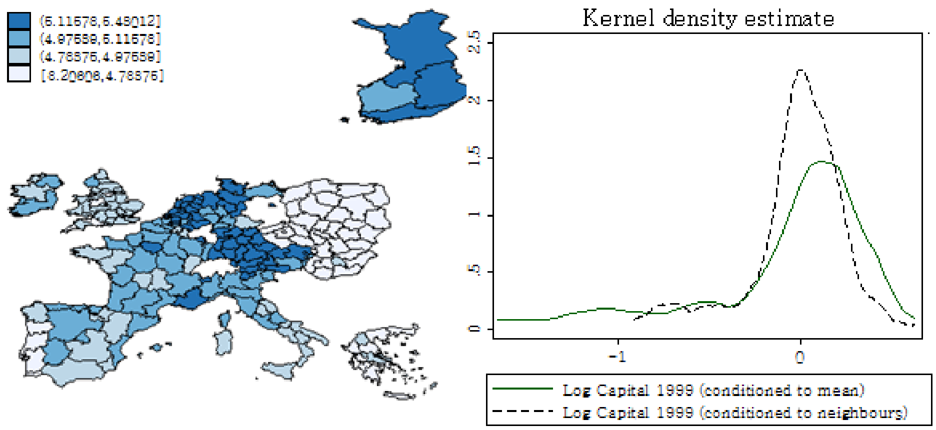

Figure 3A: Log of capital per worker 1999

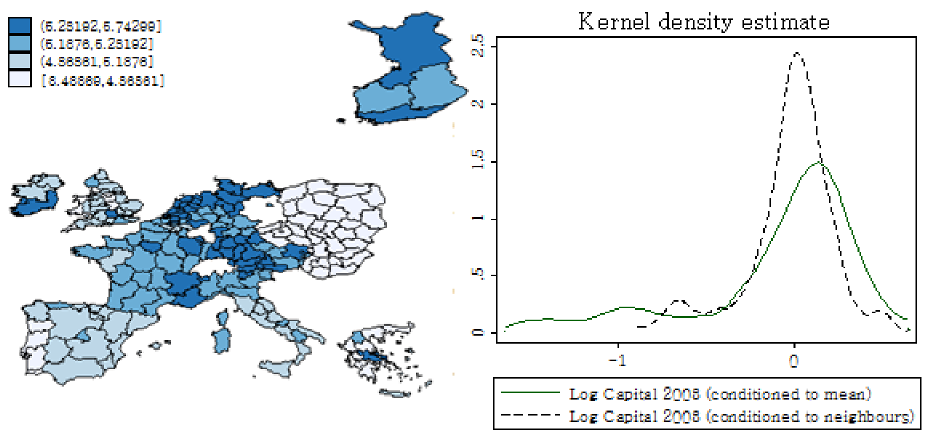

Figure 3B: Log of capital per worker 2008

A similar picture emerges when comparing the maps of the physical capital per worker distribution. Again a core-periphery persistent pattern emerges (Figure 3A and 3B). In contrast, the kernel distribution analysis does not suggest a clear bipolar situation neither in 1999 nor 2008. Instead, the density function has a long left-tail of lagging regions. Once again, when conditioning physical capital to that of neighbour regions (dashed line), the distribution which emerges is mainly unimodal and more concentrated towards the mean, specially in 1999. In 2008, despite conditioning, a small lagging group emerges at the left of the distribution.

As stated before, absorptive capacity is usually measured through human capital. In particular, some literature tends to approach similar situations through tertiary-level human capital, as it is understood that high skills are needed to assimilate new technology (Manca, 2011; Leiponen, 2005). The data employed measures the percentage of workers with tertiary-level education over the whole workforce. These data, extracted from Eurostat Regio database, includes the same sample as described before.

In this case positive spatial correlation is again present, but the core-periphery pattern is less clear (Figures 4A and 4B). In contrast to physical capital, human capital is not a strictly productive factor, as can also be related to social policies. In particular, some peripheral areas as Spain are endowed with high levels of tertiary human capital, while the opposite is true for some core regions. With respect to CEE, the situation is in general of low levels of human capital. In relative terms, regions in which the countries capitals are located seem to be better endowed than other CEE regions. A similar pattern emerges in 2008, but with a slight improvement in Polish regions human capital: an important group of regions are situated in a superior quantile than for instance, most Portuguese or Italian regions.

