Exploratory Spatial Data Analysis and Spatial Econometric Modeling for the Study of Regional Productivity Differentials in European Union, From 1975 To 2000*

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SUMMARY

Economic processes are often characterized by spatial autocorrelation: the coincidence of value similarity to locational similarity. As a consequence of spatial autocorrelation, analysts observe spatial regional clusters. Recent advances in the areas of spatial statistics/econometrics offer tools for the investigation of the aforementioned issues. Following the exploratory spatial data analysis of Le Gallo and Ertur (2003) on European regional per capita GDP we use such tools to investigate the evolution of regional productivity disparities in the European Union and the extent to which the existing interregional inequalities in productivity can be attributed to differences in sectoral composition between regions and/or to uniform productivity gaps across sectors. At the exploratory stage we observe a core-periphery pattern similar to the one observed in the study of regional GDP. At the modeling stage the inclusion of spatial dependencies produces estimations significantly different from the ones presented at previous studies.

KEYWORDS: *spatial autocorrelation, exploratory spatial data analysis, European regions, productivity disparities, spatial seemingly unrelated regressions*

INTRODUCTION

European integration has stimulated numerous studies of regional economic convergence within the European Union. One approach[24] dealing with the dynamics of regional inequality in Europe is presented by Esteban (1994) who examines to what extent disparities can be attributed to regional differences in various factors, beginning by breaking down per capita income into production per worker, employment rate and participation

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[24] A summary of the main findings in this area is to be found in Armstrong (2002) or Terrasi (2002).

rate. His findings suggest that regional differences in productivity are the main reason for regional inequality in per capita income in the European Union[25].

In order to gain a deeper insight into regional inequality in income per capita, Esteban (2000) analyzes the causes that generate regional productivity disparities in Europe. He uses shift share analysis to additively decompose regional productivity differentials with respect to the European mean into three components: structural, regional and allocative factors[26]. Using simple econometric tools, he demonstrates that productivity differentials in the E.U. are uniformly distributed across sectors e.g. each region's industry mix contributes relatively little to regional dispersion in average productivity.

The empirical methods used by Esteban (2000) at regional level do not take into account spatial effects, particularly spatial autocorrelation, defined as the coincidence of value similarity with locational similarity (Anselin, 2001). However, there are a number of factors – trade between regions, technology and knowledge diffusion and more generally regional spillovers- that lead to geographically dependent regions. Because of spatial interactions between regions, geographical location is important in accounting for their economic performance. The role of spatial effects in economic processes needs to be examined using the appropriate spatial statistics and econometric methods. Such studies appeared in the literature after the mid-nineties; see Rey and Montouri (1999) and Le Gallo and Ertur (2003) and references therein for a literature review.

This paper aims at investigating regional productivity disparities and their relation with the three aforementioned shift shared components in space and time. It extends Esteban's approach by performing shift-share for several years, by allowing for intertemporal covariance between the different years and by explicitly taking into account spatial autocorrelation. Using a dataset that corresponds to 205 NUTS 2 European regions from 1975 to 2000 we find that spatial autocorrelation is indeed an unavoidable feature. We use recently developed tools of exploratory spatial data analysis to identify global and local spatial autocorrelation and thus characterize the way economic activities are located in the E.U. and the way this pattern of location has changed over time. Moreover, we employ spatial seemingly unrelated regressions (SUR) to model the temporal evolution of the relation of productivity with each one of its shift share components while at the same time accounting for spatial dependencies.

In section 2, we set out Esteban's (2000) shift share decomposition where regional productivity growth is modeled as the sum of three components: structural, differential and allocative. Section 3 presents the sample of 205 European regions over the 1975–2000 period as well as the spatial weight matrices used in this paper. In section 4, we perform exploratory spatial data analysis methods (ESDA) on productivity and the three shift share components. In the fifth section we present shortly, due to space constraints, the main steps of the modeling stage and the most important of our results. The interested reader will find a detailed description in Kamarianakis and LeGallo (2003).

THE SHIFT-SHARE APPROACH

In this section, regional labor productivities are decomposed via traditional shift-share analysis as depicted in Esteban (1972, 2000). A number of studies have focused on analyzing changes in employment and productivity as determinants of income growth using shift-share analysis or a related methodology. First used by Dunn (1960) as a forecasting technique for regional growth employment, the shift-share approach has been applied more recently by Esteban (1972, 2000) to analyze productivity changes among the European regions.

