TI 2005-041/3
Tinbergen Institute Discussion Paper

# Forecasting Regional Labour Market Developments Under Spatial Heterogeneity and Spatial Autocorrelation

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PAPER PREPARED FOR THE
KIEL WORKSHOP ON SPATIAL ECONOMETRICS
KIEL (GERMANY) 8-9 APRIL, 2005

# FORECASTING REGIONAL LABOUR MARKET DEVELOPMENTS UNDER SPATIAL HETEROGENEITY AND SPATIAL AUTOCORRELATION

## A COMPARISON OF VARIOUS STATISTICAL METHODS

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**PN183SL**

THIS VERSION: 13 FEBRUARY 2005

**ABSTRACT**
Because of heterogeneity across regions, economic policy measures are increasingly targeted at the regional level. As a result, the need for economic forecasts at a sub-national level is rapidly increasing. The data available to compute regional forecasts is usually based on a pseudo-panel that consists of a limited number of observations over time, and a large number of areas (regions) strongly interacting with each other. In such a situation, the application of traditional time-series techniques to distinct time series of regional data may then become a sub-optimal forecasting strategy.
In the field of regional forecasting of socio-economic variables, both linear and non-linear models have recently been applied and evaluated. However, often such analyses tend to ignore the spatial structure of the data and the spatial interactions that are likely to exist among regions.
In this paper, we evaluate the ability of different statistical techniques – namely spatial lag and spatial error models – to correct for misspecification due to neglected spatial autocorrelation in the data set. Our empirical application concerns short-term forecasts of employment in 326 West German labour market regions. We find that the superimposed spatial structure that is required for the estimation of spatial models improves the forecasting performance of non-spatial forecasting models.

Key Words: Space-Time Data, Regional Forecasts, Spatial Heterogeneity, Spatial Spillovers
JEL Classification: C21, C23, E27, R19

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## 1. INTRODUCTION

Nowadays there is a large body of theoretical and empirical literature concerned with forecasting macro-economic variables. Various studies on forecasts of macroeconomic time-series have recently been carried out, among others, by Boomsma (1999), Dua and Miller (1995), Fauvel et al. (1999), Partridge and Rickman (1998), Rickman (2002), Stock and Watson (1998, 2002), and Swanson and White (1997a, 1997b). Such literature focuses normally on time-series data, that is, it uses a large number of observations over time to forecast the future behaviour of a given economic variable, usually at national or macro level.

Since in practice substantial labour market disparities can be found for small regions, the prediction of the future behaviour of single regions in a national economy is gaining increasing attention. It has often been noted that the variability of labour market aggregates is much higher across regions of the same country than across national economies (see, e.g., Overman and Puga, 2002 and OECD, 2000). Furthermore, empirical analyses show that regions are affected by local-specific shocks, and react differently to national shocks (see, e.g., Blanchard and Katz, 1992 for the US and Decressin and Fatás, 1995 for the EU). Therefore, to counteract disparities among regional labour markets, and to make an efficient use of available public funds, national governments are – for several reasons – always in need of reliable regional forecasts to complement the ones computed at national level.

In the first place, the computation of forecasts for such small, open and highly interacting regional economies represents an intriguing challenge. To better represent the similarities and differences across regions, as well as the interactions among them, panel data sets should be used. Nevertheless, the use of panel data techniques to compute economic forecasts is still not very common, as this approach incorporates advantages as well as difficulties. In the context of regional forecasting experiments, the number of regions for which the forecasts have to be made is generally much higher than the number of time periods for which regional data are available. As a result, statistical techniques that are commonly used in time-series analysis – generally characterised by a large number of observations over time – are not easily generalised and applied to panel data.

Secondly, the problem of neglected spatial heterogeneity might arise. If labour market disturbances are asymmetrically distributed across regions (see, e.g., Blanchard and Katz, 1992 and Decressin and Fatás, 1995), a panel estimator imposing equal slopes for coefficients that are heterogeneous across regions might lead to incorrect forecasts. On the other hand, it has been found that pooling data generated by models with similar, but non-identical parameter structure might improve the model's performance (Hoogstrate et al., 2000).

On the third place, regions are open, small and highly interconnected economies that show a high degree of interaction with the neighbouring local economies. For this reason, the economic development of each region is probably highly affected by (and is likely to have a high impact on) the economic development of other regions. Neglecting such spatial autocorrelation and dependence might result in biased estimation coefficients and, therefore, in sub-optimal forecasts. The use of space-time data allows spatial autocorrelation and spatial spillovers to be explicitly modelled.

There is, however, a variety of statistical tools, so that the need emerges for a robustness analysis in an empirical testing. In the present paper we focus on the German regional labour market. Blien and Tassinopoulos (2001) and Bade (2005) have recently proposed new methodologies to compute labour market forecasts for German regions. Blien and Tassinopoulos (2001) suggest a combination of top-down and bottom-up techniques to compute short-term forecasts for West-German regions. Their forecasts take into account regional autonomous trends that are then combined with expectations about the development of single industrial sectors, by means of an entropy-optimising procedure. Bade (2005) uses an extension of the ARIMA approach to forecast long-term development of regional shares in national employment. None of these analyses exploits the information about cross-regional relationships to improve the results.