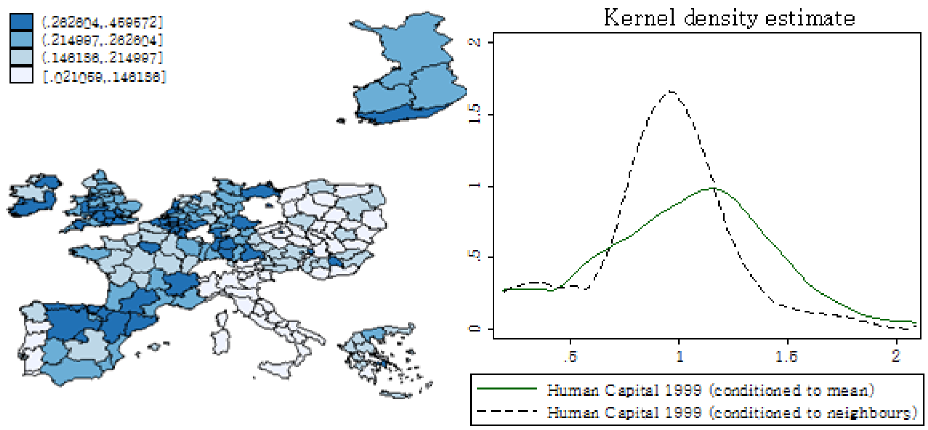

Figure 4A: Human capital 1999

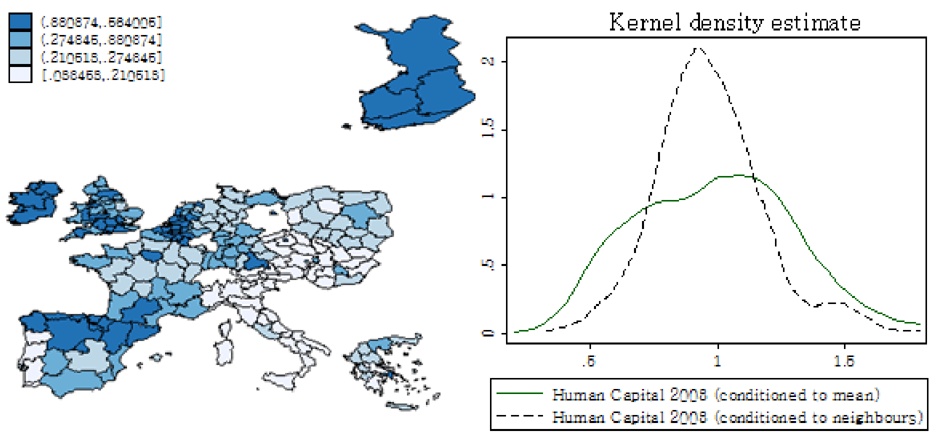

Figure 4B: Human capital 2008

The kernel-density distributions, at the right of Figures 4A and 4B, do not suggest a bipolar situation as the case of GVA, or a left tail scheme as physical capital. In 1999 there was a small lagging group (mainly CEE, Italian and Portuguese regions), but in 2008 the distribution is more concentrated towards the mean. As in the case of physical capital, when conditioning human capital to that of neighbour regions (dashed line), the distribution which emerges is unimodal and even more concentrated towards the mean for both years, which confirms once more the incidence of spatial dependence. The degree of spatial association of the referred variables can be summarized by Moran's I and Geary's C statistics. The Moran's

I is defined as:

$$I = \frac{N}{S_0}\frac{z'Wz}{z'z}$$

where z is the vector of the N observations in deviation from the mean, W is a spatial weight matrix, and S_0 is a scaling factor equal to the sum of all elements of W. The second statistic, the Geary's C, is quite similar, but uses the variance instead of the covariance of the attribute. All the analysis of the present section was performed using a square-distance inverse weight matrix (row-normalized)[6]. Table 1 represents the results for 1999 and 2008. Results clearly confirm the positive spatial correlation of all variables, as the null hypothesis of absence of spatial correlation is rejected in all cases at a significance level of 1 percent.

Figure 5 reproduce the Moran Scatterplot for GVA, which compares the reference variable with its spatial-lag for years 1999 (left) and 2008 (right). The spatial correlation again is evident, as regions are neighbour of those of similar condition (high or low productivity). Despite this, the high-high quadrant reflects much more concentration than the low-low. Once more, the situation is persistent as the 2008 situation is quite similar to 1999. A similar representation is made for physical capital (Figure 6). The same comments made for GVA apply to this case.

Table 1: Spatial Autocorrelation Statistics

Year	Statistics	Log GVA	Log Capital	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***	0.540***	0.499***
	Geary's C	0.387***	0.427***	0.580***

Note: (***) represents significance at 1 percent

[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).

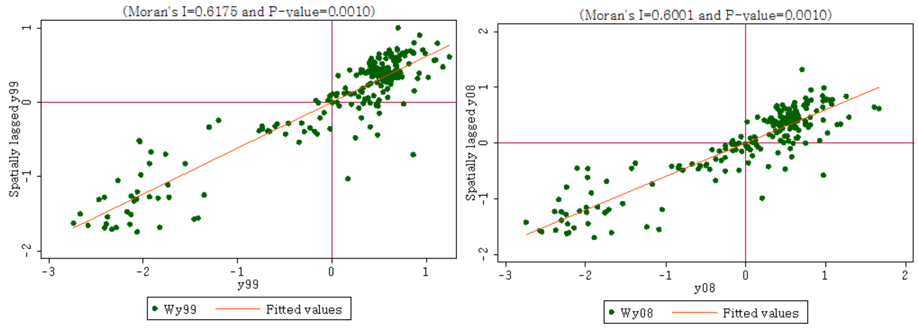

Figure 5: Moran Scatterplot Log GVA 1999 (left) and 2008 (right)

