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The Spatial Hierarchy of Technological Change and Economic Development in Europe

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Abstract
This paper discusses the possibility of a spatial hierarchy of innovation and growth dynamics in Europe. A spatial hierarchy is understood as a geographical clustering of regions, where important differences exist in terms of innovation and growth dynamics between the clusters. The literature on regional growth and innovation is briefly scanned. After this, a database on European regional growth and innovation dynamics is presented. Spatial correlation analysis and spatial principal components analysis are used to explore the possibility of a spatial hierarchy in Europe. The results point to a hierarchy consisting of four groups: South Europe, East Europe, and two groups in West and North Europe. Growth and innovation performance in these clusters is discussed, and some policy conclusions are drawn.

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1. Introduction

Regional policy is becoming more and more important in the EU, especially because of the eastward enlargement of the Union. The challenge of regional *cohesion*, since long one of the key policy aims at the European level, has become much larger now that the EU has been enlarged to 27 Member States, and all these new members have relatively low GDP per capita levels, as well as economic systems that are still much influenced by their communist past. Although cohesion is a policy aim that suffers from its broad definition, it is clear that large regional differences in GDP per capita are not consistent with it. At the same time, economic growth in the strongest regions of Europe is an important source of competitiveness of Europe as a whole vis-à-vis the rest of the world.

Innovation has since long been suggested as one of the key factors in regional growth (e.g., Fagerberg and Verspagen, 1994), and the topic therefore plays a large role in discussions, if perhaps not in the policy practice of the so-called European Structural Funds, surrounding regional cohesion. Innovation has the potential to both increase and decrease regional income differentials. In addition, because innovation and knowledge flows are found to be spatially concentrated, it has the potential to create spatial patterns, hierarchies in particular, of high and low growth (Storper and Walker, 1989).

Although there is much work on innovation and economic growth among European regions (Fagerberg, Caniëls and Verspagen, 1997, Bottazzi and Peri, 2003, to name just a few), the evidence on the overall spatial patterns of interaction between the two phenomena is still scarce. It is the aim of this paper to provide such an overview, by using a concrete dataset covering a broad range of 30 variables, and a set of 154 regions covering the EU-25, as well as a range of impressionistic quantitative techniques. The perspective will be very much explicitly a spatial one, i.e., the importance of the role of geographical space is acknowledged in the empirical methods and the data collection process. Although there is a need for it, the paper does aim to develop or apply a theoretical framework that can precisely outline and identify the causal relationships between technology, economic growth and the factor that (jointly) drive them.

The paper is organized as follows. Section 2 provides a brief overview of the theoretical work on technology, economic growth and regional disparities in living standards. In Section 2, we will explain the geographical classification that is used throughout the analysis, as well as the spatial weighting scheme. Section 4 briefly introduces the data. Section 5 looks at a basic indicator of spatial dependence, i.e., Moran coefficients for spatial correlation, in order to describe the basic tendencies of spatial interaction between our variables. Section 6 adopts an exploratory econometric method aimed at pointing to the proximate causes of the spatial correlation patterns observed in the previous section. Section 7 provides the final piece of empirical analysis, and uses a combination of spatial principal components analysis and cluster analysis to classify regions. We obtain 4 groups of regions, which we interpret as the spatial hierarchy of growth and innovation in Europe. Section 8 summarizes and concludes.

2. Theoretical background

Technological change is now central in the theory of economic growth. It is recognized as an important driver of productivity growth and the emergence of new products from which consumers derive welfare. The relationship between technological change and economic growth and development can be analyzed from a variety of theoretical perspectives (Verspagen, 2004). All of these stress how technological change itself depends not only on the work by scientists and engineers, but also on a wider range of economic and societal factors, including institutions such as intellectual property rights and corporate governance, the working of markets, a range of governmental policies (science and technology policy, innovation policy, macroeconomic policy, competition policy, etc.), historical specificities, etc.

While it is beyond the scope of this contribution to survey these approaches and factors in a detailed way, there is at least one general conclusion that may be derived with regard to the technology economy relationship. This is the tendency for technology to be both a factor of divergence of development levels between parts of the world, and, in other eras of areas, to be a factor of convergence. Maddison (2005) has documented from an empirical perspective the widely differing growth experience at a global level over the last millennium. Divergence of growth rates leads to dramatic income differentials that are only vary partially counteracted by convergence trends, and which have led to one of the most pressing global issues today, i.e., that of widely varying income levels between different parts of the world. According to the World Bank's World Development Indicators (2006 version), the ratio between GDP per capita in the richest and poorest country in the world has grown from 67 in 1985 to 114 in 2005. Between regions in a relatively homogenous set of countries such as Europe, the differences are much smaller, but still sizeable. In the dataset of 154 regions that will be explored in this contribution, the ratio of GDP per capita in the richest and poorest region was 6 in 1995, and it grew to 6.66 in 2002.

Differences in the ability of countries or regions to generate or assimilate technological change are an important driver of such differences (Fagerberg, 1995). One of the central mechanisms that makes technology a potentially diverging factor is the property that knowledge itself is an important factor in producing knowledge (Dosi, 1988). Thus, those (firms, regions, countries) who already possess an advantageous position in generating technological change for growth, are likely to remain in a good position.

This phenomenon of increasing returns is potentially counteracted by another characteristic of technology and knowledge, i.e., that it is a non-rival good that may spill over to others than the ones who originally introduce an innovation. In other words, technology may be imitated at lower costs than at which it is introduced. This is a great potential source of (global) welfare, since it greatly increases the potential pay-off of technological change without proportionally increasing the costs of it. However, spillovers also pose an incentive problem (Arrow, 1962), because threatened imitation discourages investment in technology that is undertaken for private benefits.

At the macro level, the beneficial effect of technology imitation and spillovers is seriously hampered by the same phenomenon that causes technology to possess increasing returns: in order to imitate technology, a certain, substantial level of knowledge is required at the end of the imitator (e.g., Abramovitz, 1986). This may lead to a vicious circle, or low-growth trap (Verspagen, 1991), because countries without substantial knowledge about modern technologies will both generate low growth and be unable to benefit from imitation.

Thus, technology spillovers play a central role in processes of divergence and convergence of welfare levels. At the regional level, technology spillovers have an important spatial component, as it has been argued that spillovers don't easily travel over large distances. This is a phenomenon that has been discussed from a wide variety of perspectives, such as business studies (Von Hippel, 1994), economic geography (Morgan, 2004), and economics (Jaffe, Trajtenberg and Henderson, 1993). The most often quoted reason for such a tendency of knowledge spillovers to be geographically concentrated, is that knowledge transfer has important tacit dimensions. While certain parts of knowledge may be codified, for example in written materials, other, important parts are embodied in the minds of practitioners, and can only be transferred by face-to-face interaction. Even with jet air travel and the internet, being located in proximate geographical space thus provides important advantages for transmitting and receiving knowledge spillovers (e.g., Johnson et al, 2002).

It is not hard to imagine (see, e.g., Martin and Ottaviano, 1999, for a formal exposition, or Storper and Walker, 1989, for a more appreciative perspective) that such a tendency can lead to geographical hierarchies of economic development and growth, or core-periphery patterns. Fagerberg, Verspagen and Caniëls (1997) have argued that in Europe, technology and innovation may have had such a diverging influence over the past decades. But the (empirical) work on the spatial dimension of technology spillovers has largely ignored the issues, and has mainly addressed the matter whether spillovers are geographically concentrated or not. This work, at least in economics, is mainly based on patent citations (e.g., Jaffe, Trajtenberg and Henderson, 1993, for the US, Maurseth and Verspagen, 2002 and Bottazzi and Peri, 2003, both for Europe), and concludes that there is indeed a tendency for spillovers between nearby locations to be more frequent than between far-away places.

But it is also clear that spillovers, and patent citations, may also occur over large distances, and the work on the geographic concentration of patent citations has not tackled the question of how strong the local and non-local parts of spillover influence growth rates and growth rate differentials. In fact, this literature most often does not even ask the question as to what is the impact of geographically concentrated spillovers on the location of invention or innovation activities. Obviously, if technology transfer is easier over close distances, there is an incentive to locate R&D (and other innovation related) activities close together in space. But the patent citations literature sees this as something that needs to be controlled for, rather than something that needs to be explained and used as a starting point for further analysis.

The reason for this is that the two phenomena, location of R&D and technology spillovers as indicated by patent citations, are hard to distinguish from a causal point of view. If R&D is concentrated (for whatever other reason that spillovers), spillovers will automatically occur over shorter distances, simply because the two parties in the spillover are located close together. Thus, without an exact overview of why R&D and innovation activities are historically co-located, it is hard to make a clear assessment of causality. Therefore, researchers (following Jaffe, Trajtenberg and Henderson, 1993) have focused on the question if patent citations (as an indication of spillovers) are more concentrated than could be expected on the basis of the pre-existing pattern of concentration of R&D.

Such a strategy, even if useful for the specific context in which it is used, does not bring us further in terms of assessing the importance of geographically concentrated technology flows and their potential role in the geography of economic development and economic growth. In order to address this issue, we need to develop sharper analytical and empirical tools to disentangle the exact causal mechanisms and put them to the test.

Having said this, we should hastily add that it is not the aim of this paper to address completely this ambitious research question. Rather, the current contribution wants to set the empirical stage for such a collective endeavour, by outlining some of the stylized facts and stylized patterns of technological change and economic development at the European regional level. The research questions that we will ask are, first, whether any spatial concentration can be observed in growth rates and the potential variables that determine them across the European geography; and second, whether there is any indication that this has led to a spatial hierarchy in Europe that reflects the specific advantages that some parts of the EU have over others in generating economic welfare from investment in technological change.

