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Regional dynamics of economic performance in the EU: To what extent spatial spillovers matter?

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Abstract

This paper investigates the main determinants of economic performance in the EU from a regional perspective, covering 253 regions over the period 2001-2008. In addition to the traditional determinants of economic performance, measured by GDP per capita, the analysis accounts for spatial effects related to externalities from neighbouring regions. The spatial Durbin random-effect panel specification captures spatial feedback effects from the neighbours through spatially lagged dependent and independent variables. Social-economic environment and traditional determinants of GDP per capita (distance from innovation frontier, physical and human capital and innovation) are found to be significant. Overall, our findings confirm the significance of spatial spillovers, as business investment and human capital of neighbouring regions have a positive impact – both direct and indirect – on economic performance of a given region.

Keywords: Spatial Durbin Models, spatial spillovers, economic performance.

JEL Classification: 017, 031, 018, R12.

Non-technical summary

The trend decline in potential growth in most advanced economies started well before the Global Financial Crisis and the debate on «secular stagnation» has gained further importance recently. The evidence is even stronger in Europe where not only potential growth has gradually declined over the past decades, but also trend output per capita has been lagging behind the United States. In the literature, weaker growth in Europe is explained to a large extent by productivity differences, in turn related to the lag in technological diffusion. Given the heterogeneity in Europe, not only across countries but also across regions, understanding the process of growth and innovation requires to take space dynamics into account. Notably, spatial spillovers may matter to explain concentration effects, agglomeration economies and industry clusters. The EU policies aiming at fostering market integration within Europe, have also focused on measures to alleviate regional fragmentation. With a more integrated European market, economic growth in one region enlarges the market capacity and stimulates the mobility of production factors and the process of innovation diffusion. As a result, cross-regional spillovers make economic growth across regions strongly interdependent, fostering market integration and promoting economic growth.

This paper investigates the main determinants of economic performance, measured by GDP per capita, in the EU from a regional perspective. In addition to the traditional determinants (such as investment, human capital development and innovation), our analysis accounts for spatial effects related to externalities from neighbouring regions. Following the regional growth literature, we develop specifications for economic performance depending on three main factors : internal innovative efforts, socio-economic local factors conducive to innovation and spatially-bound knowledge spillovers. Compared to existing work, the value added of our research is twofold : (1) we take advantage of granular information by using a new database covering 253 European regions over 2001-2008 including new variables on innovation, physical and human capital; and (2) we exploit both the space and time dimensions of the dataset through the estimation of a spatial Durbin fixed-effect panel model, which captures spatial feedback effects from the neighbours through spatially lagged dependent and independent variables.

Our results show that social-economic environment and traditional determinants of economic performance (distance from innovation frontier, physical and human capital and innovation) are significant. They also confirm the relevance of spatial spillovers, whereby strong indirect effects reinforce direct effects. In particular, we find that business investment and human capital of the neighbouring regions have a positive impact – both direct and indirect – on economic performance of a given region. At the same time, the structural inefficiencies related to labour market rigidities and/or skill mismatch are found to hinder economic performance. These results encourages the pursuit of structural reforms in stressed European countries and if possible at the regional level in order to boost growth and competitiveness.

Overall, our results confirm the existence of high-income clusters (mostly located in the centre of Western Europe) and their positive effects on the development of the neighbouring regions. From a policy perspective, this implies that the creation of growth poles specialised in innovative and high growth potential activities could be a strategy for Europe to catch up with the US in terms of technology and trend output.

1 Introduction

The trend decline in potential growth in most advanced economies started well before the Global Financial Crisis and the debate on «secular stagnation» has gained further importance recently[1]. The evidence is even stronger in Europe where not only potential growth has gradually declined over the past decades, but also trend output per capita has been lagging behind the United States. In the literature, weaker growth in Europe is explained to a large extent by productivity differences, in turn related to the lag in technological diffusion. Given the heterogeneity in Europe, not only across countries but also across regions, understanding the process of growth and innovation requires to take space dynamics into account. Notably, spatial spillovers may matter to explain concentration effects, agglomeration economies and industry clusters.

The European Commission launched in 2010 a strategy – « Europe 2020 » – to « deliver smart, sustainable and inclusive growth » (European Commission, 2010a). In this context, the Commission also designed a regional policy contributing to smart growth (European Commission, 2010b) to « unlock the growth potential of the EU by promoting innovation in all regions (...) by creating favourable conditions for innovation, education and research so encouraging R&D and knowledge-intensive investment and moves towards higher value added activities ». Overall, such policies aim at fostering market integration within Europe, while alleviating regional fragmentation.With a more integrated European market, economic growth in one region enlarges the market capacity and stimulates the mobility of production factors and the process of innovation diffusion. As a result, cross-regional spillovers make economic growth across regions strongly interdependent, fostering market integration and promoting

[1] See e.g. L. Summers, Why stagnation might prove to be the new normal, December 15, 2013. http://larrysummers.com/commentary/financial-times-columns/why-stagnation-might-prove-to-be-the-new-normal/

economic growth.

The knowledge and innovation capacity of the European regions depends on many factors including education, the availability of skilled labour force and R&D intensity. However, it appears that performance in R&D and innovation varies markedly across the EU regions (European Commission, 2010b) (see Figure 1). The way innovation affects economic performance in the traditional approaches has been recently questionned by empirical analyses. Indeed, the diffusion of innovation appears more complex than the traditional linear innovation model, whereby research leds to innovation, leading in turn to economic growth (Bush, 1945 ; Maclaurin, 1953). These approaches have been challenged by recent empirical work considering research and innovation together with social and structural conditions in each region (Rodriguez-Pose and Crescenzi, 2008 ; Usai, 2011). The diffusion of innovation also depends on cross-regional spillovers and recent empirical analyses depart from pure knowledge spillovers (as in Jaffe et al., 1993) to also consider socioeconomic spillovers (as in Crescenzi et al., 2007).

While considering the traditional determinants of regional economic performance (such as investment, human capital development and innovation), our analysis also puts emphasis on spatial effects related to the externalities from neighbouring regions. Spillover effects on production have been mostly studied in an international context using endogenous growth models (Aghion and Howitt, 1992) and differences in innovation capacity appear to explain in such models part of persistent differences in economic performance across countries and regions (Grossman and Helpman, 1991). Applied to regional growth, Rodriguez-Pose and Crescenzi (2006) propose an empirical model whereby regional economic performance depends on three main factors : internal innovative efforts, socio-economic local factors conducive to innovation and spatially-bound knowledge spillovers. Compared to existing work, the value added of our research is twofold : (1) we take advantage of granular information by using a new database covering 253 European regions over 2001-2008 including new variables on innovation, physical and human capital; and (2) we exploit both the space and time dimensions of the dataset through the estimation of a spatial Durbin random-effect panel model, which captures spatial feedback effects from the neighbours through spatially lagged dependent and independent variables.

Our results show that social-economic environment and traditional determinants of economic performance are found to be significant. Overall, our findings confirm the existence of significant spatial spillovers. In addition, business investment and human capital in the neighbouring regions is found to have a positive impact – both direct and indirect – on economic performance of a given region.