[25] In contrast to the situation in Europe, Browne (1989) and Carlino (1992) report the main cause of regional inequality in per capita income in the United States to be regional variability in unemployment rates.

[26] A detailed description of these factors lies in the next section.

Esteban's approach can be formulated as follows: let p_i^j be sector *j*'s employment share in region *i* so that $\sum_j p_i^j = 1$ for all regions *i*. We denote by p_{EU}^j sector *j*'s employment share at the European level. Thus, we shall also have $\sum_j p_{EU}^j = 1$. Similarly, we denote by x_i^j the productivity per worker in sector *j* and region *i*, respectively x_{EU}^j at the European level. In our case eight sectors are concerned: agriculture, construction, total energy and manufacturing, distribution, transport and communications, banking and insurance, other market services and non-market services. Based on the above, the following equalities hold:

$$x_i = \sum_j p_i^j x_i^j \qquad (1a) \qquad \text{and} \qquad x_{EU} = \sum_j p_{EU}^j x_{EU}^j \, . \qquad (1b)$$

The regional differential in productivity per worker between region *i* and the European average is therefore: $x_i - x_{EU}$.

Esteban (2000) shows that the regional differential in productivity per worker can be attributed to three possible causes. The first one is due to the specialization of a region in the more productive sectors, which would result in a regional aggregate productivity above the mean, even if the productivity of each single sector is the same at any location. It may result from local advantages that have been growing with history. The second cause comes from each region's sector-by-sector productivity differential to the average, assuming that the sectoral composition of the regional industry is the same than the one at the European level. It may come from previous investments in technology, human capital and public infrastructures. The third cause of differential in productivity per worker is due to a combination of both.

In order to assess the extent to which each of these component impacts on the different levels of regional productivity per worker compared to the EU average, the three components of the regional deviation in productivity are defined as follows:

a) *The industry-mix component* μ_i of region *i* measures the differential in productivity per worker between region *i* and the EU average due to the specific sectoral composition of its industry. Here we assume that the productivity per worker in each sector is the same across all the regions and the European average. We thus write: $\mu_i = \sum_j \left(p_i^j - p_{EU}^j\right) x_{EU}^j$ (2)

   μ_i takes positive values if the region is specialized (i.e. $p_i^j > p_{EU}^j$) in sectors with high productivity compared to the European level or de-specialized (i.e. $p_i^j < p_{EU}^j$) in sectors of low productivity. μ_i is at a maximum if the region is specialized in the most productive sector. Note that (2) can be rewritten as:

   $$\sum_j p_i^j x_{EU}^j = x_{EU} + \mu_i \qquad (3)$$

b) *The productivity differential component* π_i focuses on productivity differentials due to region i's sector by sector productivity differential to the EU average, assuming that the region's industry mix coincides with the European one. We then define π_i as: $\pi_i = \sum_j p_{EU}^j \left(x_i^j - x_{EU}^j\right)$ (4)

   π_i takes on positive values if the region has sectoral productivities above the European average. Equation (4) can also be written as follows: $\sum_j p_{EU}^j x_i^j = x_{EU} + \pi_i$ (5)

c) *The allocative component* α_i is a combination of the two previous components and is defined as follows:

   $$\alpha_i = \sum_j \left(p_i^j - p_{EU}^j\right)\left(x_i^j - x_{EU}^j\right) \qquad (6)$$

This component is positive if the region is specialized, relative to the European average, in sectors whose productivity is above the European average, and negative if below it. α_i is at its maximum if the region is completely specialized in the sector with the largest productivity differential with respect to the European average. This component is an indicator of the efficiency of each region in allocating its resources over the different industrial sectors. The allocative component can also be viewed as measuring the covariance between the two previous components. The gap between regional and European average productivities decomposed into the three components can be formulated as follows:

$$y = x_i - x_{EU} = \mu_i + \pi_i + \alpha_i \, . \qquad (7)$$

In order to measure the role played by each component in explaining regional differences in aggregate productivity per worker, Esteban computes the relative weight of the variance of each component in the overall observed variance. From (7) we have:

$$\mathrm{var}(y) = \mathrm{var}(\mu) + \mathrm{var}(\pi) + \mathrm{var}(\alpha) + 2\left[\mathrm{cov}(\mu,\pi) + \mathrm{cov}(\mu,\alpha) + \mathrm{cov}(\pi,\alpha)\right]. \qquad (8)$$