In the same vein as Blien and Tassinopoulos (2001), our study aims at computing short-term forecasts of employment at regional level, using data on West-German regions as an empirical case study. However, the estimations in this analysis are computed by means of panel data techniques. In this respect, our study resembles more the one by Baltagi and Li (2004), who use panel data on individuals living in the US to predict per-capita cigarette consumption, accounting for spatial spillovers and spatial heterogeneity. However, our approach differs from Baltagi and Li (2004) in some aspects. First, our data do not refer to individuals, but to labour market aggregates, averaged at regional level. Second, while Baltagi and Li (2004) only allow for spatial heterogeneity in the intercept terms, we also allow for spatially heterogeneous slopes. Finally, while Baltagi and Li (2004) only evaluate spatial error models, we also assess and compare the results of spatial lag models.

Our findings confirm that models taking into account spatial autocorrelation by means of spatial error models tends to result in forecasts that are on average more reliable than those models accounting for spatial autocorrelation by means of spatial lags. This will be demonstrated in the rest of our paper, which is organised as follows. Section 2 highlights the specific regional forecasting problem and suggests a range of models that can be used to compute such forecasts. Next, Section 3 estimates and compares the empirical models for German labour markets proposed in Section 2. Finally, Section 4 offers concluding remarks.

## 2. Regional Forecasts

### 2.1. The Forecasting Problem

The aim of the models estimated hereafter is to compute forecasts of the level of employment in year $t$, for a panel of $R$ regions observed over $T$ previous time periods. Our forecasting problem may therefore be formalised in the following way:

$$E_{rt} = f(E_{1r(t-1)}; E_{2r(t-1)}; \dots E_{9r(t-1)}) + \varepsilon_{rt} \tag{1}$$

where the dependent variable $E_{rt}$ is the total number of workers employed in region $r$ at time $t$. The independent variables are the number of workers employed in each economic sector $s$ ($s$ = 1 … 9) in region $r$ at time $(t-1)$ (i.e., $E_{1r(t-1)}; E_{2r(t-1)}; \dots E_{9r(t-1)}$). The term $\varepsilon_{rt}$ is the remaining disturbance terms, which is assumed to meet the usual assumptions.[1]

Finally, $f$ represents the functional form through which the set of inputs is combined to approximate the output. For this analysis we assume a linear additive

[1] As a sensitivity analysis, we estimated all models also by adding the average regional wage of full-time workers employed in region $r$ and time $(t-1)$ among the regressors. The resulting models are less successful in forecasting employment at time $t$. The reason for these result might be the rather aggregated level of the wage variable, see below. The results are not shown here but are available upon request.

relationship. In the naïve no-change forecasting model, (1) might be specified in the following standard form:

$$E_{rt} = \Sigma_s E_{sr(t-1)} + \varepsilon_{rt} = E_{r(t-1)} + \varepsilon_{rt} , \tag{2}$$

where the coefficients of $E_{1r(t-1)}; E_{2r(t-1)}; \ldots E_{9r(t-1)}$ are all equal to 1. Such extrapolative forecasts are not very sophisticated and call for more advanced statistical tools.

### 2.2. MODEL COMPARISON

The models' performance is analysed on *ex post* forecasts for the last three time periods for which the data is available (see below), by means of statistical indicators common in the time-series literature (see, e.g., Swanson and White, 1997a, 1997b, and Fauvel et al., 1999). However, given the panel structure of the data, for each time period $t$ we have $R$ – rather than only one – forecasts, with $R$ being the total number of regions (i.e., 326). The above mentioned indicators are then computed on one-year *ex post* forecasts over all regions, separately for the three time periods for which the *ex post* forecasts are computed. As a result, our indicators summarise the forecasts' variability across regions, rather than across time. Thus, the forecasting error for the *ex post* forecast of time $t$ is computed as the difference between the actual total number of employees in region $r$ in the year $t$ ($E_{rt}$) and the total number of employees in region $r$ in the year $t$ that is predicted by the model ($E^f_{rt}$). The global error is, therefore, computed as the sum across regions of (a function of) the forecasting errors.

The statistical indicators we use to compare our models on the *ex post* forecast are the Mean Absolute Error (MAE = $1/R * [\Sigma_r |E_{rt} - E^f_{rt}|]$); the Mean Absolute Percentage Error (MAPE = $1/R * [\Sigma_r |(E_{rt} - E^f_{rt}) / E_{rt}|]$); and the Mean Square Error (MSE = $1/R * [\Sigma_r |E_{rt} - E^f_{rt}|^2]$). The MSE is then decomposed into its three components: the Bias Proportion (BP = $(E_t - E^f_t)^2 / MSE$); the Variance Proportion (VP = $(\sigma^f - \sigma)^2 / MSE$); and the Covariance Proportion (CP = $2\sigma^f\sigma[1 - \rho(E_t E^f_t)] / MSE$). In these last three formulas, $E_t$ and $E^f_t$ are, respectively, the average – across regions – of the total number of people employed and of its forecast. The terms $\sigma^f$ and $\sigma$ are the standard deviations – computed across regions – of the forecasted and observed values. Finally, $\rho$ is the correlation coefficient between the forecasted and the observed series of values. Clearly, $\rho$ too is computed on cross-sectional – rather than on time-series – data.[2]

To be suitable for real empirical applications, a forecasting model needs to outperform the no-change-forecasting model. Such a model's characteristic can be easily analysed by means of the U-Theil inequality coefficient (the Theil statistic), which is computed as the ratio between the MSE of each model and the MSE of the no-change model (Granger and Newbold, 1986). The proposed model outperforms the no-change model when the U-Theil inequality coefficient is lower than 1 (see, e.g., Fauvel et al., 1999; Swanson and White, 1997a).