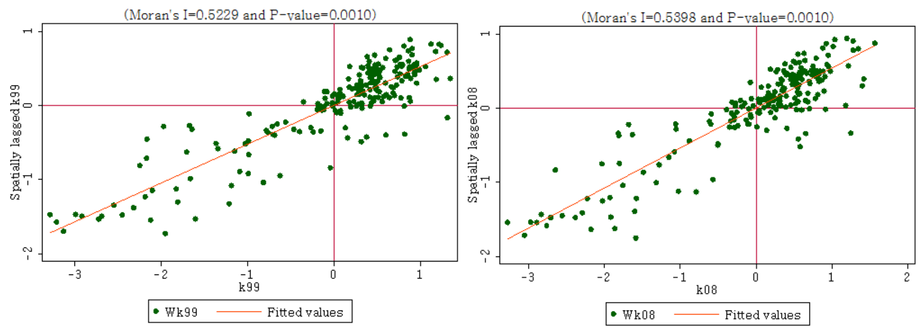

Figure 6: Moran Scatterplot Log Capital 1999 (left) and 2008 (right)

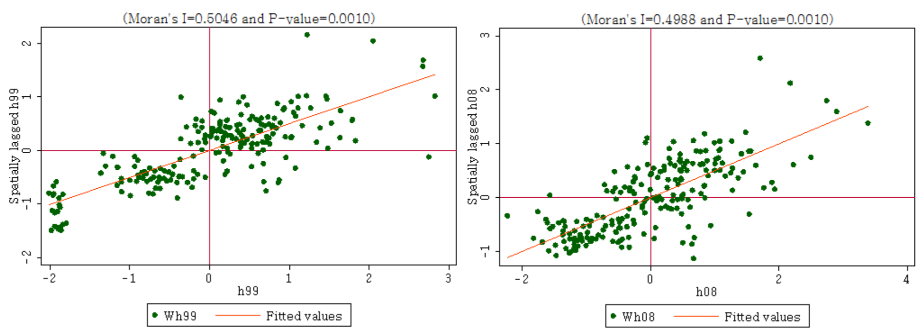

Figure 7: Moran Scatterplot Human Capital 1999 (left) and 2008 (right)

Even if the situation appeared to be slightly less clear in the maps, Figure 7 confirms the spatial correlation of the human capital variable, and once more, the situation appears to be persistent as the similar picture emerges from 1999 and 2008.

To sum up, the spatial pattern is evident, and as a result this dimension must be incorporated to the analysis. For that reason, the theoretical model exposed in section 2 appears to be suitable, as it explicitly takes this issue into account.

3.2 Econometric Results

Estimation of (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

[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.

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 is performed through Maximum Likelihood, and the results are exposed in Table 2, 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 (in the 2002 equation rejection of the null hypothesis is obtained only at 10 percent). A complete description of the estimation procedure is detailed in the appendix.

A first look at the results confirms a high value for α, 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, 2006b), but closer to Koch (2006a) 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 sample of 91 countries).

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: ϕ is never significant, while λ is significant at 1 percent in all the following estimations. This means that human capital seems to have a direct role in the absorption of spillovers

[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.

form capital accumulation. This may explain why in Koch's articles the parameter ϕ 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 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 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 (γ and δ) are significant at 1 percent in all periods, showing once more the spatial dependence present among European regions, as exposed previously in the exploratory analysis. The direct measure γ averages stable values of 0.9, while the measure which incorporates absorptive capacity through human capital (δ) descends from 0.75 in 1999, to 0.48 in 2008. 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. Another interesting result that reflects the importance of human capital is the analysis of elasticity, through equations (7) and (8). Each region has its own elasticity level, not only because of differences in physical and human capital, but also because of its different geographic locations. For that reason, the elasticity results will be exposed as regional averages for three groups: core,

[10] Koch (2006b) found ϕ to be not significant in European regions, while Koch (2006a) estimated six regressions for 91 countries, varying weight matrices and depreciation rates, and only in one case ϕ was significant, at a 10 percent level (p-value of 0.094).