3. Regional classification and distance weights

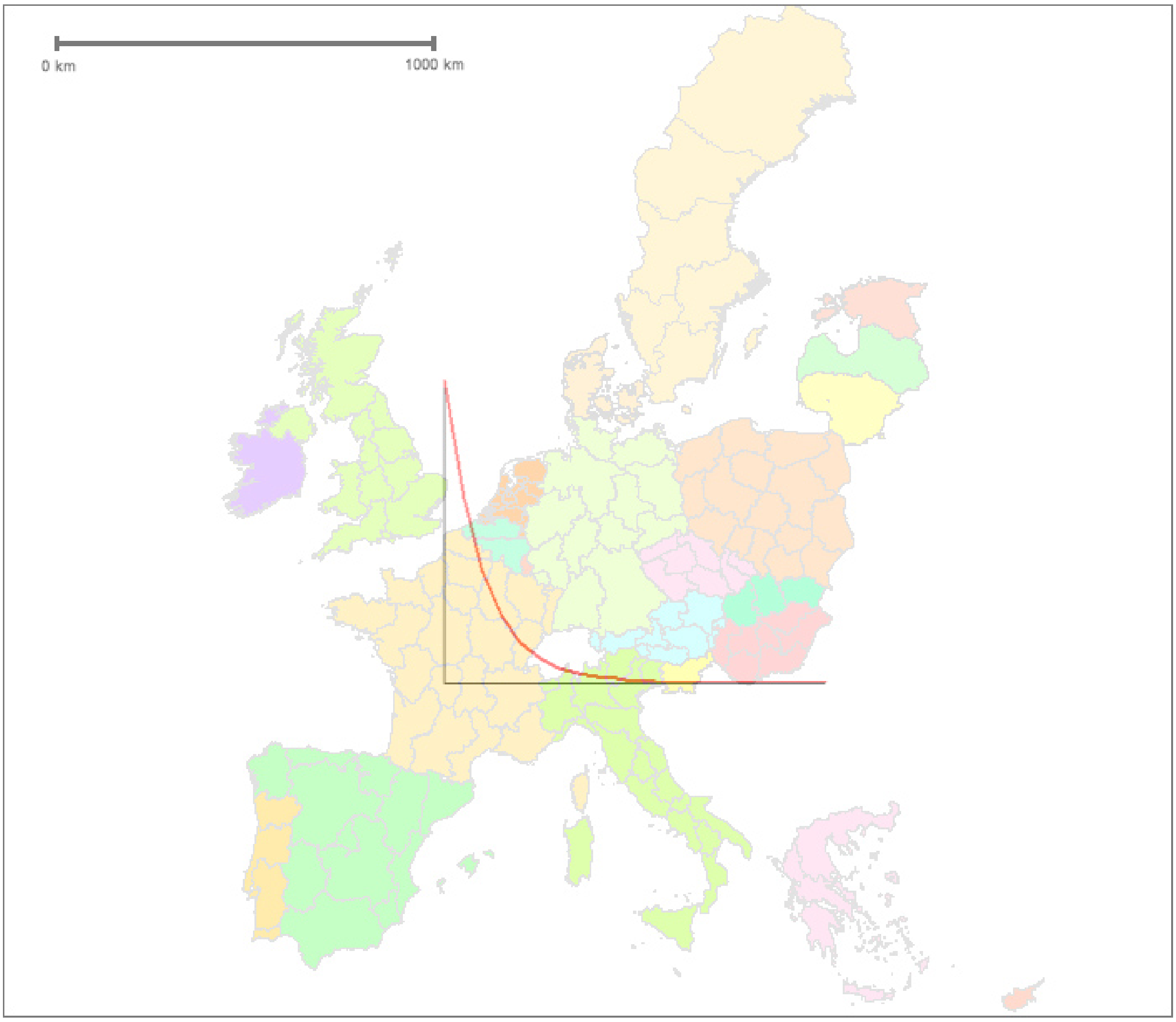
The regional classification that is used in this paper is based on the commonly used NUTS classification of regions in Europe.[1] However, we do not use the standard NUTS scheme, but instead opt to create a custom classification, which is based on a mixture between NUTS aggregation levels. We use NUTS level 0, which is the country level, for Denmark, Estonia, Ireland, Latvia, Lithuania, Luxemburg, Malta and Slovenia. The main reason why we do not break down these countries into regions is that data at any sub-national level are not available (from Eurostat). For the other countries, we created the custom regional breakdown with an aim to create regional units of approximately equal territorial size (although variations still exist, obviously), as well as to maximize data availability (data is less commonly available for more detailed breakdowns). In a fair amount of cases, we merged several regions to create larger entities. This was done especially in cases were regions at the particular level we are using correspond to (large) cities (and their immediate surroundings), because we do not want to mix in our analysis purely metropolitan environments with more general regions.[2]

Thus, we are using mostly NUTS 1 level for Belgium and Germany, and mostly NUTS 2 level for Austria, Czech Republic, Spain, Finland, France, Greece, Hungary, Italy, Poland, Portugal, Sweden and Slovak Republic, and a mix between NUTS 1 and 2 for the Netherlands and the United Kingdom. The complete list of regions used is given in the appendix, and shown on Map 1.

Our spatial analysis involves weighting by geographical distances (we use km distances as our unit throughout the paper). Although we experimented with a wide range of weights

[1] See http://ec.europa.eu/eurostat/ramon/nuts/home_regions_en.html.
[2] The exact list of regions and their definitions will be given in a future version as an Appendix.

(such as binary weights based on contiguity, nearest neighbours or threshold distance), we present results for only a single type of weights. These are based on exponential decay, and are given by the formula $w_{ij} = e^{-0.01 d_{ij}}$, where w_{ij} is the spatial weight between regions i and j, and d_{ij} is the distance between the centroids of the two regions. The exponential parameter -0.01 is arbitrary, but is chosen to reflect a fairly rapid decline of the weight with distance.[3] The exponential decay function is projected onto Map 1, where the range of the curve is scaled to reflect a distance of 1000 km. Obviously, the maximum weight is 1 (for distance 0, or, the weight of regions with themselves), and we see that the steep decay implies that the weight drops below ½ already for most of the nearest neighbours. At a distance of 500 km (which is at most 3 – 5 orders of contiguity), the weight becomes effectively zero.



Map 1. The sample of European regions, with distance weights function (exponential decay) projected

Before we use the weights in the spatial analysis, they are standardized. Usually, we use row-standardization, which means that in a region-by-region distance matrix of the exponen-

[3] Calculations with weights that decay slower generally show that spatial dependence is much lower than what is reported in this paper. Results for alternative weighting schemes are available on request.

tially decaying weights, we divide each cell by its row sum. Thus, for each region in the analysis, the sum of weight relative to all other regions in the sample is set to zero. This effectively means that we do not make any distinction between central and more peripheral regions. In some cases (the spatial principal components analysis), we use a different standardization procedure. In this case, each cell in the distance matrix is divided by the matrix total, so that all cells in the matrix add to 1. Throughout the analysis, we set the weights w_{ii} to zero for all regions i. This means that in any spatially weighted calculation, the region itself is excluded.

4. Data and sources

The analysis will be based on 30 variables, which we will now briefly present. The variable names and short definitions are listed in Table 1.[4] The first three variables relate to educational levels of the population. The primary source of these data is Eurostat. The variables measure the share of people in the population aged 16-65 of a region in 2003 with high, medium or low level education. These levels are defined by Eurostat. Next, there are 8 variables that measure the structural composition of a region, in terms of the share of employment in 8 different sectors. These sectors are agriculture, mining, manufacturing, construction, energy and utilities, services, business services and higher education & health. The latter two sectors are sub sectors of the services sectors. Although there are a number of lower level sectors that could have been used, the analysis is limited to these 8 sectors because the other more detailed sectors do not seem so crucial to the relation between innovation and growth. The structural variables measure the share of a sector in employment of a region in 2003.

The next category of variables are 6 indicators describing the general state of economic development: GDP per capita in PPP), the average growth rate of GDP per capita over the period 1999 – 2002, population density (population per square km), registered unemployment (in persons) as a percentage of the population, employed persons as a percentage of the population, and inactive persons as a percentage of the population. All variables in this category are measured in 2002.

The remaining variables relate to patenting. These variables are based on counts of patent applications at the European Patent Office (EPO). In the data we use, patent counts are summed over the period 1999 – 2002 (using priority dates), and divided by population of the region in 2002 in order to account for differences in size between regions. Obviously, patenting indicators have certain disadvantages as indicators of innovation (e.g., Griliches, 1990). But we believe that provide an interesting picture of invention and cutting-edge technology activities across Europe. As a result, however, our picture of innovation will be somewhat biased against those activities in technology that are more of an imitative nature.

The patents are assigned to regions on the basis of the reported address of the inventor. We use the Merit IPC-Isic concordance table (Van Moergastel et al., 1994) to assign patents

[4] Throughout the paper we will use the short variable names introduced here. At a later stage, we will substitute this with more meaningful labels.

to an economic industry. This concordance table is based on a detailed comparison of the content of the International Patent Classification and ISIC (rev. 2) classification schemes, and a matching of the activities described in both. The principle of the matching is that the patent is assigned to its most likely industry of origin (e.g., a textiles machine is assigned to the machinery sector, not the textiles sector). The concordance is done at the 4-digit IPC level, and a mixture of 2-, 3- and 4-digit ISIC industries (these will be introduced below when we discuss the data). We use only the manufacturing sectors in the concordance, and opt to aggregate the 22 sectors found in the concordance to 11. The concordance allows the assignment of a single IPC class to multiple ISIC industries, based on a weighting scheme. This, and the fact that we assign invenmtor regions fractionally, implies that patents are assigned fractionally, i.e., we do not necessarily have an integer number of patents in each industry.