To further simplify the comparison among each model's performance, we further compute the average of the above mentioned indicators over the three *ex post* forecasts.

### 2.3. NON-SPATIAL MODELS

To analyse whether taking into account spatial autocorrelation results in more reliable forecasts, we first estimate models that do not take into account any form of spatial autocorrelation. For simplicity, we label these models 'non-spatial'.

We estimate such non-spatial models by means of techniques especially designed for panel data. For more details on such techniques we refer to, among others, Baltagi (2001) and Hsiao (2003). Such models can be formalised as:

$$y_{rt} = \alpha_r + \alpha_t + \beta' \mathbf{Z}_{rt-1} + \varepsilon_{rt} \quad (3)$$

where $y_{rt}$ is employment in region $r$ at time $t$ (the term $E_{rt}$ of equation (1)), $\mathbf{Z}_{rt}$ contains data on employment in region $r$, time $(t-1)$, and across sectors $s$. The components of $\mathbf{Z}_{rt-1}$ are, therefore, $E_{1r(t-1)}$; $E_{2r(t-1)}$; ... $E_{9r(t-1)}$, as indicated in equation (1). The terms $\alpha_r$ and $\alpha_t$ are region- and time-specific characteristics, respectively, while $\varepsilon_{rt}$ is the remaining error term. Finally, $\beta$ is the vector of parameters to be estimated.

In a recent paper, Diebold and Kilian (2000) find that, in time-series models, pre-testing for unit roots is needed for a better selection of the forecasting model.

[2] Many statistical tests which have been proposed to compare models' performance (such as the test proposed by Diebold and Mariano, 1995) in time-series analysis, cannot be straightforwardly generalised to a panel data setting. In time-series analysis, the correlation runs only in one direction, from past to current and future observations, but not vice versa. When cross-sections are involved (as in the case of panel data), since each region may affect all other regions involved in the estimation, the correlation usually runs in more directions. This might eventually have an effect on the reference distribution of the tests, with the consequence that the naïve application of such tests to our forecasts would probably lead to misleading results.

Since the employment data seem to be non-stationary,[3] these panel model estimations have been computed on the growth rates – rather than on the levels – of the data.

There might be some collinearity problems among the explanatory variables in (3). Such collinearity might lead to inflated standard errors of the estimators. However, this does not seem to be a big problem here, since the focus of this empirical exercise is on comparative forecasting, rather than interpreting. Furthermore, from an economic point of view, forcing some of the $\beta$ coefficients to be 0 (and therefore assuming that such variables do not have any economic relevance) might be a questionable choice.

The model in (3) can be estimated by means of the fixed effects (FE) estimator or by means or the random effects maximum likelihood (ML) estimator. In the first case, the region-specific characteristics are modelled by means of regional dummies, while in the second case both regional effects $\alpha_r$ and error term $\varepsilon_{rt}$ are assumed to be random and normally distributed. In both cases the time-specific characteristics are modelled by means of time dummies.

By estimating a single regression coefficient for each independent variable, the above models implicitly assume the slope of the variables of interest to be invariant across regions. This estimation choice might significantly decrease the time necessary to compute such forecasts. However, in some cases, the estimation of one single region-invariant regression coefficient, which might be conceived of as the average of region-specific coefficients, might lead to misleading inference. Hoogstrate et al. (2000) analyse the problem of pooling data generated by models with a similar, but non-identical, parameter structure. They find that, for short time series, the model's performance can be improved by pooling the data.

Nevertheless, when the region-specific characteristics are very dissimilar, taking into account some sort of spatial heterogeneity might lead to improved results. Since our data set comprises a relatively large number of regions, we can easily compute group-specific regressions, allowing for group-specific coefficients. The groups are mutually exclusive, and each region belongs to one of the nine urbanisation groups. In our empirical analysis we will group regions on the basis of their degree of urbanisation. Given the specific structure of German labour market

[3] Given the low value of $T$, a formal test for non-stationarity would not be very powerful.

regions, this is a meaningful choice. This information is available for our data set. Equation (3) is then estimated separately for each urbanisation group ($ur$ = 1, …, $UR$):

$$y^{ur}_{rt} = \alpha_r + \alpha_t^{ur} + \boldsymbol{\beta}^{ur\,\prime}\,\mathbf{Z}^{ur}_{rt-1} + \varepsilon_{rt} \tag{4}$$

where $y^{ur}$ and $\mathbf{Z}^{ur}$ are all – and only – the observations of the dependent and independent variables belonging to that specific urbanisation group. The estimated parameters ($\alpha_t^{ur}$ and $\boldsymbol{\beta}^{ur}$) are also group-specific. The regional intercepts, as well as the error term, remain region-specific. The results for the nine urbanisation groups are then combined to allow the computation of the statistical indicators.