The paper is organised as follows : Section 2 presents the dataset and derived some stylised facts which will be explained by the empirical work. Section 3 gives the empirical specification used in this paper and the econometric approach followed to estimate it. Section 4 presents the empirical results. Section 5 concludes.

2 Dataset and stylised facts

2.1 The European Cluster Observatory dataset

The data used in this research come from the European Cluster Observatory, an initiative of the European Commission, which provides statistical information and analyses on clusters in Europe. The concept of clusters, first introduced by Porter (1990), refers to the "regional concentration of economic activities in related industries, connected through multiple types of linkages" (Ketels and

Protsiv, 2014), which support the development of new competitive advantages in emerging industries. Cluster policies are part of the Europe 2020 Strategy to rejuvenate Europe's industry. In this context, the European Cluster Observatory provides an EU-wide comparative cluster mapping with sectoral and cross-sectoral statistical analysis of the geographical concentration of economic activities and performance. The associated dataset covers a large range of series on economic performance (GDP per capita, GDP growth, productivity) as well as on its different drivers, including investment, employment, skills, education, R&D and innovation. The series are available at the NUTS 2 level for the EU.

2.2 Stylised facts on economic performance at the European regional level

We start our analysis of the dataset with some choropleth maps and scatter plots of simple correlations. Figure 1 shows the geographical distribution of GDP per capita in 2008 (end of the sample) across the EU regions. Low-income regions are concentrated in the Central, Eastern and Southeastern Europe (CESEE) countries, as well as in Southern Italy and the South of Spain and Portugal. By contrast, we can identify a concentration of high-income regions in a band going from the London area to Nothern Italy, including South-Western Germany, Austria and the South-East of France. The largest European cities are also among the regions with the highest income levels, although more dispersed geographically (e.g. Paris, Madrid, Brussels, Hamburg, Manchester, Edinburg). Figure 2 provides a similar representation for data on investment per employee. Again, regions in the CESEE countries registered the lowest levels of investment, while the highest levels are in Southern Germany, Austria and Nothern Italy. This gives some preliminary evidence of an association between income per capita level and investment expenditures. Some high investment levels are also noticeable in Greece as well as in Spain, which may be related to investment in construction during the housing boom period. Figure 3 shows a similar picture for R&D expenditure. Although the high-income regions in the centre of Europe generally shows high levels of R&D expenditure ratios, specific regions in the periphery registered the highest ratios, including Finland, the South of Sweden, the regions of Cambridge or Toulouse, all known for either large innovation centres, universities or highly innovative industries. Finally, Figure 4 shows the geographical distribution of long-term unemployment. The highest levels of long-term unemployment are concentrated on a few areas, including Eastern Germany, Slovakia, some Hungarian regions, Greece, South of Italy and the North of France. By contrast, the high-income regions have genereally very low ratios of long-term unemployed people.

Figure 5 provides some correlation analysis between GDP per capita and some variables usually associated with income or development level. As seen before, the positive correlation between income ratios and investment expenditures is confirmed. Similarly, we can notice a positive correlation between GDP per capita and innovation (R&D expenditure). Some positive association is also found between GDP per capita and education or high-skilled workers (higher education, tertiaty training, skilled migrants). Again, there seems to be a negative correlation between high income and high long-term unemployment rates, which may possibly indicate that high long-term unemployment reflects structural issues that weigh on economic development. This will be further investigated in our empirical analysis.

3 Empirical specification and econometric approach

3.1 Theoretical background

The theoretical background of our research relates to the growth theory litterature and the specification chosen can be seen as a Solow (1953) model augmented with human capital and technology level (Mankiw et al., 1992). At the same time, the empirical specification of the model is general enough to also be consistent with the endogenous growth models (Arnold et al., 2007). The augmented Solow model is based on a production function specification whereby output is a function of physical and human capital, labour and technology. As shown by Boulhol et al. (2008), the long-run relationship derived from the augmented Solow model can be estimated either directly in levels or using a specification in growth terms. The estimation of the long-run relationship in levels has been used in the literature (see Mankiw et al., 1992; Hall and Jones, 1999; Bernanke et Gurkanyak, 2001) to analyse income level differentials and can then be applied to cross country/regional differences in economic performance, measured by GDP per capita in levels. Estimating the model in levels is also consistent with the search of steady-states relationships, which is a good benchmark to assess cross-regional structural differences. Moreover, the estimation in levels could be justified by the econometric problems related to the estimation in growth terms (see Durlauf and Quah, 1999). In a panel approach as chosen in this paper, estimation in growth terms would also be problematic as estimation techniques based on dynamic fixed-effect estimators would imply intercepts to vary across regions, relying therefore on the strong assumption that all regions would need to converge to their steady-state at the same speed.

The Mankiw et al. (1992) model can be written as:

$$Y_t = K_t^{\alpha} H_t^{\beta} \left(A_t L_t\right)^{1-\alpha-\beta} \quad (1)$$

where Y_t, L_t, K_t and H_t are output, labour, physical and human capital, respectively and A_t is the level of technology. L_t and A_t are assumed to grow at the exogenous rates n and g, respectively. The dynamics of the economy is determined by:

$$\dot{k}_t = \lambda_k \frac{Y_t}{A_t L_t} - (n+g+\delta) \frac{K_t}{A_t L_t} \quad (2)$$

$$\dot{h}_t = \lambda_h \frac{Y_t}{A_t L_t} - (n+g+\delta) \frac{H_t}{A_t L_t} \quad (3)$$

where λ_k and λ_h are the investment rates in physical and human capital and δ is the depreciation rate (assumed to be the same for the two types of capital).

Assuming decreasing returns to physical and human capital ($\alpha + \beta < 1$), Eq. (2) and (3) imply that the economy converges to a steady state (denoted by $*$) defined by:

$$k^* = \left(\frac{\lambda_k^{1-\beta} \lambda_h^{\beta}}{n+g+\delta} \right)^{1/(1-\alpha-\beta)}$$

$$h^* = \left(\frac{\lambda_k^{\alpha} \lambda_h^{1-\alpha}}{n+g+\delta} \right)^{1/(1-\alpha-\beta)}$$

Substituting the two steady-state forms above into (1) and taking logs gives the equation for output per capita, which will be the theoretical basis of our empirical specification:

$$\ln\left(\frac{Y_t}{L_t}\right) = \ln A_0 + gt - \frac{\alpha}{1-\alpha}\ln(n+g+\delta) + \frac{\alpha}{1-\alpha}\ln(\lambda_k) + \frac{\beta}{1-\alpha}\ln(h^*) \quad (4)$$

Eq. (4) shows that output per capita depends on initial technology level (A_0), technological progress (g), demographic changes (n), investment in physical capital (λ_k) and the level of human capital (h^*). These variables will be included in our empirical specification, where alternative measures of these various factors will be used in the estimation.

3.2 Econometric approach

In regional science, spatial autocorrelation (or spatial dependence) refers to the situation where similar values of a random variable tend to cluster in some locations (Anselin and Bera 1998). The concept of spatial dependence is rather intuitive and has its origins in Tobler's first law of geography (1979): "Everything is related to everything else, but near things are more related than distant things."