Table 1. Explanation and definition of variables

Variable abbreviation	Short explanation
EDUPH03	Persons with high level education as a percentage of population aged 16-65, 2003
EDUPM03	Persons with medium level education as a percentage of population aged 16-65, 2003
EDUPL03	Persons with low level education as a percentage of population aged 16-65, 2003
SLAGR03	Share of agriculture in employment, 2003
SLMIN03	Share of mining in employment, 2003
SLMAN03	Share of manufacturing in employment, 2003
SLCON03	Share of construction in employment, 2003
SLENR03	Share of energy and public utilities in employment, 2003
SLSER03	Share of services in employment, 2003
SLBUS03	Share of business services in employment, 2003
SLHED03	Share of health and education in employment, 2003
GDPPC02	GDP per capita, 2002
AVG	Average yearly growth rate of GDP per capita, 1999 – 2002
PDENS02	Population density, 2002
UPOP02	Unemployed as a percentage of population aged 16-65
INPOP02	Inactive as a percentage of population aged 16-65
EPOP02	Employed as a percentage of population aged 16-65
PTOT	Patent applications at EPO during 1999 – 2002 divided by population in 2002
HERF	Herfindahl index for sectoral patenting shares (199 – 2002 totals)
	The following variables are all patent applications at EPO during 1999 – 2002 divided by population in 2002, for individual sectors:
PEC31_34	Resource based industries (food, textiles, wood, paper, printing, ISIC 31-34)
PEC3522	Pharmaceuticals (ISIC 3522)
PEC35	Chemicals, excl. pharmaceuticals (ISIC 35 – 3522)
PEC37_8	Metals, incl. basic metals (ISIC 37 + 381)
PEC3825	Computers and office machinery (ISIC 3835)
PEC382M	Machinery, excluding office machines and electricals (ISIC 382 – 3825)
PEC3832	Electronics (ISIC 3832)
PEC383M	Electricals (ISIC 383 – 3832)
PEC384	Transport equipment (ISIC 384)
PEC385	Instruments (ISIC 385)
PECOTH	Other industries (ISIC 36 + 39)

5. Patterns of spatial correlation

We start the empirical part of this paper by providing an overview of observed spatial correlation between the (categories of) indicators in our database. This analysis is based on the Moran coefficient of spatial correlation. This calculation of this coefficient starts from the calculation of a so-called spatial lag of a particular variable. For any region *i*, the spatial lag of variable *X* is defined as the weighted average of the value of *X* in all other regions in the sample, where we use the spatial weights in the calculation of this average. Note that because our spatial weights decay rapidly with distance, this effectively means that the spatial lag of a variable contains the average values of *X* found in the geographical neighbourhood of the regions in the sample.

The Moran spatial correlation coefficient is defined as the correlation (measured in the usual way, i.e., Pearson correlation) between a variable *X* and the spatial lag of variable *Y*. One common way of investigation is to look at the case $X = Y$, i.e., the correlation between a variable and its own spatial lag. But this corresponds to just the diagonal values in the spatial correlation matrix (variable by variable) that we will consider here. A high positive (negative) spatial correlation means that high values of variable *X* tend to be surrounded by high (low) values of variable *Y*.

We calculate the Moran coefficients for all combinations of the list of 39 variables that was discussed previously. Note that by definition, the correlation matrix that we obtain in this way is not symmetric, and hence we need to look at correlations between variables in a bi-directional way. Appendix 2 documents the full spatial correlation table, while Appendix 1 provides box plots reflecting the (non-spatially weighted) distribution of the variables. The box plots show that most variables are distributed fairly symmetrically, although there are a few that show long tails on the right side. Notably, such long tails are found for the shares of particular sectors (agriculture, mining, construction, health and education) in total employment, for the growth rate of GDP per capita, for population density (this is particularly strong), and for many of the patenting variables (total patenting, and at the sectoral level particularly electronics and computers).

Because the theoretical distribution for the Moran coefficient is hard to express, statistical significance is usually assessed using Monte Carlo analysis. In this way, the empirical distribution is obtained by permutating the actual values of the variables in the correlation over the regions a large number of times. However, the standard deviations that we obtain using these methods are generally fairly low, so that the large majority of the coefficients in the 30x30 matrix is actually very highly significant. This means that in general, spatial correlation in the dataset is strong. In order to single out the particularly strong correlations, we look in particular at the values that are higher or lower than 1½ standard deviations (+/- 0.374).

Overall, positive correlations (58% of the cases) are more somewhat frequent than negative correlations (42%). There are 77 (9%) pairs of variables that show a positive correlation that is higher than 0.374, and 29 (3%) pairs that have a correlation below –0.374. Strongly positive spatial correlations are particularly frequent along the diagonal of the matrix: 17 out of 30 diagonal values (57%) show a correlation that is higher than 0.374. The variables with strong positive spatial correlation (along the diagonal of the correlation matrix) are the educational variables (all three levels), 5 of the 8 sectoral employment shares variables (agriculture, construction, utilities, services, health & education), GDP per capita, the 3 employment variables (unemployment, inactive population, and employment, all as a % of population), 4 out of 11 of the sectoral patenting per head variables (resource based industries, basic metals, machinery and other industries), and finally the patenting herfindahl index.

Off the diagonal, positive spatial correlation is particularly frequent along the row and column of the GDP per capita, and within the patenting per head block. The patenting sectors that have high spatial correlation along the diagonal of the matrix are also the ones that are spatially correlated with each other (off the diagonal) and the economic variables. GDP per capita correlates strongly with services and in particular business services, employment, and the same patenting sectors as mentioned before.

The other strong correlations that are found off-diagonal are mostly negative. This is especially frequent for the sectoral employment shares variables (services and agriculture, and services and utilities), the general economic variables (unemployment and GDP per capita), and the education variables (low and medium level education).

6. An econometric exploration of observed spatial correlation

The observed patterns of spatial correlation may be explained by various theoretical mechanisms, as briefly discussed in Section 2. While a full-fledged analysis of the causal mechanisms underlying the observed correlations is beyond the scope of this paper, we can make use of a number of econometric techniques to try to obtain a preliminary indication of the nature of such explanations. This starts from the common idea, found in spatial modeling (and spatial econometrics) that observed spatial correlation of a variable may be rooted in at least three separate categories of explanation.

To briefly discuss these categories, let us use the symbol Y to denote the (endogenous) variable for which we are interested to explain the sources of spatial correlation, and use the symbol X to refer to a set of variables that may be invoked to explain Y. The first possible explanation for any observed spatial correlation in Y is that within each spatial unit (region) Y depends on X, and X is spatially correlated. In a sense, this is the least interesting option of the three, since it transfers the explanation to explaining the spatial correlation in X.

A second possibility is that, in addition to Y being dependent on X within each spatial unit, there is some mechanism, call it a spillover, that directly leads spatial dependence of Y, i.e., high values in Y (possibly caused by X) in one region directly spillover to neighbouring regions. The third and final possibility is that Y is a stochastic variable that involves some stochastic 'error' process in addition to the influence in X, and that the errors in this process are spatially correlated. One possible source of such spatial correlation in the error term of a stochastic model is related to mobility of people: if people live in different (but close-by) regions than they work, the correlated error-model would be a good model for explaining GDP, but also for patents (since our patents are assigned to regions on the basis of inventor address).

A standard model in spatial econometrics can be used to assess the relative contribution of these three sources:

$$Y_i = a\ \mathrm{SL}(Y_i) + b\ X_i + e_i,$$

where symbols have the same meaning as before, and, in addition, SL indicates a spatial lag (based on our usual row-standardized weighting matrix), e indicates a white noise error variable, a and b are parameters (the latter a vector if X denotes a vector, including a constant term) and the subscript i indicates regions.

This model suggests a variety in the explanations offered above for observed spatial correlation in Y. The spillover explanation would be revealed by a positive and statistically significant value for the parameter a. A second explanation is the spatial error, which can be addressed in the model by a test (e.g., Moran) for spatial dependence in the residuals of the regression. These residuals are the best estimator for the actual error terms e, and any observed spatial dependence in them suggests that the spatial error mechanism is at work. However, the model itself does not capture such a process. Thus, such a finding would be a reason for further research rather than the end conclusion.

Finally, some of the burden of explaining for the observed spatial dependence in Y falls upon X: if the variables in X are spatially correlated, this will lead to spatial correlation in Y. Again, this is more a starting point for further research than a final conclusion, since it suggests that X is in fact an endogenous variable (at least to the extent that is generated by a process with a spatial correlation), while for statistical purposes, we consider the set of variables in X as exogenous. Also, we do not include any spatially lagged variables in X, so that the only spatial concentration that is picked up in this way is concentration in a single region. In other words, the model that we employ can only be used as a preliminary and exploratory tool to detect tendencies of potential explanations, and not for offering a full-fledged causal explanation.

Table 2 presents the results of these regressions for the patenting variables as well as the level of GDP per capita (in 2002) and the average growth rate variable (YEARS). As explanatory variables, we include the education variables (medium and high level education as a percentage of population), population density (also in squared form, in order to test for congestion), the employment rate (employed persons as a fraction of the population), and the share of agriculture and services in employment (the latter two only in the equations for GDP per capita and growth.

Starting with GDP per capita, we observe that most of the variables are significant. Patenting, the share of services and the employment rate are positively correlated with GDP per capita, the two education variables are negatively correlated. Population density shows and inverse U-shape correlation. Figure 1 shows this pattern, using the mean values of all other variables than population density, and ignoring the spatial lag of GDP per capita itself. The figure shows that congestion seems to be a relevant phenomenon, beyond the maximum at approximately 0.47, GDP per capita declines as a function of population density. Note that this maximum lies in the long right tail of the population density distribution, well beyond 2 standard deviations from the mean.