In many empirical studies on labour market phenomena, the geographical unit used generally covers a small geographical area that, in many cases, may not coincide with a well-defined local labour market area. In this case, we may expect a high number of commuters between neighbouring regions, which may be one cause of regional spatial dependence and regional spatial spillovers. An increasing number of econometric techniques have been proposed to detect and remedy such difficulties. In the next section we briefly review some of them.

### 2.4. Spatial Autocorrelation

In the model presented in (4) we – roughly – try to account for spatial heterogeneity by estimating the coefficients separately for the nine urbanisation groups. However, all the above-mentioned models neglect the problem of spatial dependence. In our specific data set, which consists of small, open and highly interacting regions, spatial dependence might represent a relevant problem. Because of commuting across regions, the dependent variable of our model, viz. total employment in region $r$ at time $t$ ($E_{rt}$), is likely to be correlated with both employment and wages of the neighbouring regions. Furthermore, other unobserved regional characteristics might cause dependence and/or spatial spillovers across regions.

An increasing number of econometric techniques have recently been proposed to deal with such misspecification problems. For more details on spatial econometrics we refer to the work by, amongst others, Anselin (1988, 2001, 2002), Anselin and Bera (1998), Anselin and Florax (1995), Anselin et al. (2004), and Florax and Nijkamp (2005). We also refer here to the recent special issues of the *International Regional Science Review* and of *Geographical Analysis* on spatial econometrics (see, e.g., Anselin, 2003; Florax and van der Vlist, 2003; LeSage et al., 2004).

The analysis of the above-mentioned model misspecification usually starts from the analysis of the model's residuals. Specific statistical tests, such as the Moran's *I*, can be used to formally assess the presence of spatial dependence. In such a test, the spatial structure in the data is modelled by means of a spatial weight matrix **W**. This matrix, which imposes a structure on the covariance matrix, defines the spatial structure of our data set by specifying the neighbourhood of each region (Anselin, 2001). Such neighbourhood linkages can be defined in terms of Boolean (0-1) contiguity, distances, etc., between pairs of regions.

Since, according to Tobler's first law of geography, "everything is related to everything else, but near things are more related than distant things" (Anselin, 1988, p. 8), we base our choice of the spatial weight matrix on distances between contiguous regions. Each element of our spatial weight matrix is therefore proportional to the inverse of the Euclidean distance between the locations of the corresponding regional governments of contiguous regions. Following Buettner (1999), distances between non-contiguous regions are assumed to be infinite and the correspondent elements of the spatial weight matrix are therefore 0. This is not a highly restrictive assumption. Analogous to the case of the maximum lag length in temporal autocorrelation, some cut-off has to be assumed. The hybrid spatial weight matrix here is a good compromise between a Boolean spatial weight matrix based on contiguity and a full distance matrix.[4] More in detail, the Moran's *I* is computed as:

$$I = \frac{N}{S} \frac{(\mathbf{x}-\mu)'\mathbf{W}(\mathbf{x}-\mu)}{(\mathbf{x}-\mu)'(\mathbf{x}-\mu)} \tag{5}$$

where **x** is a vector containing the realisations of the variable of interest; $\mu$ is its mean; and **W** the spatial weight matrix. *N* is the number of observations; and *S* is a standardisation factor, coinciding with the sum of all elements in the weight matrix. The Moran's *I* has values between minus 1 and plus 1. A value of minus 1 indicates perfect negative correlation, suggesting that areas with values of **x** higher than the average are generally surrounded by areas with values of **x** lower than the average, and vice versa. A value of 1 indicates perfect positive correlation, suggesting the presence of clusters of high- and low-values of **x**. In such a situation, indeed, areas

[4] A full distance matrix is usually not ideal, because the positive dependence for regions that are close in space averages out with the negative dependence (e.g., based on some sort of hierarchical pattern) for regions further away. In their meta-analysis of simulation studies analysing the performance of tests for spatial dependence in linear regression studies, Florax and de Graaff (2004) find that the power of tests such as Moran's *I* is generally higher for relatively sparse weight matrices.

with values of **x** higher than the average are indeed generally surrounded by areas with values of **x** higher than the average, and vice versa. A value of 0 indicates the absence of spatial correlation.

When **x** is not normally distributed, the asymptotic distribution of Moran's $I$, needed to statistically test the significance of $I$, is unknown, and has to be approximated using a randomisation approach or to be generated using a permutation approach (see, for example, Anselin, 1988).