Applied to the economic growth literature, the inclusion of spatial effects implies that economic growth or convergence in a given country or region does not only depend on determinants in the own economy (e.g. savings ratio, initial GDP, population growth, technological change etc.), but also on the characteristics of the neighbouring economies (Ertur and Koch 2007).

The spatial econometric literature suggests a range of model specifications to cope with the data generating process behind spatially correlated data. Different spatial model specifications suggest different theoretical and statistical justifications. Alternative spatial regression structures arise when the spatial autoregressive process enters into combination with dependent variables (spatial autoregressive model), explanatory variables (spatial cross-regressive model) or disturbances (spatial error model). In this paper, we use a Spatial Durbin Model (SDM) which allows including simultaneously two types of spatial dependence; namely working through the dependent variable and explanatory variables[2].

3.2.1 SDM specification

To exploit the richness of the dataset in both spatial and time dimensions, we use linear spatial dependence models for panel data as described for instance in Elhorst (2012, 2013). Past studies evidenced that spatially autocorrelated data need to be modelled using appropriate econometric techniques as in the presence of spatial autocorrelation traditional model specifications may generate biased parameter estimates (Abreu et al. 2005).

In recent years, the increasing availability of the datasets following spatial units over time led to a growing interest in the specification and estimation of economic relationships based on spatial panels. Indeed, panel data specifications represent a large number of advantages compared to cross sectional studies. First of all, panel data are more informative and tend to contain more variation and less collinearity among observations (Elhorst 2014). Second, panel data specifications tend to increase efficiency in the estimation because of a greater degree of freedom. Panel specifications also allow addressing more complicated behavioural hypothesis, including effects that cannot be addressed using solely cross-sectional data (Baltagi 2013, Hsiao 2007).

Spatial variables are likely to differ in their background variables that may affect the dependent variable in a given spatial unit. Nevertheless, these space-specific variables tend to be difficult to measure or hard to obtain. For instance, being located close to the border/seaside, in an urban/rural area or at the cen-

[2] For further information on the SDM specification, see LeSage and Pace (2009).

tre/periphery may be determinant to explain a socio-economic phenomenon. Overlooking these space-specific peculiarities may again lead to biased parameter estimates. A solution to this is to introduce an intercept ξ_i into the specification that captures the effect of the space-specific omitted variables. In the same way, the inclusion of the time-period specific effects controls for spatial-invariant time effects such as a specific year marked by an overall economic recession, the business cycle, introduction of new industrial policies in a given year, change in legislation etc.

The space-time econometric model for a panel of N observations over T periods of time can be written as a SDM[3], specified as follows:

$$Y_t = \rho \mathbf{W} Y_t + \alpha \iota_N + X_t \beta + \mathbf{W} X_t \theta + \mu + \xi_t \iota_N + u_t \tag{5}$$

where Y_t is a $N \times 1$ vector of dependent variables, ι_N is an $N \times 1$ vector of ones associated with the constant term parameter α and ρ is the spatial autoregressive parameter. $\mathbf{W}$ is a non-negative $N \times N$ spatial weights matrix describing the arrangement of the units in space relative to their neighbours (with zero diagonal elements by assumption) and $\mathbf{W}Y_t$ is a spatial vector representing a linear combination of the values of the dependent variable vector from the neighbouring regions. X_t is the matrix of own characteristics and $\mathbf{W}X_t$ is the spatial lag matrix of the linear combination of the values of the explanatory variables from neighbouring observations. ρ and θ capture the strength of spatial interactions working through the dependent and explanatory variables, respectively. u_t is the stochastic error term which - for the sake of simplicity - is assumed to be i.i.d. $N\left(0, \sigma^2\right)$.While μ is the time specific fixed effect, $\xi_t \iota_N$ is the spatial fixed effect.

[3] The SDM is a global spillovers specification, which also involves higher-order neighbours (i.e. neighbours to the neighbours, neighbours to the neighbours of the neighbours, and so on), while the local spillovers specification involves only direct neighbours. More detailed information on global spillover mechanisms is provided in Section 3.2.3.

3.2.2 Fixed vs. random effects

In spatial panel models, spatial and time-period fixed effects may be treated as fixed or random effects in the same way as in traditional panel specifications[4]. In the empirical spatial econometric literature, the majority of studies take the random effect specification as point of departure. This can be explained by three main reasons (Elhorst 2014, pp. 54-55). First, the random effect specification gives a good compromise to the all or nothing way of using the cross-sectional information from the data. Second, the random effects model avoids the loss of degrees of freedom incurred in the fixed effect model associated with a relatively large N, this is also a concern for our dataset that contains a relatively large number of regions[5]. Third, the random effect specification avoids the problem that the coefficients of the time-invariant variables and variables that only vary a little cannot be estimated. Therefore, the fixed-effect model would not be suitable for the analysis of economic development, growth or convergence which traditionally include the level of initial GDP as an explanatory variable and possibly other structural variables that vary only marginally in time.

In the SDM, the inclusion of the spatially lagged dependent variable into the right-hand side creates endogeneity as the spatially lagged dependent variable $\mathbf{W}Y$ is correlated with the error term u. As a consequence, the estimation of the SDM with the OLS estimator may generate biased and inconsistent parameters and statistical inferences. Thus, in this study we use the maximum likelihood estimator proposed by Anselin (1988).

Parameters generated by spatial models which include simultaneously spa-

[4] While in the fixed effect model a dummy variable is introduced for $N-1$ spatial unit or $T-1$ time periods (to avoid perfect multicollinearity), in random effects model, μ_i and ξ_T are assumed to be i.d.d. random variables independent from each other, with zero mean and variance σ^2_μ and σ^2_ξ.

[5] Spatial fixed effects model can only be estimated consistently when N is relatively small and T is sufficiently large, since the number of observations available for the estimation of each μ is T (Elhorst 2014, pp. 41-42).

tial interactions with the dependent variable, exogenous variables and the error may be hard to interpret in a meaningful way because of the difficulty of distinguishing these interactions from each other. Therefore, in the SDM specification above we chose to only consider spatial endogenous and exogenous interactions and disregard possible spatial autocorrelation in the error term. LeSage and Pace (2009, pp. 155-158) point out that ignoring spatial autocorrelation in the error term would only cause loss of efficiency (through the inferences). On the other hand, ignoring spatial autocorrelation in the dependent or exogenous variables would mean omitting relevant explanatory variables from the regression equation and may generate biased and inconsistent estimates of model parameters.

3.2.3 Partial derivatives

In traditional linear regression analyses it is assumed that observations are independent from other. Therefore, the parameter estimates can be straightforwardly interpreted as the partial derivative of the dependent variable with respect to the explanatory variable. However, in models with spatially lagged variables the parameter estimates also include information from the neighbours, which complicates the interpretation of the estimated parameters.

By construction, in a global spatial autocorrelation specification, like the SDM, any change to an explanatory variable in a single region i will affect the dependent variable in the region itself. In addition to this, a change in an explanatory variable will potentially indirectly affect the dependent variable in all other regions (y_j, where $j \neq i$) by inducing (positive or negative) spatial externalities. In spatial models, feedback effects arise as a result of impacts passing through neighbouring regions and then back to the region itself.