Table 2 Exploratory regressions for spatial correlation

	Total		Resource-related		Pharma		Chemicals		Metals		Computers	
Spatial Lag	0.326	***	0.444	***	0.434	***	0.529	***	0.463	***	-0.175	
ln GDP pc 1995	0.346	***	0.024	***	0.020	**	0.020	**	0.052	***	0.004	
EDU Medium	0.377	*	0.021	*	0.032	*	0.027		0.057	**	-0.001	
EDU High	0.404		0.013		0.128	***	0.051		0.001		-0.001	
POP dens	1.281	*	0.052		0.120	**	0.151	**	0.009		0.280	**
POP dens square	-1.550		-0.060		-0.096		-0.164	*	-0.028		-0.316	*
employment rate	1.070	*	0.058	*	0.014		0.008		0.051		0.231	**
Constant	-4.073	***	-0.261	***	-0.234	***	-0.215	***	-0.532	***	-0.179	
H0=no Spatial Lag	5.879	**	15.31	***	12.88	***	17.92	***	14.764	***	0.867	
H0=Err not Sp. Cor	2.166		0.075		7.401	***	4.64	**	0.303		2.354	

	Machinery		Electronics		Electrical		Transport		Instruments		Other	
Spatial Lag	0.504	***	-0.179		0.127		0.455	***	0.209	*	0.309	***
ln GDP pc 1995	0.061	***	0.016		0.035	**	0.036	***	0.047	***	0.023	***
EDU Medium	0.065	**	0.023		0.031		0.043	*	0.061	*	0.024	**
EDU High	0.001		0.122		-0.012		0.023		0.147	*	-0.004	
POP dens	0.127		0.314		0.128		0.034		0.137		-0.004	
POP dens square	-0.151		-0.340		-0.173		-0.047		-0.165		0.007	
employment rate	0.060		0.391	**	0.121	*	0.034		0.179	**	0.052	**
Constant	-0.629	***	-0.414		-0.400	***	-0.374	***	-0.588	***	-0.248	***
H0=no Spatial Lag	14.86	***	0.979		0.570		8.70	***	2.329		5.969	**
H0=Err not Sp. Cor	8.29	***	0.517		0.506		7.535	***	1.340		0.043	

	GDPPC02		AVG	
Spatial Lag	0.430	***	0.372	**
Patenting	16.64	***	-0.045	
Agriculture	-0.702		-0.007	
Services	1.955	***	0.033	**
EDU Medium	-0.527	***	-0.014	***
EDU High	-0.154		0.016	
POP dens	134.0	**	0.463	
POP dens square	-142.2	*	-1.487	
employment rate	173.5	***	0.368	
lnQ95			-1.467	***
Constant	-107.3	***	13.6	***
H0=no Spatial Lag	24.39	***	8.10	**
H0=Err not Sp. Cor	17.21	***	0.44	

One, two and three starts denote significance at the 10%, 5% and 1% level, respectively.

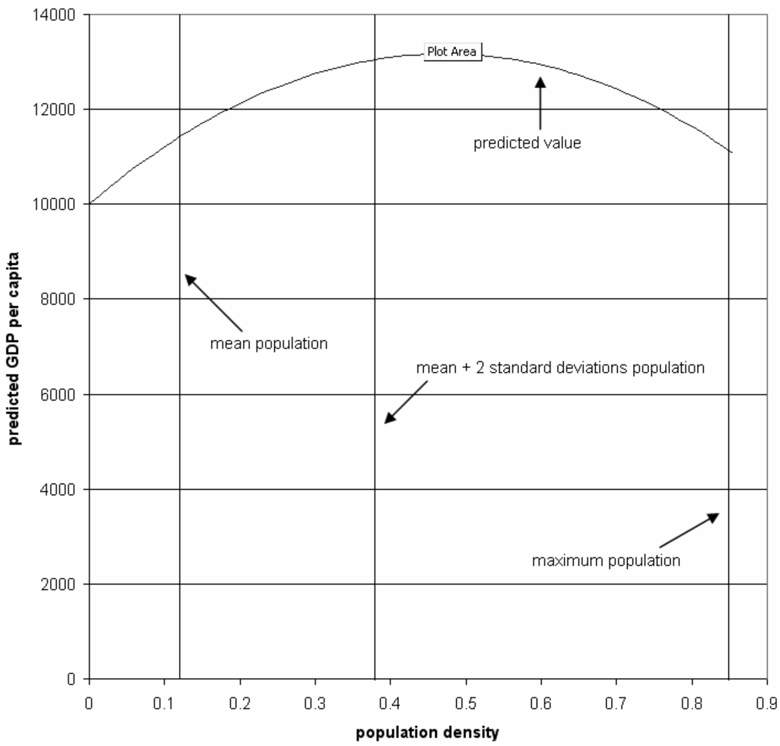


Figure 1. The partial relationship between population density and GDP per capita

GDP per capita has a Moran coefficient for spatial correlation equal to 0.59, which is a very high value in this sample. The regression results suggest that, in addition to any influence of the independent variables, the spatial lag of GDP per capita itself has a strong impact on this. This spatial lag is highly significant with a strongly positive value. In addition, the regression clearly rejects the null-hypothesis that the residuals are not spatially correlated. This suggests multiple sources of spatial correlation for GDP per capita.

The regression for the growth rate shows less significant variables. Here, services (positive), medium level education (negative), and initial (1995) GDP per capita are significant variables. The latter variable, with a significantly negative sign, suggests that there is a process of catching-up, or conditional beta convergence, that is going on in the sample. The spatial lag of the growth rate is also significant, although with a lower coefficient than the level of GDP per capita. In this case, we do not reject the null-hypothesis that the residuals in the regression are not spatially correlated. These results are consistent with the finding that the Moran coefficient for average growth is positive (and significant), but somewhat weaker than other variables, such as the level of GDP per capita.

Turning to the patenting variables, we generally find that the (log of) the 1995 GDP per capita level is very significant and positively related to patenting (10 of the 12 regressions involving patenting variables, computers and electronics are the exceptions). Also, medium level education (8 out of 12 regressions, all positive signs), the employment rate (7 out of 12 regressions, all positive signs), population density (4 out of 12 regressions, all positive signs), high level education (2 out of 12 regressions), and squared population density (2 out of 12 regressions, both pointing to congestion).

All patenting variables, except computers and electronics have substantial and positive Moran coefficients for spatial correlation. Except from computers and electronics (which both have Moran values of 0.03), the lowest Moran coefficient is found in electrical machinery, equal to 0.16. The highest value, 0.49, is found in the resource related industries. In computers, electronics and electrical machinery, we do not find a significant spatial lag, nor spatially correlated residuals. Thus, it seems that in these sectors, spatially concentrated technology spillovers are not strong enough to not lead to spatial concentration in patenting in Europe.

However, in the other 8 sectors, as well as in total patenting, we do find that the spatial lag significantly "explains" patenting, suggesting that technology spillovers play an important role. All these spatial lags are highly significant (with the exception of instruments, which is only significant at 10%). At the sectoral level, we also find fairly high values for the coefficients of the spatial lag. Compared to the 0.43 value of the spatial lag coefficient in GDP per capita, these values are substantially higher in chemicals (0.53) and machinery (0.50), while in the same order of magnitude in most other sectors (resource related, pharmaceuticals, metals, transport equipment). The spatial lag coefficient for total patenting is somewhat lower (also in instruments and other industries), suggesting that spillovers are stronger within a coherent set of patenting activities than between such sets.

There are also four sectors in which the residuals in the regression are spatially correlated, even after taking account of the spatial lag. These sectors are pharmaceuticals, chemicals, machinery and transport equipment.

Finally, we look at the non-linear effect of population density. For chemicals, this effect is similar to the observed for GDP per capita in Figure 1 above (exact figure for patenting not documented but available on request). The maximum of the curve lies slightly beyond the value for population density equal to the mean plus two standard deviations. For computers (but this is generally a much less significant regression), the maximum lies just beyond the mean value of population density, suggesting that congestion sets in much earlier in this sector.

7. Drawing correlations together: Spatial principal components analysis and cluster analysis

The large spatial correlation table that we have discussed so far contains much detailed information that is only partially summarized by the focus on the correlation values that are larger or smaller than the arbitrary cut-off value of 1½ standard deviations. This large set of correlations, and the underlying spatial patterns in the data are the revelations of the technology and economic growth relationship that we wish to outline for the EU-25. We therefore apply a method, admittedly impressionistic rather than aimed at the causal relationships, that will outline the main relationships between in the data. The method consists of two phases, the first of which is aimed at outlining the relationships between the variables, and the second step aimed at outlining the relationships between the regions.

The first step consists of the spatial principal components technique that is proposed by Wartenberg (1985). Like conventional principal components analysis, this is a way to summarize the correlation table of the variables in our analysis. The analysis works by extracting, by means of an eigenvalue decomposition of the correlation table, a number of components, or dimensions, that are linear combinations of variables. The components are found by optimizing the fraction of the total variance in the data that is accounted by them, such that the first component accounts for the largest possible fraction of total variance, the second for the largest possible fraction of the remaining variance, etc. The number of factors that is extracted is determined by the eigenvalues that result from the decomposition: all components with eigenvalues larger than one are retained. The only difference between the spatial principal components analysis and conventional principal components analysis is the calculation of the correlation coefficients: the spatial variant uses the Moran coefficients, while conventional principal components analysis uses normal correlation coefficients.[5]

We extract three components representing a total of 88% of the total variance in the 30 variables. Interestingly, a conventional principal components analysis, not taking account of the spatial structure in the data (i.e., using a weighting matrix with one over the number of regions, 154, on the diagonal and zeros otherwise), extracts seven components, accounting for only 79% of the total variance (detailed results of the conventional analysis not documented but available on request). This means that when viewed from a spatial perspective, the dimensionality of the data is lower as compared to a non-spatial perspective, suggesting that space adds order to the data.

The factor loadings (coefficients in the linear combinations representing the factors) are documented in Table 2. The first component can be interpreted as a general indication of relative backwardness. Relatively high factor loadings are found for the share of agriculture in employment, and unemployment. On the other hand, relatively strongly negative loadings are found for GDP per capita, and most of the patenting per head variables (including total patenting per head, but not patenting in ICT-related sectors, such as S3825 and S3832). This component accounts for two thirds of the total variance, which indicates that the general development level is the major divide between regions in our dataset.