If not correctly modelled, the spatial autocorrelation in the employment variable, which is the target of our forecasting experiment, might have an influence on the accuracy of the non-spatial forecasting models that we proposed in the previous sections. Using the Moran statistic, we can analyse whether the proposed models are able to correctly represent the spatial relationships between regions. An insignificant value of the Moran statistic computed on the model's forecasting errors might suggest that the errors are randomly distributed across regions. On the other hand, a significant value of the Moran statistic suggests that the model is not able to correctly identify spatial clusters in the data. This means, therefore, that the positive and the negative forecasting errors are spatially clustered. In this case, there might be room for model improvement by means of spatial econometric techniques.

However, even when the forecasting errors do not show significant spatial autocorrelation, then taking into account spatial dependence and spillovers by means of spatially-lagged variables or a spatial error structure might improve the forecasting performance of the models. It is important to note that in this context the Moran's $I$ statistic should not be regarded as a diagnostic test for model misspecification. Being computed on the models' forecasting errors rather than on the models' residuals, the Moran's $I$ can only suggest directions in which to improve the model's forecasting performance.

The spatial autocorrelation of the models' residuals suggests the presence of some sort of misspecification, which might be reduced either by adding spatially-lagged variables to the initial model (spatial lag models), or by formally modelling the residual spatial autocorrelation (spatial error models). A model combining these two modelling strategies might also be estimated. Specific tests are commonly used to discriminate between these three options (see, e.g., Anselin et al., 1996). However, as will be shown in the following sections, in our case not all these options are feasible.

### 2.5. SPATIAL MODELS

In this section we suggest some ways to take into account spatial autocorrelation in the forecasting process. For simplicity, we label the models in this section 'spatial'.

First, we may extend the structure of the above non-spatial models with spatial lags of the dependent and/or explanatory variable. The spatial lag model can be formalised by adding the spatially weighted variable on the right-hand side of (3), thus obtaining:

$$y_{rt} = \alpha_r + \alpha_t + \beta' \mathbf{Z}_{r(t-1)} + \gamma\, \Sigma_j\, (w_{jr}\, Wages_{jt}) + \varepsilon_{rt} \tag{6}$$

where equation (6) differs from equation (4) only in regard to the term $\Sigma_j\ (w_{jr}\ Wages_{jt})$, which is the 'spatial lag' of wages in region $r$ at time $t$ and $\gamma$, which is the corresponding vector to be estimated.[5] The weights $w_{jr}$ are the elements of the above mentioned weight matrix **W**. In order to compute the spatial lags, we adopt the assumption of contemporaneous spatial correlation, but an absence of direct intertemporal spatial dependence. The spatial lag is then simply computed by pre-multiplying the wage vector at each time $t$ by the weight matrix **W**.

However, because the focus of our analysis is on forecasting, the term $\Sigma_j\ (w_{jr}\ Wages_{jt})$ is not known at time $t$. We therefore model spatial effects by including spatial lags of average wages at time $(t-1)$ rather than $t$ (i.e. $\Sigma_j\ (w_{jr}\ Wages_{jt-1})$):

$$y_{rt} = \alpha_r + \alpha_t + \beta' \mathbf{Z}_{r(t-1)} + \gamma\, \Sigma_j\, (w_{jr}\, Wages_{jt-1}) + \varepsilon_{rt} \tag{7}$$

The term $\Sigma_j\ (w_{jr}\ Wages_{jt-1})$ should then capture the effect that or wages in the neighbouring regions have on regional employment of the subsequent year. This specification might be seen as a special case of the model proposed by Elhorst (2001), in which the coefficients of the spatial lags at time $t$ are set equal to 0.

Similarly to the non-spatial case, the spatially lagged variable should not bring in additional endogeneity problems (see, e.g., Anselin, 1988). The model in (7) can be estimated by means of the fixed effects estimator or by means of the random effects maximum likelihood. As an alternative to the estimation of the model on the complete data set, we can also in this case assume (limited) spatial heterogeneity by estimating the model separately on different groups of regions, by rewriting (7) in a

[5] As a sensitivity analysis, we also computed models using the spatial lag of total employment rather than the spatial lag of average daily wages. Alternatively, we computed models using both the spatial lag of total employment and the spatial lag of average daily wages. The resulting models perform worse than the models in which we only add the spatial lag of average daily wages. The results are not shown here but are available on request.

similar way as (4). The spatial lag in (7) is computed by pre-multiplying average daily wages in region $r$ and time $t$ by the spatial weight matrix. As a result, the term $\Sigma_j (w_{jr}\ Wages_{jt-1})$ can be interpreted as a weighted average of the variable *Wages* in the neighbouring regions. Of course, this variable does not change when we compute the group estimations. Also in such a situation, all neighbours of region $r$, belonging to the urbanisation group $ur$ are taken into account in the spatial lag.

The second estimation strategy consists in modelling spatial spillovers and spatial autocorrelation by means of a spatial error structure in the model, in an autoregressive way as proposed in Elhorst (2003):

$$y_{rt} = \alpha_r + \alpha_t + \boldsymbol{\beta}'\mathbf{Z}_{rt-1} + u_{rt}$$

$$\text{with} \quad u_{rt} = \lambda\ \Sigma_j (w_{jr}\ u_{jt}) + \varepsilon_{rt} \tag{8}$$

where the error term ($u_{rt}$) is assumed to be spatially autocorrelated, with spatial autocorrelation parameter $\lambda$. As before, $w_{jr}$ are the elements of the weight matrix $\mathbf{W}$, and $\varepsilon_{rt}$ is the remaining disturbance. The variance-covariance matrix that can be derived from the error structure modelled in (8) assumes the presence of global autocorrelation. In such a situation, every region is assumed to be correlated with each other region in the spatial system; the correlation is assumed to be higher for regions that are closer to each other (Anselin and Cho, 2002).