Thus, models that contain spatially lagged dependent variables exhibit a complicated derivative structure, where the standard regression coefficient interpretation of coefficient estimates as partial derivatives no longer holds:

$$\frac{\partial E\left(y_i\right)}{\partial X_{ir}} = S_r\left(W\right)_{ij}$$

Following LeSage and Pace (2009), the total impact arising from a change in explanatory variable X_r is reflected by all elements of the matrix $S_r\left(W\right)$. The matrix expression of the own and cross partial derivatives can be expressed as follows:

$$\begin{aligned} S_r\left(W\right) &= V\left(W\right)\left(I_n\alpha_1 + W\alpha_2\right) \\ V\left(W\right) &= \left(I_n - \rho W\right)^{-1} = I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + ... \end{aligned}$$

This can be broken down into direct, indirect (spatial spillovers impacts) and total impacts arising from a change in the variable X_r on average across all observations. While the diagonal elements of the $N \times N$ matrix $S_r\left(W\right)$ correspond to direct impacts, the off-diagonal elements represent indirect impacts. The direct effects can be used to test the hypothesis whether an explanatory variable has a significant effect on the dependent variable in its own economy and the indirect effects test the hypothesis whether spatial spillovers from this variable exist.

The partial derivative structure of spatial models present a reporting challenge as a dataset with N spatial units and K explanatory variables would generate K times $N \times N$ matrices of direct and indirect effects. LeSage and Page (2009) propose to report one summary indicator for direct effects which is the average of the main diagonal elements (i.e. own partial derivatives), and one summary indicator for indirect effects, which is the average of the column (or row) sums of the off-diagonal elements of the matrix[6].

4 Empirical evidence

4.1 Distance matrix

The modelling of spatial effects requires an appropriate representation of spatial arrangement of observations. Since there is no clear-cut definition for the underlying neighbourhood structure, the spatial weights matrix is generally specified based on theoretical or statistical criteria. Distance-based matrices are widely used in the literature because of their exogenous nature to economic phenomenon (otherwise endogenous distance matrices would induce high non-linearity into the model). There are several types of distance-based spatial weights matrices based on contiguity (border sharing), inverse distance or a fixed number of the nearest neighbours.

In the case of our dataset that covers the EU countries, a distance matrix based on contiguity or a fixed number of the closest neighbours may not be adequate. Therefore, we define the spatial structure as a distance decay function considering that the strength of spatial interactions declines with distance. In addition, we assume that beyond a certain critical bilateral geographic distance, interactions between provinces become negligible. To test the robustness of our results, we specify two alternative inverse distance matrices with 50 km and 100 km, as respective cut-off distances[7].

[6] The numerical magnitude of the calculation of the indirect effects based on average row or column sums are the same. The average column effect can be interpreted as the impact of changing a particular element of an exogenous variable on the dependent variable of all other regions. The alternative interpretation based on average row sums corresponds to the impact on a particular element of the dependent variable as a result of a unit change in all elements of an exogenous variable (Elhorst 2014).

[7] In our dataset 50 km was the minimum cut-off distance which allowed all regions to have at least one neighbour.

$$\mathbf{W}\{\begin{matrix} w_{ij} = 1/d_{ij}, if \quad d_{ij} < x \text{ km} \\ w_{ij} = 0, \qquad if \quad d_{ij} > x \text{ km} \end{matrix}$$

W consists of individual spatial weights wij that typically reflect the "spatial influence" of unit j on unit i. d_{ij} is the great-circle distance (calculated from the Haversine formula) between observation i and j. The distance between two regions is calculated using the longitudinal and latitudinal coordinates of their respective centroids. x is the distance beyond which spatial interactions between regions are assumed to be non-existent[8].

W is row-standardised by dividing each weight of an observation by the corresponding row sum $w_{ij} \; / \sum_j w_{ij}$. Consequently, the associated spatial autocorrelation parameters are comparable across alternative model specifications. Whereas the original inverse-distance spatial weighting matrix is symmetric, the row-standardised one is not. This implies that, region i could have a larger influence on the random variable of interest in region j and vice-versa. By convention, the distance matrix has zeros on the main diagonal, thus no observation predicts itself.

4.2 Spatial autocorrelation measure

Moran (1950)'s I statistic is the most widely used measure to detect spatial autocorrelation. The statistic reveals to what extent high (low) values of a random variables are surrounded by other high (low) values of it. Therefore, it evaluates whether the distribution pattern of a variable is clustered, dispersed, or random.

[8] Since most regions are excluded from the neighbourhood structure, the $N \times N$ dimensioned spatial weights matrix is sparse, containing a large proportion of zeros. This provides some computationally efficiency enabling the testing and specification of models with a large number of observations.

$$I = \frac{N}{S_0} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} \left(y_i - \widehat{y}\right) \left(y_j - \widehat{y}\right)}{\sum_{i=1}^{N} \left(y_i - \widehat{y}\right)}$$

where w_{ij} is the element of the spatially weighting matrix $\mathbf{W}$ corresponding to the observation pair i and j. S_0 is the sum of all w_{ij}'s and $\widehat{y}$ is the mean value of the variable of interest and N is the number of locations.

Moran's I statistic could be interpreted as the statistic measure of the co-variance of the observations in nearby provinces relative to the variance of the observations across regions. The Moran's I test is based on the null hypothesis of absence of the clustering in some geographical areas. In a given year t an index value close to 1 indicates clustering while an index value close to -1 indicates dispersion.

Moran's I statistics for GDP per capita reported below are based on two alternative distance matrix specifications. For the EU (euro area), EU50W (EA50W) corresponds to the row-standardised inverse distance spatial weights matrix with 50 km as cut off distance while the cut-off distance is 100 km in EU100W (EA100W). The positive Moran's I statistics in Figure 6 show that over the entire period of study, GDP per capita in the EU and euro area was spatially autocorrelated. In other words, GDP per capita was not randomly distributed across the EU regions and high- (low-) income region values tended to cluster geographically. In addition, higher Moran's I statistics for the EU reveal that GDP per capita in the EU shows stronger clustering compared to the euro area. As expected, the magnitude of spatial interactions decays with distance. For both the EU and the euro area, the Moran's I coefficients are smaller for the matrix using 100 km as cut-off distance. The results also show that in the EU, the level difference in Morans' I statistics generated by the two matrices are larger, probably reflecting the spread of countries across a larger geographic area.

4.3 Variables used as determinants of GDP per capita

The theoretical background presented above has determined the empirical specification used in this paper. Eq. (4) includes the initial technology level, technological progress, demographic changes or labour market conditions, investment in physical capital and the level of human capital as the determinants of GDP per capita. The dataset from the European Cluster Observatory includes several series that could be used as measures of the various determinants of regional economic performance. Table 1 presents the variables used in the empirical exercise, the expected signs and interpretation. After having tested alternative specifications including other variables available in the database we only report the most parcimonious ones with good statistical properties.