The second component is strongly dominated by differences in educational level of the labour force. A high loading is found for low level education (as a % of the population), and a low loading for medium level education. Also, the share of energy and public utilities loads high. There are few other strongly positive loadings, the share of services in employment and GDP per capita are (mild) exceptions. The patenting variables all have loadings very close to zero. The specific influence of education in this component seems to be dominated by the fact that the education variables have a strong national component. However, excluding these variables from the analysis does not influence the other results to a large extent (in that case,

[5] We follow the normal procedure in (non-spatial) principal components analysis to rescale the eigenvectors (factor loadings) such that their sum of squares is equal to the value of the corresponding eigenvalue. This reflects the property that the obtained principal components account for the specific proportion of the variance reflected by their eigenvalue.

we extract just two components, which are very close to the first and third component documented in Table 2).

The final and third component is clearly related to urbanization. Population density has a high loading, as do education & health and business services (typically sectors found in urban environments). Manufacturing has a strongly negative loading. In this case, patenting in the ICT related sectors show a relatively high loading.

Table 2. Spatial Principal Components

Variable	F1	F2	F3
EDUPH03	0.02	0.13	0.48
EDUPM03	-0.05	-0.75	-0.22
EDUPL03	0.03	0.67	0.02
SLAGR03	0.41	-0.09	-0.03
SLMIN03	0.17	-0.34	-0.11
SLMAN03	-0.21	-0.30	-0.44
SLCON03	0.08	0.29	-0.18
SLENR03	0.22	-0.51	-0.26
SLSER03	-0.19	0.28	0.43
SLBUS03	-0.32	0.11	0.30
SLHED03	0.05	0.05	0.57
GDPPC02	-0.54	0.28	0.07
AVG	0.27	0.10	-0.03
PDENS02	-0.02	-0.07	0.49
UPOP02	0.46	-0.25	-0.05
INPOP02	0.18	0.22	-0.35
EPOP02	-0.36	-0.05	0.28
PTOT	-0.39	-0.01	0.12
HERF	-0.31	0.19	0.10
PEC31_34	-0.53	0.01	0.10
PEC3522	-0.29	-0.06	0.24
PEC35	-0.39	-0.06	0.18
PEC37_8	-0.57	-0.01	-0.17
PEC3825	-0.05	0.00	0.28
PEC382M	-0.54	-0.03	-0.09
PEC3832	-0.05	0.00	0.25
PEC383M	-0.32	0.01	0.04
PEC384	-0.42	-0.01	-0.13
PEC385	-0.28	0.00	0.16
PECOTH	-0.56	0.00	-0.04
Variance (cumulative)	0.66	0.79	0.88
max	0.46	0.67	0.57
min	-0.57	-0.75	-0.44

Factor loading with an absolute value > 0.4 are highlighted.

Having summarized the (spatial) variation in our 30 variables into three major dimensions, we proceed to investigate whether these three dimensions can be used to distinguish groups of regions in the EU-27 that share similar characteristics. Such groups represent ‘archetypical’ regional development patterns.

In order to do this, we use cluster analysis. Formally, the aim of the analysis is to obtain groups of regions that are relatively homogenous in terms of the variables that we put into the clustering procedure, but are different from the regions found in the other regimes. We use the two-step clustering algorithm in SPSS to obtain groups of sectors, based on the factor scores obtained using Table 2 above. The two-step clustering algorithm has as an important advantage that the number of clusters is determined on the basis of an objective criterion (we use Aikake's information criterion for this purpose). The algorithm works by first forming a number of pre-clustering groups, and then merging these groups in a more-or-less traditional hierarchical clustering method. We perform a Bonferroni adjusted *t*-test for differences in the mean score on the three dimensions of the clusters (centroids) relative to the total sample mean. All three dimensions show at least one cluster to be different from the sample mean, and hence we retain all three components in the cluster analysis.

Table 3. Cluster centroids

Factor label		Cluster			
		1	2	3	4
	N	29	67	35	23
Relative backwardness	Mean	3.96	-1.68	5.85	-9.01
	Std. Dev.	1.52	2.38	1.88	4.63
		***	***	***	***
Lower level education	Mean	2.94	-0.56	-3.72	-0.31
	Std. Dev.	1.03	1.37	1.31	1.22
		***	***	***	
Urban development	Mean	-1.32	-0.79	-3.61	4.85
	Std. Dev.	0.96	1.54	0.87	2.91
		***	***	***	***

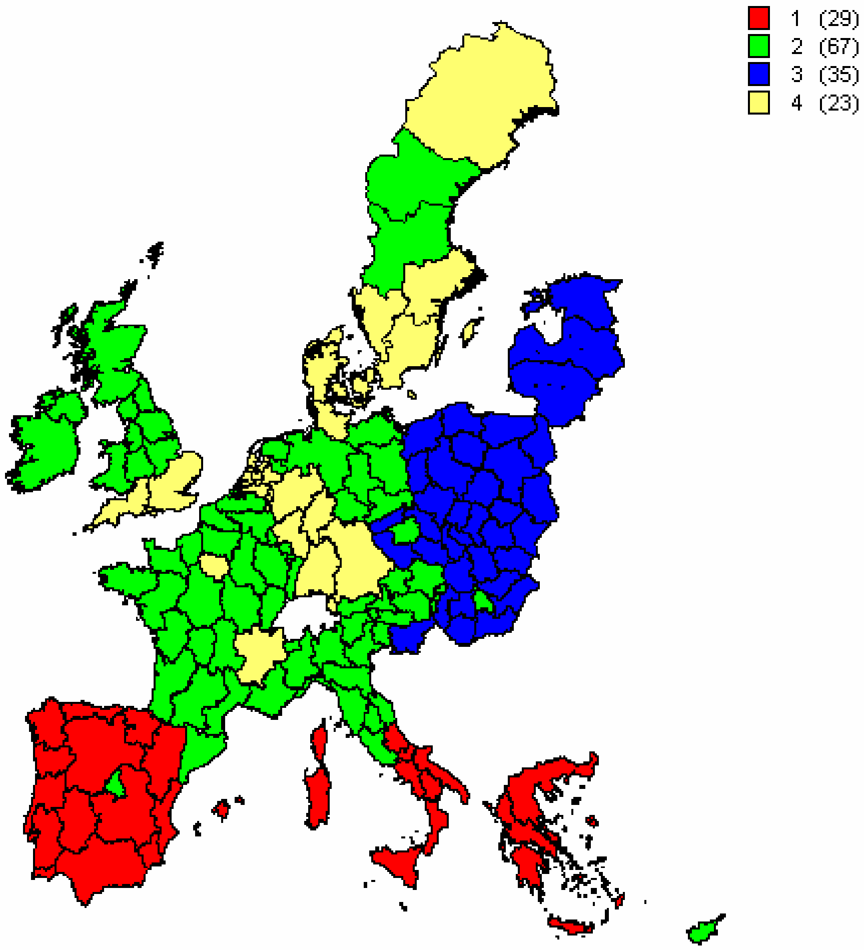
One, two and three starts indicate significant differences (at the 10%, 5% and 1% level, respectively) of the cluster centroids from the total sample mean in a *t*-test with Bonferroni adjustment.

We obtain four clusters of regions, of which one is relatively large, and the other three are of roughly equal size. The clusters and their mean scores on the three dimensions are shown in Table 3, Map 2 gives an overview of the clusters. Cluster 1 (the numbering is arbitrary) is a group of 29 exclusively Southern European regions that scores high on relative backwardness and lower level education, but low on urban development. This cluster spans the total Southern European space, with the exception of the Madrid and Barcelona regions in Spain, and the Rome (Lazio) region in Italy.

Cluster number 3 is the other cluster in the dataset that scores high on relative backwardness. This cluster exclusively comprises almost all of the regions in the so-called New Member States (NMS) of the EU. The main difference to cluster 1 is that the NMS cluster has a very much lower value on the low level education dimension. For the other two dimensions, general development and urban development, it scores lower than the average, as does Cluster 1. The Prague region in the Czech Republic and the Budapest region in Hungary are the exceptions in the Eastern European space, and they are classified outside this Cluster 2.

We thus find that the new member states in Eastern Europe are rather similar to the Southern European regions, with the exception of education. This confirms the popular impression of the new member states as an area that is still underdeveloped relative to the EU frontier, but also has high potential when it comes to absorbing foreign knowledge.

The two other clusters are relatively highly developed clusters of regions, they both score significantly lower on the relative backwardness dimension. This also means that these two clusters are the ones that show relatively high patenting. Cluster 2 is the largest cluster, with 67 members. It consists of a broad set of central European regions, along with most of the United Kingdom and Ireland, and few regions in the North. They score high on general development, and low on lower education. The main thing that sets them apart from the remaining Cluster 4, is a relatively level of urban development. The final Cluster 4 contains a geographical sub-cluster of German-Dutch regions, another sub-cluster of Danish and Swedish regions, and a number of isolated highly urbanized regions (such as Paris and London). It is this final cluster that has the highest level of GDP per capita and patenting in the sample.



Map 2. The European regional hierarchy of technology and development (based on cluster analysis)

8. Conclusions and outlook

The map of European patterns of technology and economic growth that was obtained in the previous section is suggestive for a number of important tendencies at the regional European level. First of all, it suggests a major spatial divide of Europe, roughly along an “arc” running from southwest to northeast. Below this arc, i.e., in South and East Europe, we generally find regions that are at a lower general development level. The enlargement of the European Union has thus created an area that indeed deserves the attention of regional policy makers.

But of course, this is hardly an original finding, as already long before the enlargement, it was clear that the new members states were at a much lower level of GDP per capita than the “old” EU-16. The analysis here does suggest, however, that the Eastern European regions are different in one crucial aspect: they have a much better educated labour force than the regions in the Southern periphery of Europe. In terms of a hierarchy of economic growth and development, this puts these regions in the new member states at an advantage, because it potentially allows them to absorb foreign technology in a much more efficient way. Whether this advantage will indeed materialize, remains to be seen when new data become available.

With regard to the regions “above the arc”, the major dividing line seems to be the general level of urbanization. The outcomes of the analysis confirms the importance of urban development (e.g., Storper and Walker, 1989) that has been signalled in the literature. Urban environments are capable of producing high economic growth and technological change. Moreover, in the most developed part of Europe, these highly urbanized regions seem to be integrated into a larger whole of spatial “corridors”, which unite them with their (direct) geographical surroundings. These areas comprising one or several large cities indeed seem to function as an integrated whole, in which economic growth and technological knowledge flow quite fluently between urban centres and their sub-urban surroundings (again, Storper and Walker, 1989, have pointed to such patterns).