The advantage of this specification strategy, compared with the use of spatially lagged dependent or independent variables like in (7), is that in (8) we make no assumption on which variable might be responsible for the spatial autocorrelation. Furthermore, by using (8) we can overcome the problem of the unavailability of the data needed to compute the spatial lag at time $t$. To estimate the spatial error model, however, we have to adopt the further assumption of normality of the residuals and to use maximum likelihood techniques (Anselin, 1988 and Elhorst, 2003). The spatial error model is therefore estimated by means of maximum likelihood (see Elhorst, 2003).

As before, the model can be estimated on the whole data set, under the assumption of homogeneous regression coefficients, or separately for distinct urbanisation groups. However, in this latter case the urbanisation-heterogeneous coefficients are not computed by means of separate group estimations since this strategy would make use of a modified weight matrix $\mathbf{W}$, in which the neighbours that do not belong to the same group are dropped. We allow instead for heterogeneous regression coefficients by multiplying the dependent and independent variables by dummies identifying each group (see, e.g., Verbeek, 2000).

After this review of various spatial-statistical issues, the next section will introduce the data set for our empirical analysis and will show the estimation results of the models introduced above.

# 3. EMPLOYMENT FORECASTS FOR WEST-GERMAN REGIONS

## 3.1. THE DATA SET

The data used in this analysis is part of a bigger data base gathered by the German Institute for Employment Research, IAB (Institut für Arbeitsmarkt und Berufsforschung). The information is collected from firms and contains micro-data about all workers employed in Germany who are covered by the social insurance system. Since such information was originally collected for the administrative purposes of the social security system, the measurement errors affecting our data are probably rather low and not systematic. For more information on this IAB data base, we refer to Blien and Tassinopoulos (2001).

We use information about labour market aggregates at the regional level, which is structured as a panel of 326 West German regions covering a period of 16 years, from 1987 to 2002. Because of its location in the East, the region of Berlin is excluded from the data set. The variables available are the number of full-time workers employed each year on June 30, classified in nine economic sectors.[6] Average regional daily wages earned by such full-time workers are available as well.[7]

To group regions that might have a similar labour market behaviour, we adopted the BfLR/BBR (Bundesforschungsanstalt für Raumordnung und Landeskunde/ Bundesanstalt für Bauwesen und Raumordnung, Bonn) definition of "type of economic region". This classification divides regions on the basis of the nine urbanisation groups discussed in the previous sections. The classification is

[6] These are: primary sector; industry goods; consumer goods; food manufacturing; construction; distributive services; financial services; household services; and social services.

[7] Sectoral wages should be preferred for our analysis than wages averaged by regions and sectors. However, such kind of information is not present in our data set. The use of such variable in our forecasting exercise might present some problems since average regional wages partly reflect the sectoral composition of regional employment.

represented by an index ranging from one to nine (see Table 1), and is computed according to the size of population and to the centrality of the location of each region (for more details we refer to Bellmann and Blien, 2001).

TABLE 1 ABOUT HERE

These data are used to compute one-step-ahead *ex post* forecasts of the volume of regional employment in 2000, 2001 and 2002. All these forecasts are computed on the same number of observations. The forecasts for the year 2000 are computed using data from 1987 to 1999, the forecasts for the year 2001 are computed using data from 1988 to 2000, and the forecasts for the year 2002 are computed using data from 1989 to 2001. This practice implies that the parameters are re-estimated for each *ex post* forecast and might therefore be different over time. As indicated above, multiple *ex post* forecasts are necessary to evaluate the stability of the model performance over time.

In the next section we summarise the forecasting results of the non-spatial models and we compare them with the results of the models extended to take into account spatial dependence and spatial spillovers.

### 3.2. NON-SPATIAL MODELS

In this section we estimate the non-spatial panel models as discussed in Section 2.3, using the data on West-German regions introduced above.[8] Baltagi and Li (2004) show how to compute the predictions of both spatial and non-spatial models.

We first estimate the model in (3) using a fixed-effects estimator (FE). The results of the three *ex post* forecasts, as well as the average model performance are shown in the first column of Table 2. While the model in (3) only allows for regional heterogeneity in the intercept term, the model in (4), also allows for some spatial heterogeneity in the regression coefficients. The second column of Table 2 shows the results of the model in (4) estimated separately for the nine types of regions introduced in the previous section (FE-1-9).

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[8] The models in this paper have been estimated using different softwares. The non-spatial models and the models using spatial lags have been estimated using Stata7, while the spatial error models have been computed using the Matlab 'sem_panel' routine by Paul Elhorst, available at http://www.eco.rug.nl/~elhorst/. The Moran statistics have mainly been computed with Spacestat.