Finally, he tests whether interregional differences in aggregate productivity per worker can be explained by a model including one single component of the shift-share decomposition (7). To this effect the following models are estimated:

$$x_i - x_{EU} = a_\mu + b_\mu \mu_i + \varepsilon_{\mu,i} \qquad i = 1,...,N \qquad (9a)$$

$$x_i - x_{EU} = a_\pi + b_\pi \mu_i + \varepsilon_{\pi,i} \qquad i = 1,...,N \qquad (9b)$$

$$x_i - x_{EU} = a_\alpha + b_\alpha \mu_i + \varepsilon_{\alpha,i} \qquad i = 1,...,N \qquad (9c)$$

where N is the total number of regions, $\varepsilon_{\mu,i}$, $\varepsilon_{\pi,i}$ and $\varepsilon_{\alpha,i}$, are error terms with the usual properties (~iid N(0, σ^2)). Using 4 datasets –three of them corresponding to 1986 and one corresponding to 1989- with different regional/sectoral combinations he finds that most of the observed interregional variance in aggregate productivity per worker is attributable to pure productivity differentials.

It should be noted though, that variance is not a typical measure of inequality since it does not satisfy the requirement of scale independence. This could give rise to a serious restriction if, as in the case at hand, the aim is to make comparisons over time. Moreover, in his regression models, Esteban does not take into account spatial dependence, which, when ignored, can result in major model misspecification (see Anselin (1988a) for further details). Recent developments in spatial econometrics offer procedures for testing for the potential presence of these misspecifications and suggest the proper estimator for models that treats spatial dependence explicitly. Based on these two aspects, we extend Esteban's analysis in two respects. First, we estimate equations (9a), (9b) and (9c) for different years in order to capture the evolution of the role played by each component in the explanation of the labor productivity gaps. Since there is no reason to assume that the different years are uncorrelated, we allow for intertemporal covariance using a Seemingly Unrelated Regressions (SUR). Second, spatial autocorrelation is explicitly taken into account, so that we estimate spatial SUR (Anselin, 1988b). In that purpose, a spatial weight matrix has to be defined for our sample, which we present in the next section.

DATA AND SPATIAL WEIGHT MATRIX

The computation of shift share components presented in the previous section is based on European regional data on gross value added and employment for nine economic sectors: agriculture, energy and manufacturing, construction, market services, distribution, transport and communications, banking and insurance, other market services and non market services. The data come from the Cambridge Econometrics database. Our sample includes 205 regions in 15 countries (NUTS2 level) over the 1975-2000 period: Luxemburg, Belgium (10), Denmark, Germany (31), Greece (12), Spain (16), France (22), Ireland (2), Italy (20), Netherlands (12), Austria (9), Portugal (5), Finland (6), Sweden (21), United Kingdom (37).

Spatial data analysis needs modelling the spatial interdependence between the observations by the mean of a spatial weight matrix W. The spatial weight matrix is the fundamental tool used to model the spatial interdependence between regions. More precisely, each region is connected to a set of neighboring regions by means of a *purely spatial pattern* introduced *exogenously* in this spatial weight matrix *W*. The elements w_{ii} on the diagonal are set to zero whereas the elements w_{ij} indicate the way the region i is spatially connected to the region j. These elements are *non-stochastic,* non-negative and finite. In order to normalize the outside influence upon each region, the weight matrix is standardized such that the elements of a row sum up to one. For a given variable *x*, this transformation means that the expression *Wx*, called the spatial lag variable, is simply the weighted average of the neighboring observations. Various matrices have been considered in the spatial statistics and spatial econometric literature: a simple binary contiguity matrix, a binary spatial weight matrix with a distance-based critical cut-off, above which spatial interactions are assumed negligible, more sophisticated generalized distance-based spatial weight matrices with or without a critical cut-off. The notion of distance can be quite general and different functional form based on distance decay can be used (for example inverse distance, inverse squared distance, negative exponential etc.). The critical cut-off can be the same for all regions or can be defined to be specific to each region leading in the latter case, for example, to *k*-nearest neighbors weight matrices when the critical cut-off for each region is determined so that each region has the same number of neighbors.