Given that the empirical modelling approach includes spillover effects from neighbouring regions through the spatially lagged dependent and explanatory variables, the drivers of economic performance will also include such external factors. We expect generally positive spillovers, confirming the economic benefits coming from knowledge or/and investment intensive neighbours. However, we cannot exclude possible crowding out effects in terms of investment (e.g. the attraction of investors in a region may reduce their investment in neighbouring regions) or human capital.

The SDM specification allows negative spillovers (indirect effects) from the neighbours although the direct effects (i.e. the impact of the explanatory variable on its own region) are positive. These potentially complex relationships could not be modelled with the use of, e.g., a spatial autoregressive model (SAR)[9], because in a SAR model the direct (the impact of a change in invest-

[9] The SAR model includes spatial interactions only through the spatially lagged dependent variable.

ment on its own economic performance) and the indirect effects (the impact of the same change on the economic performance of the neighbours and coming back to the region) have by construction the same sign. Furthermore, the ratio between the indirect and direct effects is the same in a SAR model for every explanatory variable (LeSage and Pace 2009; Elhorst 2012; Pace and Zhu 2012).

Table 1. Key variables and expected signs of the parameters

	Sign	Interpretation
Dependent variable		
GDP per capita		Measure of economic performance
Initial technogical level		
Initial GDP per capita	>0	Knowledge available and distance to technological frontier
Innovation		
R&D public expenditure	>0	Indicator of science and technology policies
Demographic/labour		
Pop. aged 15-34	>0	Young population
Skilled migrants	>0	Demographic changes from migration of skilled workers
Long-term unemployment	<0	Degree of labour market rigidity and skill mismatch
Physical capital		
Business investment	>0	Accumulation of physical capital
Human capital		
Tertiary education	>0	Socio-economic conditions in educational achievements

4.4 Empirical results

We conduct our empirical analysis based on the specification determined by Eq. (4) and using the variables included in Table 1. We run regressions both for the entire EU sample and for a sample restricted to euro area regions, using in all cases random-effect specifications as explained above. To account for country-specific effects, we include country dummies (in our regressions). These dummies capture country-specific effects, such as economic policies taken at the national level (taxation, industrial policies and regulations in product and labour markets, ...). Concerning the distance matrix, we present here results based on the matrix with 50 km as cut-off distance[10].

Table 2 and 3 present the results for the whole EU sample and a euro-area subsample respectively. After having tested a number of alternative specifications, we only report those yielding significant coefficients. The four specifications reported include the initial level of GDP per capita and business investment, but differ according to the measures of innovation, human capital or demographic/labour market indicators. Starting with the spatially lagged variables, the first interesting result concerns the large and significant spatial autoregressive coefficient $\rho\,(\mathbf{W}Y)$ confirming that being surrounded by low(high) income regions is a significant determinant of economic performance for a given region. In addition, the large spatial autoregressive coefficients in all specifications confirm the presence of significant spatial feedback effects where strong indirect effects reinforce direct effects. We also find that the investment going to the neighbouring regions, $\Phi_1\,(\mathbf{W}{*}\text{bus.inv.})$, has a positive effect on economic development of a given region, ruling out a possible crowding out effect on investment. In the same way, the availability of a well-educated human capital, $\Phi_2\,(\mathbf{W}{*}\text{tert.educ.})$, in the neighbouring regions is found to have a positive im-

[10] Results based on the matrix with 100 km are as cut-off distance are very similar to those presented here and are available upon request.

pact on own economic development, most probably through commuting and inter-regional migration of the skilled workforce.

Moving to the other explanatory variables, traditional variables used in the literature are found significant. We find in all specifications a positive impact of initial GDP per capita, which proxies the initial technology level (i.e. the closer to the technological frontier, the higher the performance). The accumulation of both physical capital (business investment) and human capital (tertiary education) appear to determine significantly regional income. Demographic factors have also a positive and significant impact on income level, such as the share of young population (population aged 15-34) or demographic changes from migration of skilled workers. Concerning innovation, only public R&D expenditure is found to be statistically significant, which may point to the role of European governments in financing innovation, either to complement market failures or to provide financing at seed and initial stage. Finally, the negative coefficient of long-term unemployment is likely to signal that labour market rigidities and/or skill mismatch create inefficiencies hindering economic performance.

The results show the presence of significant indirect effects. We interpret the indirect effect of initial GDP per capita (which is a time invariant variable) as follows: a high level of technology also helps the development of regions around, leading to positive spillovers reinforcing the initial direct effects. The economic interpretation of the other indirect effects is rather straightforward; overall they amplify the direct impact of the explanatory variable through spatial feedbacks (i.e. the spatial multiplier effect).

The majority of country dummies come out significant, showing the relevance of country-specific effects in explaining economic performance. Therefore, the inclusion of these dummies improves the performance of the model estimations, while not qualitatively changing the outcomes of the estimations (see Appendix

Tables A3 and A4 for estimates excluding country dummies for the EU and the euro area samples respectively).

Finally, the results for the euro area subsample are fairly similar to those of the whole EU, showing that our specification is robust to different country samples. A few differences are however worth pointing out. First, the spatial autoregressive coefficient $\rho\,(\mathbf{W}Y)$ is higher for the EU sample, which leads to significantly larger feedback effects complementing the direct effects. Moreover, the coefficient of initial GDP per capita is higher for the euro area as regards the direct effects, meaning that the initial level of technology is more important to explain economic performance in the euro area than in the EU regions. Given the larger presence of mature economies in the euro area sample this result appears rather intuitive: an economy initially close to the technological frontier is expected to remain among the best performers over time. Indeed, technology diffusion is a slow process requiring long periods to enhance significantly economic performance. However, due to data limitations, the initial GDP in 2000 is too close to the end period of 2008 to allow for the diffusion process to fully take place. Concerning total effects, the EU sample has nevertheless stronger coefficients associated with initial GDP per capita, driven by stronger indirect effects.

5 Concluding remarks

Our results show that social-economic environment and traditional determinants of economic performance (distance from innovation frontier, physical and human capital and innovation) are significant. They also confirm the relevance of spatial spillovers, whereby strong indirect effects reinforce direct effects. In particular, we find that business investment and human capital of the neighbouring regions have a positive impact – both direct and indirect – on economic performance of a given region. At the same time, the structural inefficiencies related to labour market rigidities and/or skill mismatch are found to hinder economic performance. These results encourages the pursuit of structural reforms in stressed European countries and if possible at the regional level in order to boost growth and competitiveness.

Overall, our results confirm the existence of high-income clusters (mostly located in the centre of Western Europe) and their positive effects on the development of the neighbouring regions. From a policy perspective, this implies that the creation of growth poles specialised in innovative and high growth potential activities could be a strategy for Europe to catch up with the US in terms of technology and trend output. Our methodological approach focusses on the summary measures of the average spatial effects. Further resseach is warranted in identifying and quantifying the spillovers coming from specific clusters in a regional or European context. Furthermore, with better data availability exploring the sectoral dimension of the clusters would be insightful.