The analysis suggests that in the South and East, such interactions have not yet emerged very frequently. Both in the South and East, major urban centres exist that shows signs of taking on the role of urban centres in which economic growth and innovation flourishes. Madrid, Rome and Barcelona are examples in the South, Prague and Budapest in the East. But what distinguishes these cities from their counterparts at the top of the spatial hierarchy, is that they do not seem to support a surrounding area with which knowledge interactions are taking place. At this stage, the metropoles of the South and East remain isolated centres, not yet capable of generating (and using?) enough spillovers.

This suggests that regional policy in these areas is aimed specifically at such spatial interactions between large cities that already show a high level of technological capabilities, and their surroundings. Obviously, such a targeting of combinations of regions is at odds with the current practice of assigning Structural Development Funds, which is largely based on a number of criteria, such as GDP per capita, that relate to single regions.

The current analysis suggests that such an allocation mechanism runs the danger of not supporting the most promising regions in the South and the East. Instead of supporting the urban centres and the spillover effects they may have on their wider environment, the current policies run a risk of supporting the peripheral parts of the Union, where development potential is weakest. A partial reorientation of the allocation of funds towards innovation in urban centres in the South and East may be beneficial.

This is reminiscent of the discussion about equity or efficiency at the regional level. It has been argued (see Begg, 2007 for an overview) that European regional policy at large is aimed at those regions where the development potential is low, and hence that it stimulates equity at the expense of efficiency. We consider the conclusion here as middle-ground, and suggest that regional funds are aimed at specific peripheries in the EU (East and South), but with the explicit goal of creating cross-regional spillovers, targeting the urban centres in the areas.

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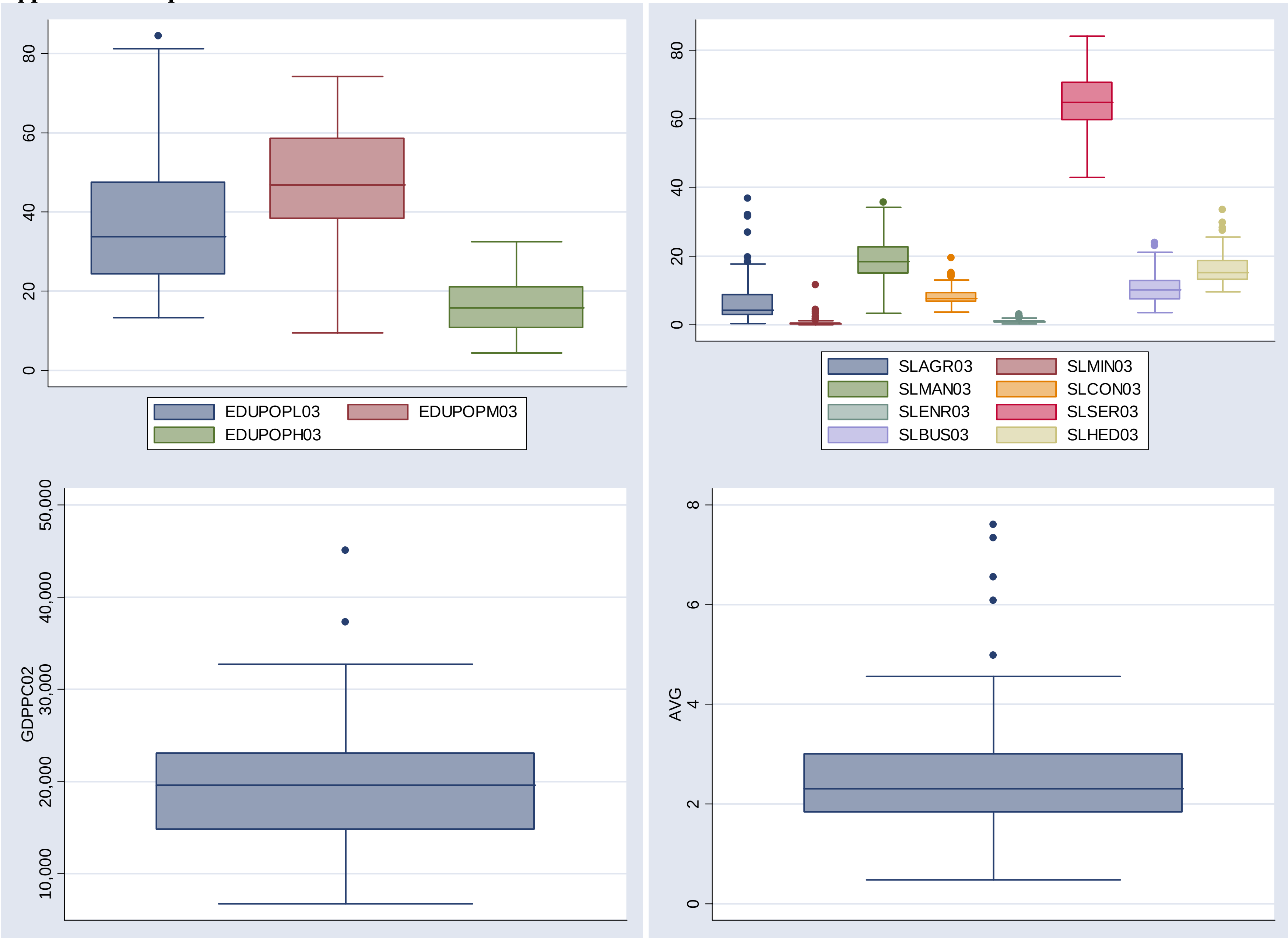
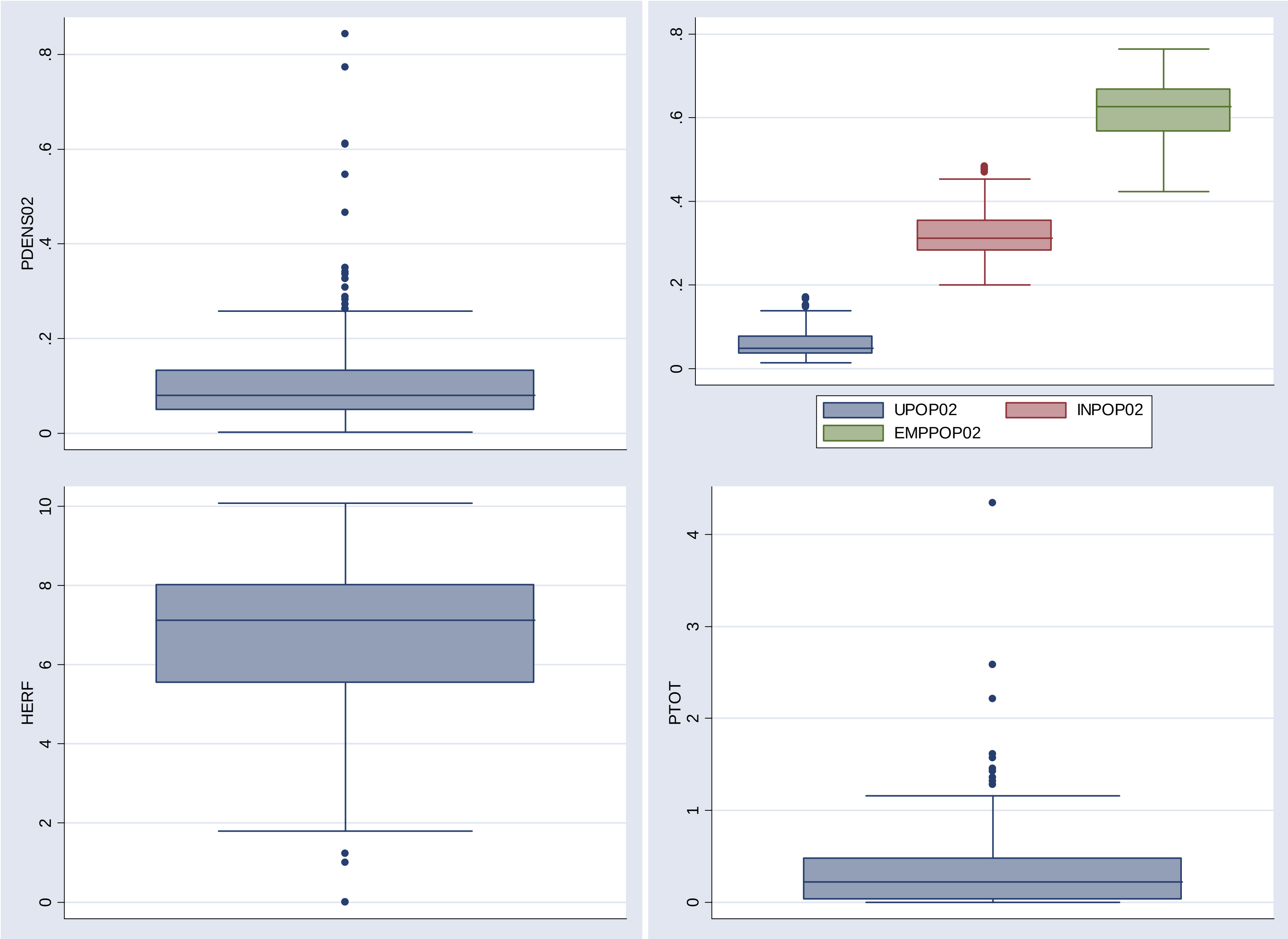
Appendix 1. Boxplots of the variables