As pointed out by Anselin (1999), the weights should be exogenous to the model to avoid the identification problems raised by Manski (1993) in social sciences. This is the reason why we consider pure geographical distance, more precisely great circle distance between regional centroids, which is indeed strictly exogenous; the functional form we use is the inverse of squared distance. The general form of the distance weight matrix *W* we use is defined as following:

$$\begin{cases} w_{ij}^* = 0 \text{ if } i = j \\ w_{ij}^* = 1/d_{ij}^2 \text{ if } d_{ij} \leq D(1) \\ w_{ij}^* = 0 \text{ if } d_{ij} \geq D(1) \end{cases} \text{ and } \quad w_{ij} = w_{ij}^* / \sum_j w_{ij}^* \qquad (10)$$

where d_{ij} is the great circle distance between centroids of regions *i* and *j*; $D(1)$ is the first quartile of the great circle distance distribution. This matrix is row standardized so that it is relative and not absolute distance that matters. $D(1)$ is the cutoff parameter above which interactions are assumed negligible. Since all analyses are conditional upon the choice of the spatial weight matrix, several alternatives have been considered to check for robustness of our results: distance-based weight matrices with different cut-offs and nearest-neighbour matrices[27].

EXPLORATORY SPATIAL DATA ANALYSIS OF PRODUCTIVITY AND ITS SHIFT-SHARE DECOMPOSITION

Using the dataset presented in the previous section, we compute the productivity of each region in deviation from the EU average and the three shift-share components for every year of the sample, 1975-2000. This section aims at showing that spatial autocorrelation characterizes the distributions of regional productivity and its shift-share decomposition.

Spatial autocorrelation can be defined as the coincidence of value similarity with locational similarity (Anselin 2001). There is positive spatial autocorrelation when high or low values of a random variable tend to cluster in

[27] Note that in the European context, the use of simple contiguity matrices is problematic since in this case, the existence of islands would implies a weight matrix that includes rows and columns with only zeros for the islands. Since unconnected observations are eliminated from the results of the global statistics, this would change the sample size and the interpretation of the statistical inference. Moreover, the weight matrix considered in this paper guarantees connections between United Kingdom and continental Europe and between Greek and Italian regions so that a bloc-diagonal structure of the weight matrix can be avoided.

space and there is negative spatial autocorrelation when geographical areas tend to be surrounded by neighbors with very dissimilar values. This effect is highly relevant in Europe since spatial concentration of economic activities in European regions has already been documented (Lopez-Bazo *et al.*, 1999, Le Gallo and Ertur, 2003; Dall'erba, 2003). Here we are interested in both global and local spatial autocorrelation.

The measurement of global spatial autocorrelation is usually based on Moran's I statistic (Cliff and Ord, 1981). For each year of the period 1975-2000, this statistic is written in the following matrix form:

$$I_t = \frac{n}{S_0} \cdot \frac{z_t^{'} W z_t}{z_t^{'} z_t} \quad t = 1,...,25 \tag{11}$$

where z_t is the vector of the n observations for year t in deviation from the mean. Moran's I statistic gives a formal indication of the degree of linear association between the vector z_t of observed values and the vector Wz_t of spatially weighted averages of neighboring values, called the spatially lagged vector. Values of I larger (resp. smaller) than the expected value $E(I) = -1/(n-1)$ indicate positive (resp. negative) spatial autocorrelation.

Table 1 displays Moran's I statistic for regional productivity in deviation from the EU average and the three shift-share components for 1975 and 2000 period for the 205 European regions of our sample. Inference is based on the permutation approach with 9999 permutations (Anselin 1995). It appears that all four variables are positively spatially autocorrelated since the statistics are significant with $p = 0.0001$ for 1975 and 2000.[28] This result suggests that the distributions of regional productivity and its three shift-share components are by nature clustered over the whole period. Comparing the results for 1975 and 2000 shows that the standardized values of the statistic slightly decrease over the period, especially for the allocative component. These results therefore indicate a very small decrease of the geographical clustering of similar regions.

Moran's I statistic is a global statistic and does not allow to assess the regional structure of spatial autocorrelation. In order to gain more insight into the way regions with high or low labor productivity are located in the European Union, we now analyze local spatial autocorrelation using Moran scatterplots (Anselin 1996), and Local Indicators of Spatial Association "LISA" (Anselin 1995). First, Moran scatterplots plot the spatial lag Wz_t against the original values z_t. The four different quadrants of the scatterplot correspond to the four types of local spatial association between a region and its neighbours: HH a region with a high[29] value surrounded by regions with high values, LH a region a with low value surrounded by regions with high values, etc. Quadrants HH and LL (resp. LH and HL) refer to positive (resp. negative) spatial autocorrelation indicating spatial clustering of *similar* (resp. *dissimilar*) values. The Moran scatterplot may thus be used to visualize atypical localizations, i.e. regions in quadrant LH or HL. Note that the use of standardized variables makes the Moran scatterplots comparable across time.