Table 2. Empirical Results - Random effect - EU sample

Dependent variable: ln(GDP per capita)	[1]	[2]	[3]	[4]
W= row-standardised inv. dist. matrix, cut-off=50 km				
$\rho\,(\mathbf{W}Y)$	0.85***	0.86***	0.71***	0.70***
Φ_1 ($\mathbf{W}$*bus.inv.)	0.003***	0.006***	0.006***	0.002***
Φ_2 ($\mathbf{W}$*tert.educ.)	-	-	0.002***	0.002***
Number of obs.	2024	2024	2024	2024
R^2	0.82	0.81	0.88	0.89
Log-likelihood	1991	1999	2217	2213
DIRECT				
GDP per capita (initial)	0.94***	0.92***	0.71***	0.70***
Business investment	0.007***	0.008***	0.005***	0.005***
R&D expenditure (% of GDP)	0.12***	0.13***	-	-
Pop aged 15-34	-	0.01***	0.01***	-
Skilled migrants	-	-	-	0.01***
Long-term unemployment	-	-	-0.02***	-0.02***
Tertiary education	-	-	0.003***	0.004***
INDIRECT				
GDP per capita (initial)	4.53***	4.80***	1.62***	1.47***
Business investment	0.05***	0.07***	0.03***	0.02***
R&D expenditure (% of GDP)	0.60***	0.67***	-	-
Pop aged 15-34	-	0.07***	0.03***	-
Skilled migrants	-	-	-	0.03***
Long-term unemployment	-	-	-0.04***	-0.04***
Tertiary education	-	-	0.02***	0.02***
TOTAL				
GDP per capita (initial)	5.48***	5.72***	2.34***	2.17***
Business investment	0.06***	0.08***	0.03***	0.02***
R&D expenditure (% of GDP)	0.73***	0.79***	-	-
Pop aged 15-34	-	0.08***	0.05***	-
Skilled migrants	-	-	-	0.04***
Long-term unemployment	-	-	-0.06***	-0.06***
Tertiary education	-	-	0.02***	0.02***

Table 3. Empirical Results - Random effect - Euro area sample

Dependent variable: ln(GDP per capita) W= row-standardised inv. dist. matrix, cut-off=50 km	[1]	[2]	[3]	[4]
$\rho\,(\mathbf{W}Y)$	0.70***	0.71***	0.66***	0.63***
Φ_1 ($\mathbf{W}$∗bus.inv.)	0.010***	0.011***	0.008***	0.007***
Φ_2 ($\mathbf{W}$∗tert.educ.)	-	-	0.003***	0.003***
Number of obs.	1264	1264	1264	1264
R^2	0.86	0.85	0.87	0.89
Log-likelihood	1599	1600	1670	1681
DIRECT				
GDP per capita (initial)	0.97***	0.97***	0.83***	0.76***
Business investment	0.006***	0.007***	0.006***	0.005***
R&D expenditure (% of GDP)	0.09***	0.09***	-	-
Pop aged 15-34	-	0.003***	0.008***	-
Skilled migrants	-	-	-	0.02***
Long-term unemployment	-	-	-0.01***	-0.01***
Tertiary education	-	-	0.003***	0.003***
INDIRECT				
GDP per capita (initial)	2.05***	2.13***	1.44***	1.16***
Business investment	0.04***	0.05***	0.03***	0.02***
R&D expenditure (% of GDP)	0.20***	0.21***	-	-
Pop aged 15-34	-	0.007***	0.01***	-
Skilled migrants	-	-	-	0.03***
Long-term unemployment	-	-	-0.02***	-0.02***
Tertiary education	-	-	0.01***	0.01***
TOTAL				
GDP per capita (initial)	3.02***	3.10***	2.27***	1.92***
Business investment	0.05***	0.05***	0.04***	0.03***
R&D expenditure (% of GDP)	0.29***	0.30***	-	-
Pop aged 15-34	-	0.01***	0.02***	-
Skilled migrants	-	-	-	0.05***
Long-term unemployment	-	-	-0.03***	-0.03***
Tertiary education	-	-	0.02***	0.01***

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Appendix

Table A1. Empirical Results - Random effect - EU sample country dummy coefficients (total effect)

Dependent variable: ln(GDP per capita) W= row-standardised inv. dist. matrix, cut-off=50 km	[1]	[2]	[3]	[4]
Germany (benchmark)	-	-	-	-
Austria	1.73***	1.85***	0.51*	0.51**
Belgium	-0.22	-0.39	-0.23	-0.20
Bulgaria	7.59***	7.42***	1.76***	1.68***
Cyprus	3.89***	3.44***	1.20*	1.37**
Czech Rep.	4.63***	4.34***	0.98***	1.10***
Denmark	-0.56	-0.57	-0.66**	-0.57**
Estonia	4.75***	4.61***	0.58	0.57
Spain	2.03***	1.64***	0.16	0.37*
Finland	2.91***	3.21***	0.31	0.33
France	2.51***	2.55***	0.95***	0.95***
Greece	3.85***	3.89***	1.24***	1.36***
Hungary	6.41***	6.20***	1.41***	1.42***
Ireland	0.44	0.02	-0.17	0.13
Italy	0.90***	0.86***	-0.12	-0.01
Lithuania	5.09***	4.92***	0.65	0.75
Luxembourg	0.73	0.69	0.95	0.29
Latvia	4.67***	4.31***	0.29	0.38
Malta	1.31	0.95	-0.28	-0.08
Netherland	-0.22	-0.36	-0.48**	-0.37*
Poland	4.40***	3.96***	0.45	0.66**
Portugal	1.63***	1.33*	-0.24	-0.07
Romania	9.00***	8.86***	2.09***	2.11***
Sweden	0.26	0.25	-0.71**	-0.64**
Slovenia	2.42*	2.00	0.22	0.40
Slovakia	5.52***	5.10***	1.35***	1.56***
United Kingdom	-0.56*	-0.65*	-0.50***	-0.45*

Table A2. Empirical Results - Random effect - EA sample country dummy coefficients (total effect)

Dependent variable: ln(GDP per capita) W= row-standardised inv. dist. matrix, cut-off=50 km	[1]	[2]	[3]	[4]
Germany (benchmark)	-	-	-	-
Austria	-0.76***	-0.73***	-0.37***	-0.37***
Belgium	-1.17***	-1.17***	-0.57***	-0.60***
Cyprus	0.78	-0.12	0.30	0.22
Spain	-1.11***	-1.09***	-0.46***	-0.47***
Estonia	1.62***	1.67***	0.66**	0.32
Finland	0.60***	0.71***	0.25	0.21
France	-0.68***	-0.65***	-0.21**	-0.21**
Greece	0.05	0.05	0.27**	0.21*
Ireland	-0.82**	-0.87**	-0.65**	-0.48*
Italy	-0.72	-0.72	-0.45***	-0.41***
Lithuania	1.37***	1.56***	0.48***	0.25
Luxembourg	-0.54	-0.62	0.31	-0.39
Latvia	1.45***	1.54***	0.44	0.19
Malta	-0.31	-0.29	-0.33	-0.37
Netherland	-1.02***	-1.02***	-0.63***	-0.56***
Portugal	-0.11	-0.10	-0.25*	-0.28*
Slovenia	-0.53	-0.56*	-0.48*	-0.43*
Slovakia	0.62***	0.62***	0.20	0.12