Table 2: Maximum Likelihood Estimation Results

Parameter	1999	2002	2005	2008
constant	-0.215**	-0.217*	-0.193*	-0.186*
	[0.104]	[0.122]	[0.115]	[0.111]
ϕ	0.032	0.017	0.007	0.000
	[0.093]	[0.103]	[0.105]	[0.108]
λ	0.036	0.075***	0.081***	0.084***
	[0.025]	[0.026]	[0.023]	[0.022]
α	0.772***	0.782***	0.782***	0.783***
	[0.060]	[0.071]	[0.073]	[0.078]
γ	0.918***	0.902***	0.888***	0.895***
	[0.029]	[0.039]	[0.042]	[0.052]
δ	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 ϕ computed using the delta method. Moran's I is computed over the residuals. (*), (**) and (***) mean significant at 10 percent, 5 percent and 1 percent.

south and central regions[11]. As expressed in (7) and (8), human capital endowment and geographic location are decisive for both elasticity measures. It was patent from the exploratory analysis that most CEE regions have relatively low endowment of human capital, with only some few exceptions in 2008. Additionally, these regions are geographically far from the core, being less exposed to spillovers as a result. For those reasons, it is not a surprise that the CEE group in Table 3 always figures at the bottom of elasticity levels compared with other regions (the only exceptions are overall capital elasticity in 1999 and 2002). The

[11]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.

Table 3: Average Productivity Elasticities

Elasticity	Regions	1999	2002	2005	2008
ξ_k local	Core	0.825	0.827	0.819	0.814
ξ_k local	South	0.834	0.828	0.817	0.810.
ξ_k local	CEE	0.823	0.819	0.810	0.805
ξ_k overall	Core	1.042	0.945	0.911	0.871
ξ_k overall	South	1.123	0.987	0.929	0.887
ξ_k overall	CEE	1.079	0.952	0.903	0.862
ξ_h local	Core	0.072	0.260	0.313	0.322
ξ_h local	South	-0.020	0.173	0.229	0.292
ξ_h local	CEE	-0.450	-0.152	-0.096	0.036

Note: Local refers to the percentage of productivity variation after a 1 percent 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 percent increase in every other region.

fact that core and southern regions reach in average higher capital elasticities than CEE suggest that agglomeration economies counteract in some degree the effect of decreasing returns. These results constitute a setback for the growth process of CEE regions, because if returns to investment are lower than in other regions, then instead of convergence, the economic integration may yield agglomeration at the core. This is the prediction of some New Economic Geography models, which suggest that economic integration operates as an agglomeration force when the core has higher returns or larger market[12]. 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 suggest that externalities help to counteract in some degree the effect of decreasing returns.

[12]See for instance the Home Market Effect or the Core-Periphery model (Combes et al, 2008; Krugman, 1991).

Human capital elasticity depend on both measures of capital, and as a result the higher levels are reached by the core, followed respectively by southern and CEE regions. An interesting pattern is the increasing trend of this elasticity levels through the years, which is more pronounced in the southern and specially 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, 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 (2009), 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.

Having said that, the low human capital elasticity levels of CEE regions may reflect that these economies are still in a transition process. Some southern regions (mainly Spanish), present higher development levels and have already reached important human capital improvements, and as a result elasticity levels are much closer (and sometimes higher) than the core.

Finally, as stated before capital intensity is also related with technology levels, through learning-by-doing externalities. As stated in (3), human capital and the spatial multiplier also have an influence on technological levels of regions. For

[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.

that reason, technology levels will be considered and some counterfactual exercises will be performed intending to decode the biggest factors which have an incidence in the TFP term. Table 4 resumes the results.

As a first analysis, it seems that some technological convergence has been produced in the period, as the TFP standard deviation has been reduced from 0.19 in 1999 to 0.16 in 2008. Despite that pattern, counterfactual analysis provide some alternative perspectives. In first place, it will be supposed that every region has the same physical capital stock, the sample mean. In this fictitious scenario, differences in TFP are only explained by human capital and by the spatial multiplier. In comparison with the unconditional situation, standard deviation is reduced from 0.19 to 0.13 in 1999 (0.16 to 0.15 in 2008). This has many lectures. In first place, it is clear that physical capital disparities contribute to TFP differences (hence the standard deviation reduction when conditioning), but that influence seems to be decreasing over the years. If conditioned, TFP standard deviation is reduced in 33 percent in 1999, but only in 11 percent in 2008. This suggests that capital deepening in some peripheral regions has probably contributed to the reduction in TFP disparities, but the margin to continue that process relying only on physical capital accumulation seems to be running out, as only 11 percent of standard deviation is reduced when conditioning in 2008. Another proof of physical capital contribution to the reduction of disparities is that if every region had the same capital, then TFP disparities would not have been reduced, in the contrary, standard deviation would have increased from 0.13 in 1999 to 0.15 in 2008, meaning technological divergence.