	1975			2000		
Variable	*Moran's I*	*St. dev.*	*St. value*	*Moran's I*	*St. dev.*	*St. value*
Productivity differential	0.720	0.032	22.754	0.690	0.032	21.899
Industry-mix component	0.658	0.032	21.146	0.573	0.032	18.237
Productivity differential component	0.704	0.032	22.404	0.681	0.032	21.674
Allocative component	0.458	0.032	15.006	0.390	0.032	12.918

[28] All computations are carried out using SpaceStat 1.90 (Anselin 1999) and Arcview 3.2 (Esri).
[29] High (resp. low) means above (resp. below) the mean.

Notes: the expected value for Moran's *I* statistic is -0.005 for all variables. All statistics are significant at 1% level.

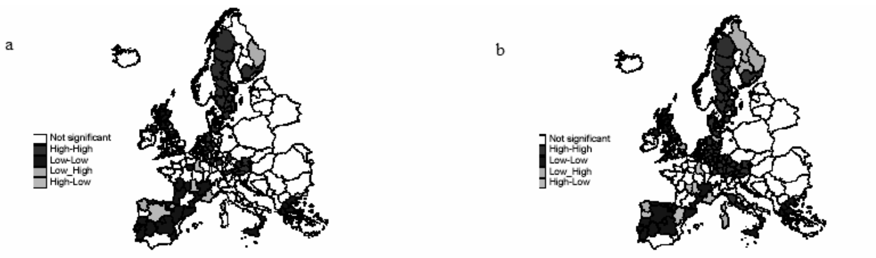
Table 1: Moran's *I* statistics for regional productivity and the three shift-share components for 1975 and 2000

Second, Anselin (1995) defines a Local Indicator of Spatial Association (LISA) as any statistics satisfying two criteria: (i) the LISA for each observation gives an indication of significant spatial clustering of similar values around that observation; (ii) the sum of the LISA for all observations is proportional to a global indicator of spatial association. The local version of Moran's *I* statistic for each region i and year t is written as:

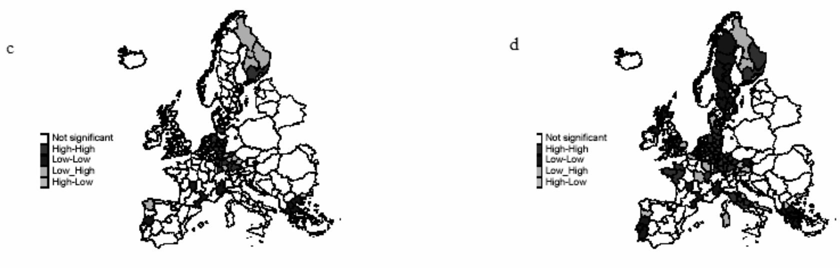
$$I_{i,t} = \frac{(x_{i,t} - \mu_t)}{m_0} \sum_j w_{ij} (x_{j,t} - \mu_t) \quad \text{with} \quad m_0 = \sum_i (x_{i,t} - \mu_t)^2 / n \qquad (12)$$

where x_{it} is the observation in region *i* and year *t*, μ_t is the mean of the observations across regions in year *t* and where the summation over *j* is such that only neighboring values of *j* are included. A positive value for $I_{i,t}$ indicates spatial clustering of *similar* values (high or low) whereas a negative value indicates spatial clustering of *dissimilar* values between a region and its neighbors. Due to the presence of global spatial autocorrelation, inference must be based on the conditional permutation approach with 9999 permutations (Anselin 1995). It should be stressed that *p*-values obtained for local Moran's statistics are actually pseudo-significance levels.

Combining the information in a Moran scatterplot and the significance of LISA yields the so called "Moran significance map", showing the regions with significant LISA and indicating by a colour code the quadrants in the Moran scatterplot to which these regions belong. Figures 1a, 1b, 1c, 1d, b display the Moran scatterplot maps using a 5% pseudo-significance level for regional productivity in deviation from the EU average, and the first shift-share component for the initial and final years of our sample.



Moran's significance map for regional productivity in deviation from the EU average in 1975 and 2000



Moran's significance map for the industry-mix component in 1975 and 2000

Figures 1a, and 1b: Moran's significance map for regional productivity in deviation from the EU average in 1975 and 2000.