Table A3. Empirical Results - Random effect - EU sample without country dummies

Dependent variable: ln(GDP per capita) W= row-standardised inv. dist. matrix, cut-off=50 km	[1]	[2]	[3]	[4]
$\rho\,(\mathbf{W}Y)$	0.83***	0.85***	0.70***	0.68***
Φ_1 ($\mathbf{W}$*bus.inv.)	0.005***	0.008***	0.008***	0.005***
Φ_2 ($\mathbf{W}$*tert.educ.)	-	-	0.002***	0.002***
Number of obs.	2024	2024	2024	2024
R^2	0.69	0.68	0.79	0.80
Log-likelihood	1924	1935	2158	2152
DIRECT				
GDP per capita (initial)	0.48***	0.50***	0.52***	0.49***
Business investment	0.008***	0.008***	0.006***	0.005***
R&D expenditure (% of GDP)	0.12***	0.12***	-	-
Pop aged 15-34	-	0.02***	0.01***	-
Skilled migrants	-	-	-	0.01***
Long-term unemployment	-	-	-0.02***	-0.02***
Tertiary education	-	-	0.004***	0.004***
INDIRECT				
GDP per capita (initial)	2.11***	2.38***	1.11***	0.94***
Business investment	0.06***	0.09***	0.04***	0.02***
R&D expenditure (% of GDP)	0.53***	0.58***	-	-
Pop aged 15-34	-	0.08***	0.03***	-
Skilled migrants	-	-	-	0.03***
Long-term unemployment	-	-	-0.04***	-0.04***
Tertiary education	-	-	0.01***	0.01***
TOTAL				
GDP per capita (initial)	2.59***	2.88***	1.64***	1.43***
Business investment	0.07***	0.09***	0.04***	0.03***
R&D expenditure (% of GDP)	0.65***	0.71***	-	-
Pop aged 15-34	-	0.09***	0.05***	-
Skilled migrants	-	-	-	0.04***
Long-term unemployment	-	-	-0.05***	-0.06***
Tertiary education	-	-	0.02***	0.02***

Table A4. Empirical Results - Random effect - Euro area sample without country dummies

Dependent variable: ln(GDP per capita) W= row-standardised inv. dist. matrix, cut-off=50 km	[1]	[2]	[3]	[4]
$\rho\,(\mathbf{W}Y)$	0.69***	0.70***	0.63***	0.58***
Φ_1 ($\mathbf{W}$*bus.inv.)	0.011***	0.012***	0.009***	0.009***
Φ_2 ($\mathbf{W}$*tert.educ.)	-	-	0.004***	0.003***
Number of obs.	1264	1264	1264	1264
R^2	0.71	0.68	0.82	0.84
Log-likelihood	1529	1530	1632	1644
DIRECT				
GDP per capita (initial)	0.68***	0.69***	0.69***	0.63***
Business investment	0.007***	0.007***	0.006***	0.005***
R&D expenditure (% of GDP)	0.08***	0.08***	-	-
Pop aged 15-34	-	0.005***	0.010***	-
Skilled migrants	-	-	-	0.02***
Long-term unemployment	-	-	-0.01***	-0.01***
Tertiary education	-	-	0.003***	0.003***
INDIRECT				
GDP per capita (initial)	1.33***	1.42***	1.02***	0.77***
Business investment	0.05***	0.05***	0.03***	0.03***
R&D expenditure (% of GDP)	0.15***	0.16***	-	-
Pop aged 15-34	-	0.01***	0.01***	-
Skilled migrants	-	-	-	0.02***
Long-term unemployment	-	-	-0.02***	-0.02***
Tertiary education	-	-	0.01***	0.01***
TOTAL				
GDP per capita (initial)	2.01***	2.11***	1.71***	1.40***
Business investment	0.05***	0.06***	0.04***	0.03***
R&D expenditure (% of GDP)	0.23***	0.24***	-	-
Pop aged 15-34	-	0.01***	0.02***	-
Skilled migrants	-	-	-	0.04***
Long-term unemployment	-	-	-0.03***	-0.03***
Tertiary education	-	-	0.02***	0.01***