The second counterfactual scenario supposes that every region has the same level of human capital. As a result, differences in TFP will be explained by physical capital and the spatial multiplier. In this case, standard deviation is reduced from 0.19 to 0.12 in 1999 (0.16 to 0.08 in 2008). This suggests that human capital plays an important role in explaining disparities, and that influence seems to be increasing through the years: when conditioning, TFP standard deviation is reduced in 38 percent in 1999 and in 53 percent in 2008. If every region had the same human capital, disparities would have been reduced from 0.12 in 1999 to 0.08 in 2008, that's a much more intense reduction of disparities than the observed. Then, human capital helps to explain past, but also present TFP disparities. When conditioning at the same time for similar levels of human and physical capital, disparities are greatly reduced, from 0.19 to 0.03 in 1999 and from 0.16 to 0.06 in 2008. This reflects the joint importance of both capital measures in explaining TFP disparities, which is more pronounced in 1999 as in the following years physical capital decreases its incidence. In any case, differences derived from interaction among physical and human capital seems te be a major source of disparities. The final scenario will suppose no spatial interactions, this is like considering each region as an isolated economic area, and as a result its TFP depends only on its physical and human capital endowment. In that case, standard deviation would have been reduced from 0.19 to 0.03 in 1999 and from 0.16 to 0.04 in 2008. This represents a reduction of disparities of 85 percent in 1999 and of 75 percent in 2008. This reflects that spatial interactions are a major source of technological differences, but its influence has slightly decreased during the period considered. Figure 8A reflects the kernel-density of the TFP distribution for 1999. The uncon-

Table 4: Standard Deviation of TFP under specific scenarios

Conditioned to:	Dependent on:	1999	2002	2005	2008
Not conditioned	$k, h, space$	0.189	0.189	0.175	0.163
$k = k_{mean}$	$h, space$	0.126	0.147	0.147	0.145
$h = h_{mean}$	$k, space$	0.117	0.090	0.075	0.076
$k = k_{mean}, h = h_{mean}$	$space$	0.028	0.051	0.047	0.063
$\gamma = \delta = 0$	k, h	0.029	0.039	0.041	0.042

ditioned TFP distribution in 1999 reflects a pattern with huge disparities, clearly seen at the big left-tail. When conditioning on same physical capital, and specially on the same human capital, the distribution becomes more concentrated towards the mean. The biggest changes to the TFP distribution come after conditioning on both similar human and physical capital, and when supposing no spatial interactions. In the first case, the distribution becomes more concentrated, and the big left-tail disappears. These reflects the importance of physical and human capital interactions, as the joint-conditioned scenario yields a vastly superior change in pattern than the simple conditioned scenario of either human or physical capital. Finally, conditioning on no spatial interactions creates a clear unimodal distribution highly concentrated towards the mean, confirming the relevance of spatial interactions to explain TFP disparities in EU.

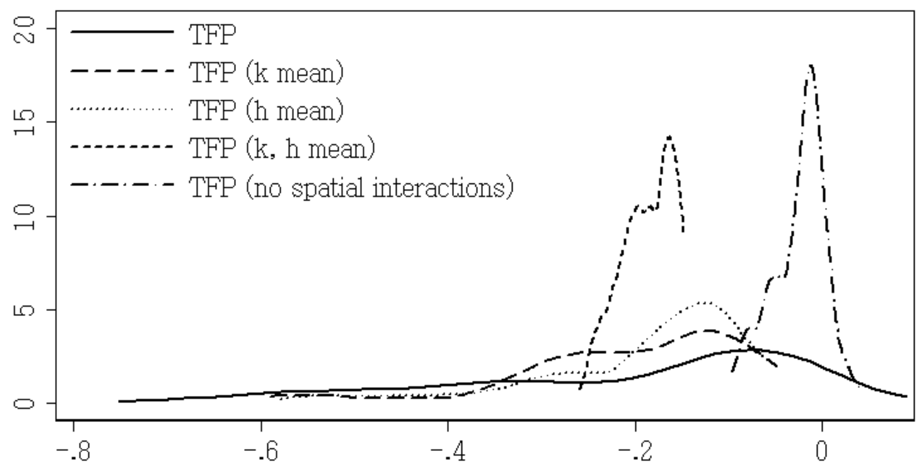

Figure 8A: TFP kernel-density 1999

The same representation is made for 2008 (Figure 8B). Clearly the unconditional TFP distribution evolves to a twin-peak scheme, which reflects once more that reduction of disparities does not necessarily means catch-up. When conditioning to same physical capital, the situation does not change significantly, although the twin-peak pattern is smoother. This suggests that physical capital differences may contribute, at least in part, to explain the actual bipolar pattern. The human capital conditioned distribution reflects a considerable reduction of disparities but with a clearly pronounced twin-peak situation; this means that actually human capital differentials are a source of disparities but are not the reason behind the actual bipolar pattern. Interestingly, when conditioning jointly for similar physical and human capital across regions, for the first time the bipolar scheme is clearly reduced, which reflects that the differences in interaction among physical and human capital appears to be a clear source of the twin-peak distribution. Finally, the distribution of the TFP considering no spatial interactions is much more concentrated towards the mean, this reflects the spatial dependence is key for explaining technological disparities among European regions. Despite that, the twin-peak distribution is not completely offset. To sum up, in 2008 spatial interactions seem to be the main source of disparities, but the twin-peak pattern is mainly explained by differences in interaction among physical and human capital.