The random effects estimator is usually considered as an alternative to the fixed effects estimator. However, our data refer to regions rather than to individuals. In this case the data refer to the whole population of 326 regions, and the regional-specific effects ($\alpha_r$) can hardly be interpreted as a random variable. As expected, the Hausman (1978) test rejects the random effects in favour of the fixed effects model. Furthermore, also Baltagi and Li (2004), using individual data to predict cigarette consumption, find that the fixed effects performs slightly better than the random effects model.

To allow an easier comparison with the spatial models, we further estimate models (3) and (4) by means of random effects maximum likelihood estimators. The results of the model computed on the whole data set (ML) are shown in column (3) of Table 2, while the results of the model allowing for some regional heterogeneity in the regression coefficients (ML-1-9) are shown in column (4).

TABLE 2 ABOUT HERE

The results of the four models seem to exhibit a rather heterogeneous behaviour. On average the maximum likelihood estimations seem to perform better than the fixed effects estimations. The models accounting for spatial heterogeneity seem to perform slightly worse than the corresponding models assuming spatial homogeneity. This result suggests that there might not be significant differences in the behaviour of urban versus rural regions, and that pooling such heterogeneous coefficients might therefore lead to more reliable forecasts.

Most of the models offer better forecast than the naïve no-change model both for 2000 and 2001, while none of them is able to perform the naïve no-change model for 2002. This result is rather surprising because the squared errors of the models forecasts in 2002 are rather low, compared with the errors for the remaining years. This might suggest that in 2002 all models tend to overestimate (in absolute terms) the changes in regional employment, and that the trend line in the employment development might be flattening, and that it might soon change its sign. In such a situation the naïve model offers the best forecasts.

On average, the best model of Table 2 is the model estimated in column (3). This model has the lowest absolute and squared errors. Furthermore, it seems to be the only one that, on average, is able to outperform the naïve no-change model.

By largely neglecting the presence of spatial autocorrelation and spatial spillovers, the models shown in Table 2 may represent sub-optimal solutions to the forecasting problem, at least in case of panel data. In the next section we will extend these non-spatial models to correct for spatial spillovers and spatial autocorrelation. We start however, with an analysis of the spatial autocorrelation of the variable of interest and of the forecasting errors of the non-spatial models.

### 3.3. Spatial Autocorrelation

When the data is collected at the administrative level, the actual unit of analysis might not correspond to the theoretically correct one. In our case, the 326 West German regions are likely not to correspond to a well-defined "local labour market area" concept (see Fischer and Nijkamp, 1987). Furthermore, local labour market areas might be subject to changes over time: for example, due to improvements in the area's accessibility level.

In our specific data set, which consists of small interacting regions, spatial dependence might represent a relevant issue. Because of commuting across regions, the dependent variable of our model, viz. total employment in region $r$ at time $t$ ($E_{rt}$), is likely to be correlated with both employment and wages of the neighbouring regions. Furthermore, other unobserved regional characteristics might cause dependence and/or spatial spillovers across regions. The presence of spatial dependence, represented by spatial clusters, can be easily spotted by mapping the variable of interest.

Figure 1 shows the employment levels of the 326 West German districts in the year 2000. The figures for 2000 suggest that high-employment regions tend to be located close to other high-employment regions, while low-employment regions tend to be located close to other low-employment regions. These clusters of high- and low-employment regions might indicate the existence of positive spatial autocorrelation across the observations of our data set.

FIGURE 1 ABOUT HERE

To statistically assess the presence of spatial autocorrelation in the variable of interest, we can compute the Moran test. Table 3 shows the Moran's *I* statistic computed on employment – levels, changes and growth rates – data. The **x** vector of equation (5), therefore, contains data on regional employment levels or regional employment growth rates, alternatively. The probabilities in Table 3 are computed using the randomisation approach. The Moran statistics computed on the level data are all positive and significant, supporting the conclusions from Figure 1, and suggesting the presence of clusters of high- and clusters of low-employment regions. The Moran's *I* computed on the employment changes growth are almost always significant. This clearly suggests the presence of spillovers across regional labour markets.

TABLE 3 ABOUT HERE

To analyse whether the proposed non-spatial models are able to correctly model the spatial characteristics of the employment variable, we have computed the Moran's *I* statistic on the forecasting errors of each model. Because of the different regional sizes, the Moran's *I* statistic is computed on the relative forecasting errors (divided by total regional employment). Table 4 shows the Moran's *I* statistic computed on the relative forecasting errors of the models compared in Table 2 for the three *ex post* forecasts. The test shows that, in many cases, the models are unable to capture the spatial autocorrelation in the employment variable, thus showing highly significant spatial autocorrelation in the relative forecasting errors. In this respect, the heterogeneous maximum likelihood model (ML-1-9) shows a slightly better performance than the other models.

The positive (and significant) coefficient of the Moran statistics in Table 4 suggest that the forecasting errors are positively correlated over space: regions for which a positive forecasting error is made, tend to be located close to other regions for which the model made a positive error, and vice versa.