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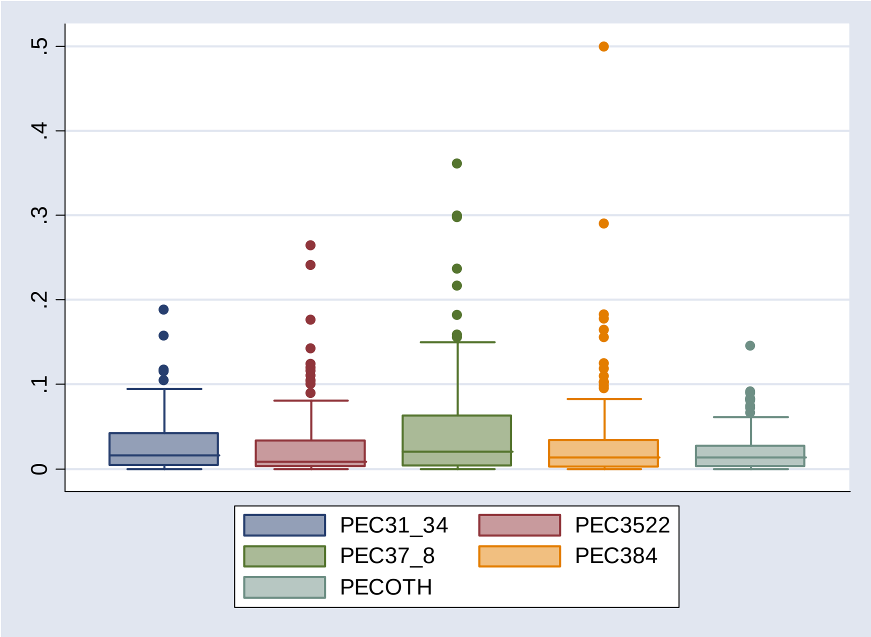
INPOP02
EMPPOP02
HERF
PTOT



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.2
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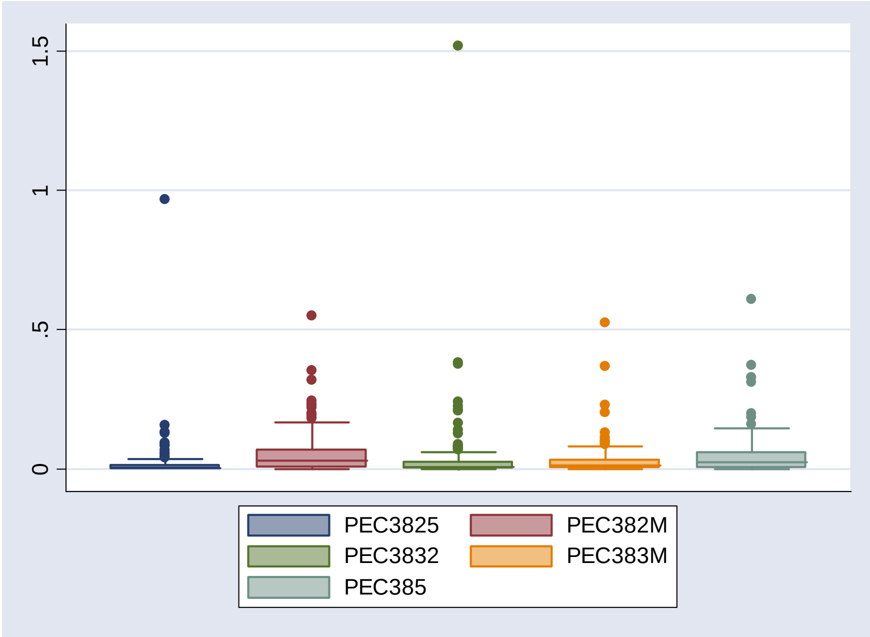
PEC31_34
PEC3522
PEC37_8
PEC384
PECOTH



0
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1
1.5
PEC3825
PEC382M
PEC3832
PEC383M
PEC385

Appendix 2. Spatial correlation table

	EDUPH03	EDUPM03	EDUPL03	SLAGR03	SLMIN03	SLMAN03	SLCON03	SLENR03	SLSER03	SLBUS03	SLHED03	GDPPC02	AVG	PDENS02	UPOP02	INPOP02	EPOP02	PTOT	HERF	PEC31_34	PEC3522	PEC35	PEC37_8	PEC3825	PEC382M	PEC3832	PEC383M	PEC384	PEC385	PECOTH
EDUPH03	0.53	-0.11	-0.11	-0.25	-0.10	-0.13	-0.04	-0.28	0.31	0.25	0.35	0.29	-0.07	0.08	-0.20	-0.41	0.40	0.20	0.27	0.21	0.24	0.21	0.15	0.11	0.16	0.12	0.12	0.12	0.22	0.16
EDUPM03	-0.09	0.83	-0.76	0.11	0.18	0.31	-0.49	0.45	-0.22	-0.08	0.12	-0.26	-0.07	-0.06	0.24	-0.15	0.00	0.04	-0.15	0.01	0.03	0.01	0.06	-0.01	0.06	0.01	0.01	0.04	0.05	0.05
EDUPL03	-0.12	-0.76	0.77	-0.01	-0.13	-0.25	0.48	-0.32	0.09	-0.03	-0.25	0.13	0.10	0.03	-0.15	0.31	-0.16	-0.11	0.03	-0.09	-0.13	-0.10	-0.12	-0.03	-0.12	-0.06	-0.06	-0.08	-0.14	-0.11
SLAGR03	-0.22	0.08	0.01	0.53	0.11	-0.03	0.00	0.30	-0.38	-0.36	-0.29	-0.46	0.27	-0.15	0.40	0.21	-0.35	-0.29	-0.42	-0.36	-0.27	-0.26	-0.30	-0.12	-0.31	-0.12	-0.20	-0.22	-0.27	-0.33
SLMIN03	-0.14	0.20	-0.14	0.19	0.16	0.12	0.02	0.25	-0.26	-0.19	-0.16	-0.26	0.05	-0.05	0.22	0.06	-0.15	-0.14	-0.17	-0.18	-0.12	-0.12	-0.15	-0.06	-0.14	-0.06	-0.10	-0.10	-0.13	-0.17
SLMAN03	-0.16	0.29	-0.21	0.01	0.11	0.28	-0.09	0.20	-0.21	-0.07	-0.18	-0.07	-0.03	-0.10	0.07	0.07	-0.09	-0.01	-0.04	-0.01	-0.05	-0.04	0.04	-0.04	0.04	-0.05	0.01	0.04	-0.03	0.03
SLCON03	-0.06	-0.42	0.43	-0.01	0.04	-0.07	0.54	-0.11	-0.09	-0.14	-0.35	-0.06	0.16	-0.06	-0.04	0.21	-0.14	-0.21	0.00	-0.24	-0.20	-0.19	-0.20	-0.10	-0.20	-0.12	-0.14	-0.14	-0.19	-0.20
SLENR03	-0.25	0.50	-0.38	0.33	0.21	0.23	-0.18	0.49	-0.41	-0.31	-0.21	-0.48	0.16	-0.14	0.39	0.16	-0.30	-0.20	-0.34	-0.27	-0.18	-0.19	-0.21	-0.10	-0.20	-0.10	-0.14	-0.14	-0.19	-0.23
SLSER03	0.32	-0.20	0.07	-0.42	-0.20	-0.19	-0.08	-0.39	0.50	0.39	0.47	0.45	-0.22	0.21	-0.37	-0.28	0.38	0.30	0.37	0.36	0.30	0.29	0.27	0.16	0.27	0.17	0.19	0.19	0.29	0.30
SLBUS03	0.25	-0.07	-0.03	-0.38	-0.16	-0.05	-0.17	-0.33	0.39	0.37	0.38	0.43	-0.30	0.20	-0.32	-0.27	0.35	0.33	0.35	0.42	0.31	0.31	0.33	0.16	0.33	0.16	0.22	0.22	0.29	0.35
SLHED03	0.36	0.10	-0.24	-0.29	-0.11	-0.17	-0.35	-0.23	0.45	0.36	0.70	0.31	-0.19	0.19	-0.24	-0.38	0.40	0.31	0.26	0.32	0.32	0.26	0.26	0.17	0.25	0.22	0.17	0.18	0.34	0.27
GDPPC02	0.26	-0.25	0.14	-0.48	-0.21	-0.05	-0.05	-0.47	0.44	0.42	0.30	0.59	-0.32	0.14	-0.47	-0.26	0.42	0.37	0.45	0.47	0.31	0.34	0.41	0.14	0.39	0.14	0.28	0.29	0.31	0.43
AVG	-0.05	-0.06	0.07	0.23	0.04	-0.03	0.14	0.17	-0.20	-0.25	-0.18	-0.30	0.31	-0.15	0.11	0.16	-0.17	-0.22	-0.25	-0.27	-0.20	-0.21	-0.22	-0.09	-0.24	-0.09	-0.17	-0.19	-0.20	-0.25
PDENS02	0.12	-0.03	-0.02	-0.16	-0.05	-0.07	-0.09	-0.14	0.21	0.21	0.20	0.16	-0.18	0.26	-0.14	-0.10	0.14	0.14	0.16	0.18	0.18	0.19	0.05	0.13	0.10	0.10	0.10	0.04	0.11	0.12
UPOP02	-0.19	0.23	-0.14	0.45	0.17	0.04	-0.06	0.37	-0.37	-0.34	-0.23	-0.49	0.14	-0.13	0.55	0.20	-0.41	-0.27	-0.38	-0.36	-0.21	-0.23	-0.30	-0.12	-0.28	-0.12	-0.20	-0.20	-0.23	-0.35
INPOP02	-0.41	-0.17	0.33	0.25	0.04	0.03	0.19	0.18	-0.26	-0.27	-0.39	-0.28	0.17	-0.05	0.23	0.61	-0.56	-0.31	-0.17	-0.34	-0.30	-0.27	-0.30	-0.14	-0.29	-0.17	-0.19	-0.21	-0.32	-0.31
EPOP02	0.39	0.02	-0.18	-0.39	-0.11	-0.04	-0.11	-0.31	0.37	0.36	0.40	0.44	-0.19	0.10	-0.43	-0.55	0.62	0.36	0.31	0.42	0.32	0.31	0.36	0.16	0.35	0.19	0.24	0.25	0.34	0.40
PTOT	0.20	0.03	-0.11	-0.30	-0.13	0.01	-0.22	-0.22	0.30	0.33	0.32	0.38	-0.24	0.14	-0.27	-0.30	0.35	0.34	0.26	0.41	0.33	0.33	0.38	0.11	0.37	0.12	0.23	0.28	0.30	0.35
HERF	0.23	-0.17	0.07	-0.38	-0.13	-0.05	0.01	-0.35	0.34	0.30	0.22	0.43	-0.23	0.13	-0.35	-0.15	0.28	0.22	0.38	0.28	0.21	0.22	0.22	0.10	0.23	0.09	0.17	0.17	0.21	0.25
PEC31_34	0.20	0.01	-0.09	-0.38	-0.16	0.02	-0.26	-0.29	0.36	0.42	0.33	0.49	-0.30	0.17	-0.35	-0.33	0.41	0.41	0.32	0.49	0.38	0.38	0.44	0.16	0.44	0.16	0.29	0.34	0.37	0.44
PEC3522	0.24	0.03	-0.13	-0.27	-0.11	-0.02	-0.20	-0.19	0.29	0.30	0.32	0.31	-0.21	0.15	-0.20	-0.30	0.31	0.33	0.23	0.37	0.34	0.33	0.32	0.15	0.33	0.15	0.23	0.25	0.30	0.30
PEC35	0.22	0.02	-0.11	-0.28	-0.11	-0.01	-0.20	-0.20	0.28	0.31	0.26	0.35	-0.23	0.16	-0.22	-0.26	0.30	0.33	0.25	0.38	0.35	0.36	0.31	0.15	0.34	0.14	0.25	0.26	0.29	0.32
PEC37_8	0.14	0.06	-0.11	-0.31	-0.13	0.06	-0.22	-0.22	0.27	0.32	0.28	0.41	-0.25	0.04	-0.29	-0.29	0.35	0.37	0.25	0.42	0.30	0.30	0.43	0.12	0.42	0.15	0.27	0.33	0.35	0.40
PEC3825	0.12	-0.01	-0.04	-0.13	-0.06	-0.04	-0.12	-0.11	0.17	0.18	0.19	0.16	-0.10	0.15	-0.13	-0.15	0.17	0.12	0.12	0.17	0.17	0.17	0.13	0.03	0.14	0.03	0.06	0.09	0.11	0.13
PEC382M	0.15	0.05	-0.11	-0.32	-0.13	0.06	-0.21	-0.21	0.27	0.32	0.25	0.40	-0.25	0.07	-0.27	-0.28	0.34	0.36	0.25	0.43	0.32	0.32	0.42	0.12	0.40	0.14	0.27	0.31	0.33	0.39
PEC3832	0.13	0.01	-0.06	-0.14	-0.06	-0.04	-0.13	-0.11	0.17	0.17	0.23	0.16	-0.10	0.12	-0.13	-0.18	0.19	0.13	0.11	0.18	0.17	0.16	0.16	0.03	0.15	0.03	0.06	0.10	0.12	0.13
PEC383M	0.12	0.01	-0.06	-0.21	-0.10	0.02	-0.15	-0.16	0.20	0.23	0.19	0.28	-0.19	0.10	-0.20	-0.19	0.24	0.23	0.19	0.29	0.23	0.25	0.27	0.06	0.27	0.06	0.16	0.22	0.20	0.25
PEC384	0.12	0.03	-0.08	-0.22	-0.09	0.05	-0.14	-0.15	0.18	0.20	0.17	0.29	-0.19	0.02	-0.18	-0.20	0.23	0.27	0.19	0.32	0.23	0.24	0.32	0.08	0.31	0.10	0.22	0.25	0.23	0.29
PEC385	0.22	0.05	-0.13	-0.28	-0.12	-0.01	-0.20	-0.20	0.28	0.29	0.35	0.32	-0.21	0.11	-0.23	-0.32	0.34	0.30	0.23	0.37	0.30	0.29	0.36	0.10	0.33	0.12	0.20	0.24	0.28	0.32
PECOTH	0.15	0.04	-0.10	-0.35	-0.15	0.06	-0.21	-0.25	0.29	0.36	0.26	0.45	-0.27	0.12	-0.35	-0.30	0.39	0.36	0.29	0.45	0.31	0.32	0.42	0.12	0.41	0.12	0.26	0.31	0.32	0.42