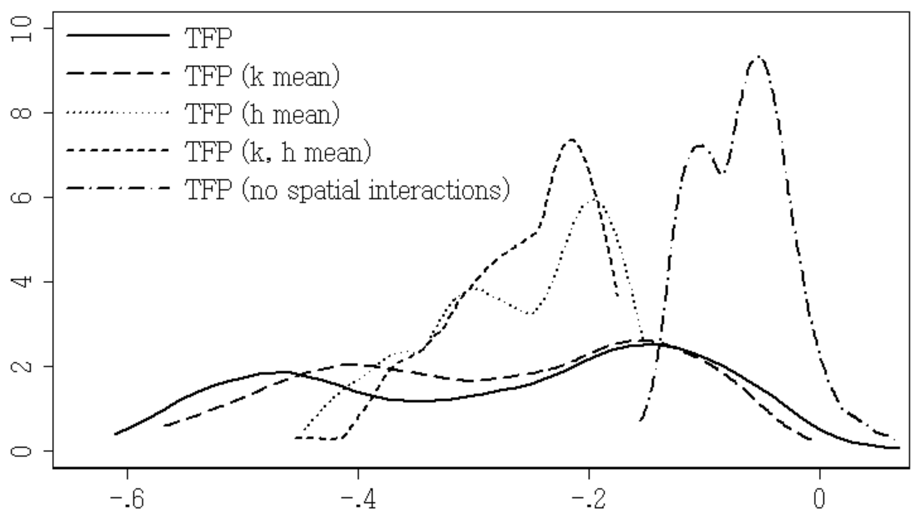

Figure 8B: TFP kernel-density 2008

Changes in relative positions are expressed in Figures 9 to 13. In the first case, of unconditional TFP, the situation clearly reflects a persistent core-periphery pattern (Figure 9). The situation after conditioning on same physical capital changes little, only some CEE regions are relatively improved in this scenario, specially in 2008 (Figure 10). When conditioning on the same human capital (Figure 11), relative positions suffer some changes, as regions with relatively low levels of human capital are benefited in this scenario (mainly Italian), in expense to those better endowed with skilled workers (as Spanish of Finnish regions). Despite that, the core-periphery pattern remains, and is persistent through the years.

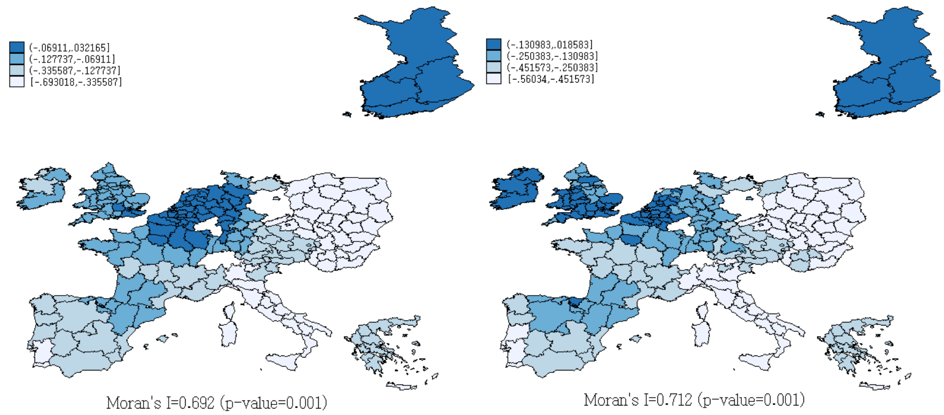

Figure 9: TFP 1999 (left) and 2008 (right)

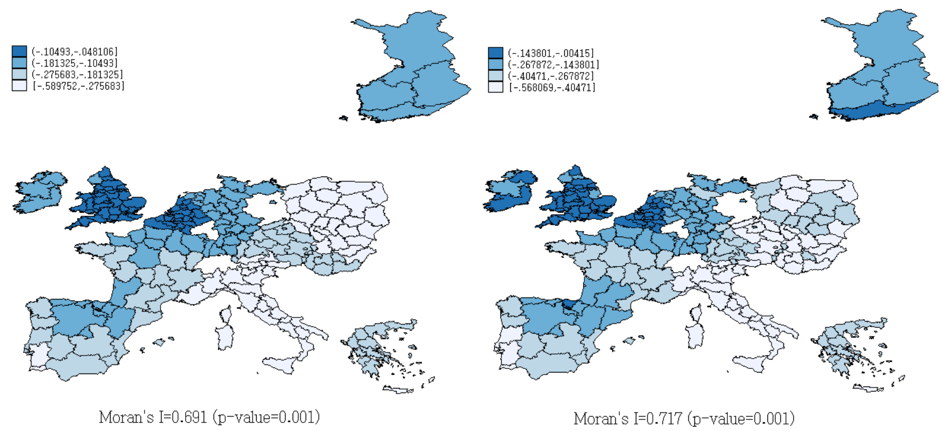

Figure 10: TFP (k = k_{mean}) 1999 (left) and 2008 (right)