Figures 1c and 1d: Moran's significance maps for the industry-mix component in 1975 and 2000.

Concerning first the Moran significance maps for regional productivity, a relative stability of the spatial patterns can be observed between 1975 and 2000. It appears that most European regions are characterized by positive local spatial association, i.e. they are significantly located in the HH or the LL quadrant. The significant HH regions are mostly to be found in Germany, Sweden and Austria. The regions in these countries therefore perform well in terms of productivity compared to the EU average. On the contrary, the significant LL regions are located in the South of France, Spain, Greece, South of Italy and most UK regions. The examination of these maps also allows detecting atypical regions characterized by negative local spatial autocorrelation. For example, some French, UK and Spanish regions perform well compared to their neighbours since they are significantly HL.
The Moran significance maps for the three shift-share components in 1975 and 2000 are analysed next.[30] It appears that the spatial patterns for the first two components are relatively similar to that of labour productivity while the spatial pattern for the third component seems reversed. Therefore, we can expect a positive relationship between regional productivity, the industry-mix and the productivity differential components and a negative relationship between regional productivity and the allocative component. All the results presented in this section reveal the presence of a significant and positive spatial autocorrelation for all variables that is persistent over the period. This feature should be taken into account in our econometric estimations that are presented next.
All the results presented in this section reveal the presence of a significant and positive spatial autocorrelation for all variables that is persistent over the period. This feature should be taken into account in our econometric estimations that are presented next.

SPATIAL SUR MODELING: A SYNOPSIS

Esteban (2000) directly estimates models (9) presupposing a linear relationship between productivity and the three components of its shift-share decomposition. The linearity assumption needs to be tested though; some components may be very strongly related to productivity in a nonlinear fashion. For that reason we first perform a specification search on the pooled data. Thus, we applied the Box-Cox method that seeks (via maximum likelihood) an optimal power transformation for the response. Despite the fact that we allowed polynomial forms of the explanatories (up to third order) the optimum power ranged between 0.9 and 1.2 in every case, indicating very little changes in our final relations. We continued by applying two nonparametric transformation procedures; the first proposed by Young et al. (1976)[31] and the second by Tibshirani (1986)[32]. In both cases, we neither observed clear functional relationships nor a significant improvement in the relationships between the transformed variables.

Since specification search indicates that no dramatic strengthening of linear relations occurs by a parametric or non-parametric transformation, we now fit a regression model on the pooled data. The main results of this analysis are displayed in table 2. It appears that the coefficient associated to the first and second shift-share component are significantly positive while the coefficient associated to the third component is significantly negative. These results are consistent with those previously obtained for ESDA. Compared to Esteban (2000), we observe a significantly worse fit for the first and a much better fit for the third component. The second model performs the best according to the information criteria.

Pooling the data implies that we cannot capture its temporal dimension. In particular, it is interesting to estimate how the relation of productivity with each shift-share component evolves through time. For that purpose, we performed seemingly unrelated regressions (SUR) that allow the coefficients to be different in each time period and intertemporal dependence through the covariance matrix of the system of the regression

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[30] Due to space constraints we present only the figures that correspond to the first component. The interested reader will find the two remaining ones in Kamarianakis and Le Gallo (2003).
[31] The SAS PROC TRANSREG procedure was used in that purpose.
[32] The R software-acepack package was used in that purpose.

equations. Since tests of spatial dependence indicated the significance of spatial lag (for the first and third component) and of spatial error (for the second component) we finally estimated spatial SUR models as formulated in Anselin (1988). Details on coefficient estimation and implication of the results can be found in Kamarianakis and Le Gallo (2003).

	Industry mix component	**Regional component**	**Allocative component**
$\hat{a}$	-0.291 (0.012)	-1.671 (0.000)	-3.439 (0.012)
$\hat{b}$	1.985 (0.000)	0.891 (0.000)	-1.821 (0.000)
R2	0.2273	0.9065	0.2394
R2 adjusted	0.2271	0.9065	0.2393
LIK	-17491.227	-111429.732	-17445.712
AIC	34986.453	22863.464	34895.424
SC	34999.764	22876.774	34908.734
$\hat{\sigma}^2$	70.595	8.540	69.484

Notes: *p*-values are in brackets. *LIK* is value of the maximum likelihood function. *AIC* and *SC* are stand respectively for the Akaike and the Schwartz information criteria.
Table 2: Ordinary least squares regression results on the pooled data

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