Values > 1½ standard deviations are shaded green, values < than – 1½ standard deviations red.

Appendix 3. Regions used in the analysis

AT11	Burgenland
AT12_13	Niederösterreich + Vienna
AT21	Kärnten
AT22	Steiermark
AT31	Oberösterreich
AT32	Salzburg
AT33	Tirol
AT34	Vorarlberg
BE1_2	Arr. Admin. Bruxelles-Capitale - Admin. Arr. Bruss+Vlaams
BE3	Wallone
CY	Kypros / Kibris
CZ01_02	Praha + Stredni Cechy
CZ03	Jihozapad
CZ04	Severozapad
CZ05	Severovychod
CZ06	Jihovychod
CZ07	Stredni Morava
CZ08	Moravskoslezsko
DE1	Baden-Wurttemberg
DE2	Bayern
DE3_4	Berlin + Brandenburg
DE5_9	Bremen + Niedersachsen
DE6_F	Hamburg + Schleswig-Holstein
DE7	Hessen
DE8	Mecklenburg-Vorpommern
DEA	Nordrhein-Westfalen
DEB	Rheinland-Pfalz
DEC	Saarland
DED	Sachsen
DEE	Sachsen-Anhalt
DEG	Thüringen
DK	Denmark
EE	Estonia
ES11	Galicia
ES12_3	Asturias & Cantabria
ES21_2_3	País Vasco, Navarra & Rioja
ES24	Aragón
ES3	Comunidad de Madrid
ES41	Castilla y León
ES42	Castilla-la Mancha
ES43	Extremadura
ES51	Cataluña
ES52	Comunidad Valenciana
ES53	Illes Balears
ES61	Andalucía
ES62	Región de Murcia
FR1	Île de France
FR21	Champagne-Ardenne
FR22	Picardie
FR23	Haute-Normandie

FR24	Centre
FR25	Basse-Normandie
FR26	Bourgogne
FR3	Nord - Pas-de-Calais
FR41	Lorraine
FR42	Alsace
FR43	Franche-Comté
FR51	Pays de la Loire
FR52	Bretagne
FR53	Poitou-Charentes
FR61	Aquitaine
FR62	Midi-Pyrénées
FR63	Limousin
FR71	Rhône-Alpes
FR72	Auvergne
FR81	Languedoc-Roussillon
FR82	Provence-Alpes-Côte d'Azur
FR83	Corse
GR1	Voreia Ellada
GR2_3	Kentriki Ellada & Attiki
GR4	Nisia, Aigaio, Kriti
HU10	Kozep-Magyarorszag
HU21	Kozep-Dunantul
HU22	Nyugat-Dunantul
HU23	Del-Dunantul
HU31	Eszak-Magyarorszag
HU32	Eszak-Alfold
HU33	Del-Alfold
IE	Ireland
ITC1	Piemonte
ITC2	Valle d'Aosta
ITC3	Liguria
ITC4	Lombardia
ITD1_2	Trentino-Alto Adige
ITD3	Veneto
ITD4	Friuli-Venezia Giulia
ITD5	Emilia-Romagna
ITE1	Toscana
ITE2	Umbria
ITE3	Marche
ITE4	Lazio
ITF1	Abruzzo
ITF2	Molise
ITF3	Campania
ITF4	Puglia
ITF5	Basilicata
ITF6	Calabria
ITG1	Sicilia
ITG2	Sardegna
LT	Lithuania
LU	Luxembourg (Grand-Duché)
LV	Latvia
MT	Malta
NL1	Noord-Nederland
NL21	Overijssel
NL22	Gelderland
NL23	Flevoland
NL31	Utrecht
NL32	Noord-Holland
NL33	Zuid-Holland
NL34	Zeeland
NL41	Noord-Brabant
NL42	Limburg (NL)
NO1	Oslo og Akershus
NO2	Hedmark og Oppland
NO3	Sør-Østlandet

NO4	Agder og Rogaland
NO5	Vestlandet
NO6	Trøndelag
NO7	Nord-Norge
PL11	Lodzkie
PL12	Mazowieckie
PL21	Malopolskie
PL22	Slaskie
PL31	Lubelskie
PL32	Podkarpackie
PL33	Swietokrzyskie
PL34	Podlaskie
PL41	Wielkopolskie
PL42	Zachodniopomorskie
PL43	Lubuskie
PL51	Dolnoslaskie
PL52	Opolskie
PL61	Kujawsko-Pomorskie
PL62	Warminsko-Mazurskie
PL63	Pomorskie
PT11	Norte
PT15	Algarve
PT16_17	Centro (P) + Lisboa
PT18	Alentejo
PT2	Região Autónoma dos Açores
SE01_2	Stockholm & Ostra Mellansverige
SE03_9	Sydsverige + Smaland med oarna
SE06	Norra Mellansverige
SE07	Mellersta Norrland
SE08	Övre Norrland
SE5A	Västsverige
SI001_2_3	Pomurska + Podravska + Koroska
SI004_5_E	Osrednjeslovenska +Zasavska + Savinjska
SI006_A_D	Spodnjeposavska+Notranjsko-kraska+Jugovzhodna Slov
SI009_B_C	Gorenjska + Goriska + Obalno-kraska
SK01_02	Bratislavsky kraj + Zapadne Slovensko
SK03	Stredne Slovensko
SK04	Vychodne Slovensko
UKC	North East
UKCHI	Channel Islands
UKD	North West
UKE	Yorkshire and the Humber
UKF	East Midlands
UKG	West Midlands
UKH_I_J	South East
UKK	South West
UKL	Wales
UKM	Scotland
UKMAN	Isle of Man
UKN	Northern Ireland

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