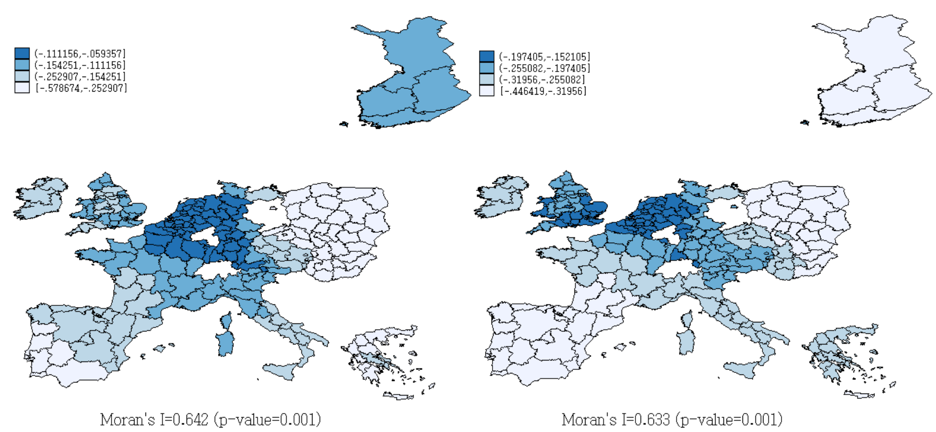

Figure 11: TFP (h = h_{mean}) 1999 (left) and 2008 (right)

The joint conditioned scenario of similar human and physical capital reflect some important changes (Figure 12). Finnish, Spanish and southern-French regions are relegated, while CEE regions improve considerably, being situated in higher quantiles. This reflects that the lack of both human and physical capital in the CEE regions is clearly hurting its development. It seems that CEE regions are missing the benefits of interaction between both capital measures. Finally, Figure 13 reflects the scenario conditioned to no spatial interactions. In this case clearly Spanish regions improve significantly, in contrast to CEE regions, which remain at the bottom levels. This reflects that geography may be the main limitation for Spanish regions, while the lack of interaction among human and physical capital appears to be the main actual limitation for the development of CEE regions. Italian regions appear to be lacking human capital, and Portuguese regions seem to be hurt by both geography and factor endowment. Moran's I statistics exposed at the bottom of the referred Figures suggest that the spatial correlation is present in every scenario, even when supposing $\gamma = \delta = 0$. In this latest case, despite being significant, Moran's I reaches the lowest levels, as expected.

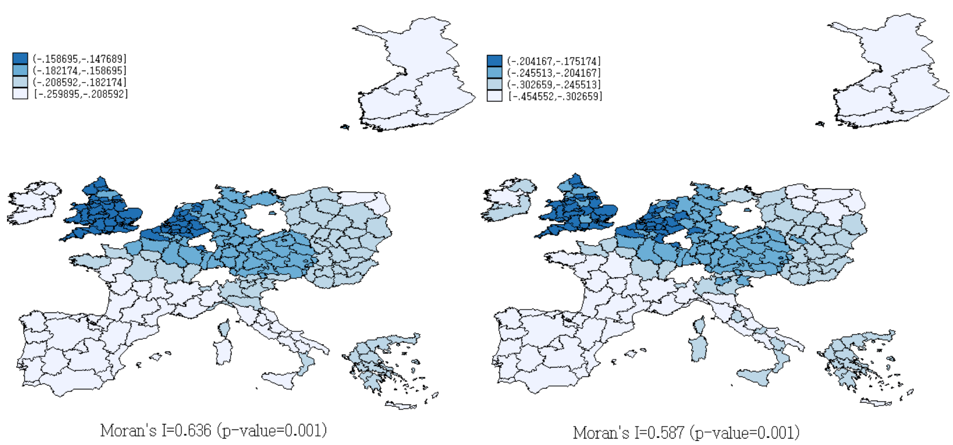

Figure 12: TFP ($k = k_{mean}, h = h_{mean}$) 1999 (left) and 2008 (right)

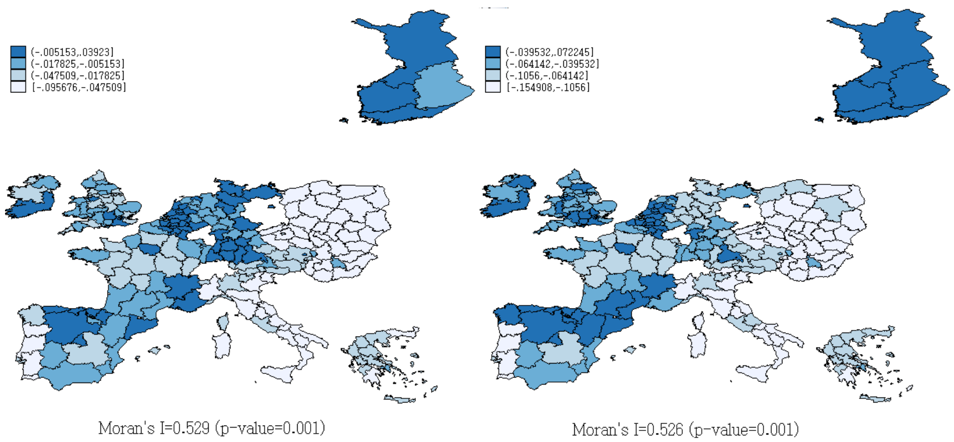

Figure 13: TFP ($\gamma = \delta = 0$) 1999 (left) and 2008 (right)