Figures

Figure 1 – GDP per capita (EUR) - 2008

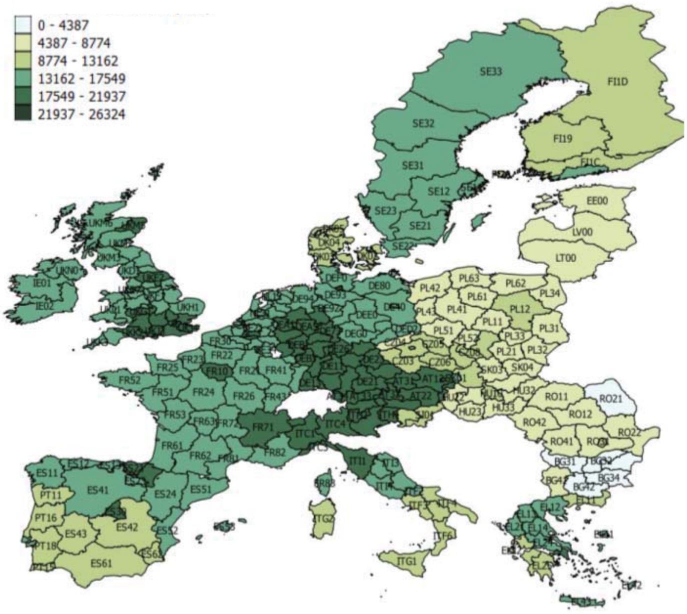


Figure 2 - Business investment per employee (thousand EUR/employee) - 2008

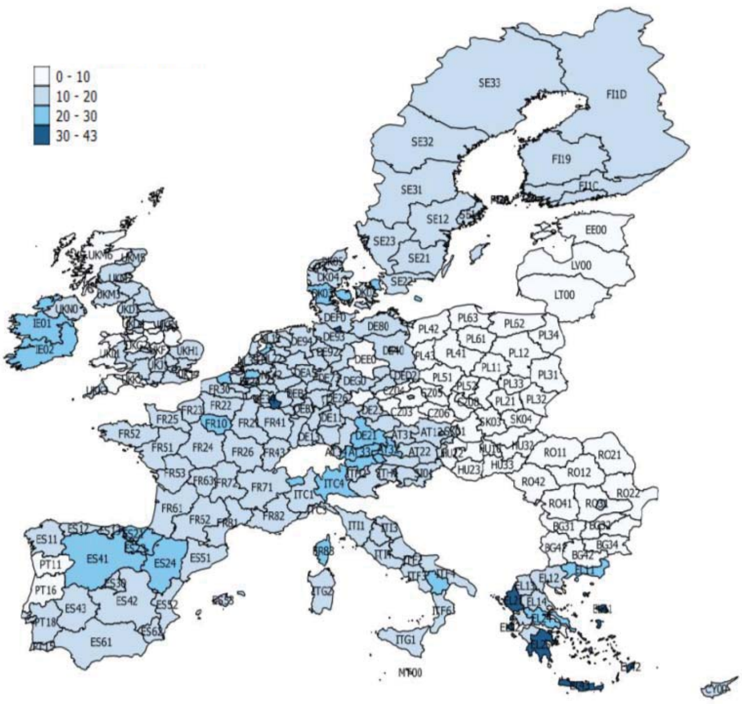


Figure 3 – R&D total expenditure (as % of GDP) - 2008

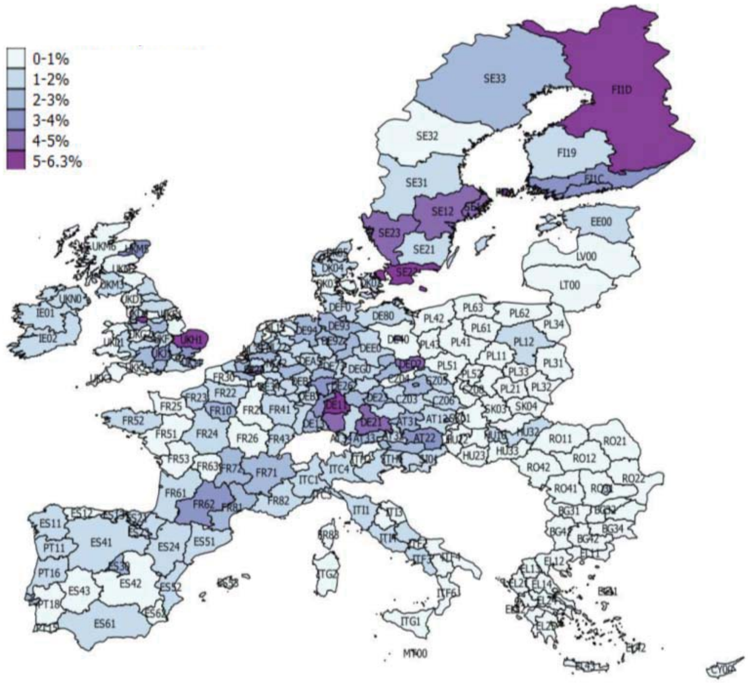


Figure 4 – Long-term uneployment - 2008

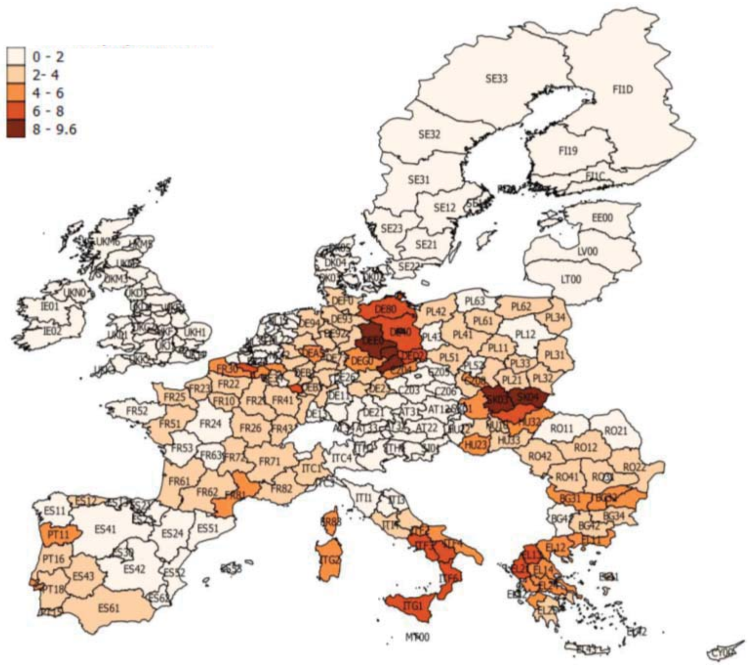


Figure 5 – Correlations between GDP per capita and selected factors (2001-2008)

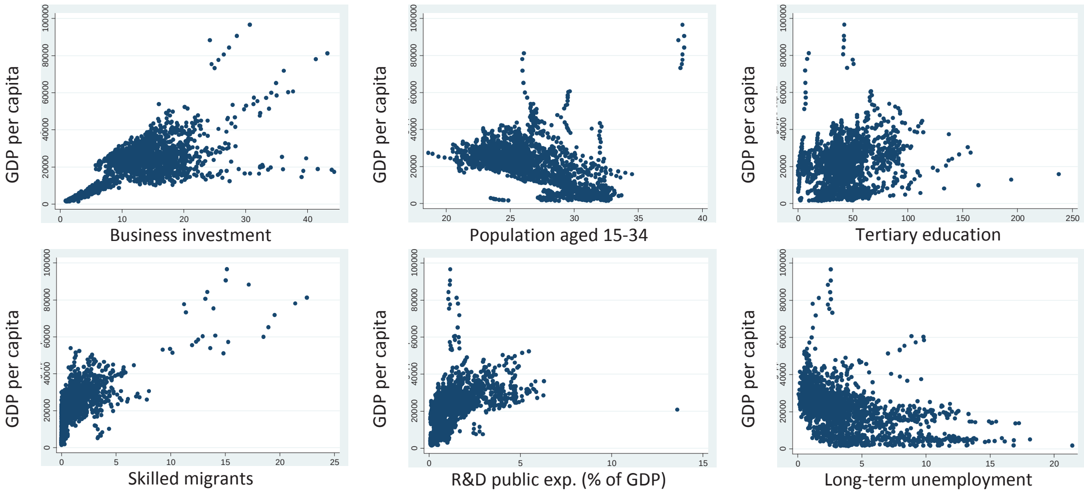
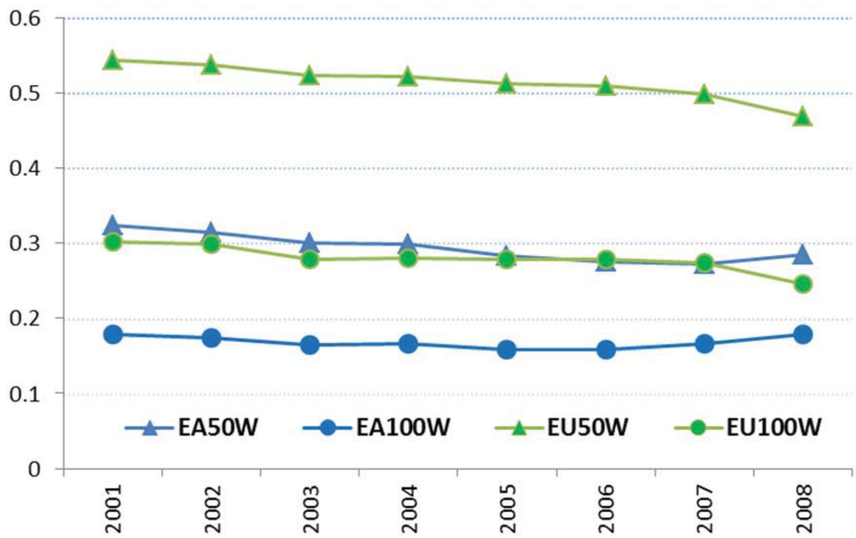


Figure 6 - Moran's I coefficients for GDP per capita for the European Union and Euro Area cross-sections (2001-2008)



Note: All reported Moran's I coefficients are statistically significant at the 1% level (based on z-scores, GDP per capita in natural logarithm.

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