These results suggest that disparities can be reduced with investment in physical and human capital in peripheral regions, but complete convergence will be difficult, because there seems to be a poverty trap generated by geographic location. Clearly geography is a limiting factor in some southern regions. For CEE regions a joint-increase of human and physical capital will yield TFP improvements, because this is the main limitation for these regions to catch-up. Despite that, once being better endowed with physical and human capital, these regions will still face the geographical limitation of being far from the spillover influence of the core. The influence of geography can be seen as the only CEE regions which were able to stand in middle quantiles of the unconditioned TFP distribution in 2008 were those geographically closer to the core inside each country.

Even if geography do not seem to be the main limitation for CEE regions in this study, in the analysed sample there are only four of these countries, which are the closest geographically to the core: Czech Republic, Hungary, Slovakia and Poland. If the whole CEE countries were considered, the poverty trap which emerges in Figures 2B and 9B will surely be considerably larger, and geographical location will surely emerge as a limiting factor. In particular, regions of Bulgaria and Romania are among the farthest and poorest of the continent, and were not considered in the sample due to lack of data. This supposition is helped by the results reached by other studies. In particular, Bosker (2009) concluded in his study that some CEE regions may (very slowly) catch-up the western neighbours, but in the process other regions will be left behind in relative poverty. A similar conclusion was reached by Monastiriotis (2011), who stated that despite a national catch-up process, regional evolutions in CEE were divergent, with a tendency of club formation of lagging regions.

If the enlargement of the eighties is considered as a reference, the perspectives do not improve significantly for the lagging CEE regions. After the entrance of Greek, Spanish and Portuguese regions, disparities and polarization actually increased among its regions between 1985 and 2000 (Mora et al, 2004). The better positioned regions of those countries converged towards the core, leaving behind the poorest regions. This duality of behaviour was also linked to geography, as the inner periphery received the positive effects of integration faster than the outer periphery. The contrast among Spanish regions is a clear example of the incidence of proximity to the rest of Europe (López-Bazo et al, 1999).

4 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.

Actually, interaction between physical and human capital is relevant to explain TFP disparities, specially in the case of regions of CEE, which will need to be better endowed in both capital measures to be able to achieve some technological catch-up. Regardless of that, an increase of physical and human capital 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 as well. 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 (2004) 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 effects of 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 had the levels of physical and/or human capital of the core. Additionally, given the fact that only the better positioned regions of the south and centre 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. Also, innovation activity can be included in the analysis. In that sense, an interesting extension would consist in linking the TFP term to Research and Development, something which was not possible in the present article due to lack of data. In particular, given the 2020 European objective of investing 3 percent of GDP in Research and Development, an interesting exercise would consist in simulate TFP and productivity disparities under the compliance of that target.

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Appendix

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:

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

where ε 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:

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

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.

$$X_0 = \begin{pmatrix} 1 & k_1 & h_1k_1 & \gamma \sum_j^N w_{11j}k_j + \delta h_1 \sum_{j=1}^N w_{21j}k_j \\ 1 & k_2 & h_2k_2 & \gamma \sum_j^N w_{12j}k_j + \delta h_2 \sum_{j=1}^N w_{22j}k_j \\ 1 & k_3 & h_3k_3 & \gamma \sum_j^N w_{13j}k_j + \delta h_3 \sum_{j=1}^N w_{23j}k_j \\ \vdots & \vdots & \vdots & \vdots \\ 1 & k_N & h_Nk_N & \gamma \sum_j^N w_{1Nj}k_j + \delta h_N \sum_{j=1}^N w_{2Nj}k_j \end{pmatrix}$$

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

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

where β is a vector of parameters. Then, OLS its applied to the following equations: (i) X_0 on y, (ii) X_0 on W_1y, and (iii) X_0 on hW_2y, 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:

$$\ln L_c = C + \ln |I - \gamma W_1 - \delta h W_2| - \tfrac{N}{2} \ln[\tfrac{(e_0 - \gamma e_{L1} - \delta e_{L2})'(e_0 - \gamma e_{L1} - \delta e_{L2})}{N}]$$

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

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

β_{ML} represents a 4x1 vector of parameters. With those estimations, the structural parameters $(\mu, \phi, \lambda, \alpha)$ 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. Finally, considering $\phi = \Psi - \alpha$, the variance of the implied parameter ϕ is computed through the delta method.