TABLE 4 ABOUT HERE

The results of Table 4 suggest that there might still be room for improvement of the proposed model, by means of spatial econometric techniques. By including further (spatial) variables among the regressors, we might be able to improve the performance of the proposed non-spatial models.

In the next subsection we will estimate the spatial models proposed in the previous section, and evaluate the relevance of econometric techniques in improving the forecasting performance of non-spatial models.

### 3.4. SPATIAL MODELS

In this section we estimate the spatial panel models as suggested in Section 3.4, starting from the spatial lag model in (7), in which we include the spatial lag of average daily wages. The models using the spatial lag of wages are denoted by the superscript 'W'. The fixed effects estimations computed on the whole data set ($FE^W$) are shown in the first column of Table 5, while fixed effects estimations computed on the nine urbanisation groups ($FE^W$-1-9) are shown in the second column. The maximum likelihood estimations computed on the whole data set ($ML^W$) are in column (3), while maximum likelihood estimations computed on the nine urbanisation groups ($ML^W$-1-9) are in column (4).

The results in Table 5 show that the models accounting for spatial correlation by means of the spatial lag generally perform at most slightly better than the corresponding 'non-spatial' models. The only exception is the model in the first column of Table 5 ($FE^W$), which seem to outperform its non-spatial counterpart for two out of three *ex post* forecasts. While almost all models seem to outperform the naïve no-change model for the forecasts of 2000 and 2001, all Theil's U statistics for 2002 are higher than 1.

The average performance of the four models over the three *ex post* forecasts shows that the maximum likelihood models perform better than the fixed effects ones, and that the models assuming spatial homogeneity show better results than the models accounting for it. Also in this case the best model is the model in column (3) which seems the only one able to outperform the naïve no-change model. The general conclusion, however, is that the spatial lag models do not seem to outperform the non-spatial ones.

TABLE 5 ABOUT HERE

The last two columns of Table 5 show the results of the models in which spatial autocorrelation is modelled in the error term rather than by using spatially lagged variables. While the model in column (5) is computed on the whole data set, the model in column (6) is computed separately for the nine types of regions, as explained in the previous sections. The two spatial error models clearly outperform the other model proposed, in terms of both absolute and squared errors. The spatial error models clearly outperform also the naïve no-change model in almost all cases. Finally, these last results confirm the previous finding that pooling all regions, thus neglecting the possible spatial heterogeneity, leads to better results. The result that homogeneous models offer better forecasts than the heterogeneous ones might be due to the choice of the variable that is supposed to drive the heterogeneity (the urbanisation level of each region).

We can finally conclude that spatial econometric techniques seem to improve the forecasting performance of models using space-time data. More specifically, modelling spatial autocorrelation in the residuals appears to be a choice that produces, on average, the best results.

## 4. CONCLUDING REMARKS

In this paper we propose and evaluate different statistical techniques – namely spatial lag and spatial error models – to correct for misspecification due to neglected spatial autocorrelation, in the context of regional forecasts. We estimate and compare a number of different models designed to compute short-term *ex post* forecasts of regional employment in 326 West German regions. The main purpose of our analysis has been to assess whether spatial econometric techniques – namely spatial lag and spatial error models – represent a convenient way to improve the forecasting performance of non-spatial models.

Our results suggest the superimposed spatial structure that is required for the estimation of spatial lag and spatial error models – represented by means of a contiguity weight matrix – improves the forecasting performance of the non-spatial forecasting models. Furthermore, taking into account spatial autocorrelation by means of spatial error models results in forecasts that are on average more reliable than those computed by means of models using spatial lags. Therefore, the general conclusion is that in case of panels characterised by a large number of cross-sections, but a small number of observations over time, the forecasts can be improved by simply taking into account cross-sectional spatial autocorrelation.

This analysis shows that spatial econometric techniques might represent a valid tool to improve forecasts at regional level. However, our empirical application is limited to a case study of employment forecasts for West German regions, so that the results presented in this paper might be specific to the area and variables under investigation. Future research should further investigate in particular the issue of neglected spatial autocorrelation in forecasts by using simulation techniques, in order to obtain results that can be generalised to different situations.

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# TABLES

Table 1: Aggregation of West-German regions in nine types of regions

| Group | Type | No. of districts |
|---|---|---|
| A. Regions with urban agglomeration (118 regions) | | |
| | 1. Central cities | 39 |
| | 2. Highly-urbanised districts | 42 |
| | 3. Urbanised district | 23 |
| | 4. Rural districts | 14 |
| B. Regions with tendencies towards agglomeration (119 regions) | | |
| | 5. Central cities | 21 |
| | 6. Highly-urbanised districts | 61 |
| | 7. Rural districts | 37 |
| C. Regions with rural features (90 regions) | | |
| | 8. Urbanised districts | 43 |
| | 9. Rural districts | 47 |

Table 2: Comparison of the non-spatial models' *ex post* forecasts in the 326 regions

| Statistical Indicator | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | *Ex post* forecasts for the year 2000 | | |
| | FE | FE-1-9 | ML | ML-1-9 |
| MAE | 1308 | 1990 | 835 | 844 |
| MAPE | 0.01515 | 0.02348 | 0.01114 | 0.01119 |
| RMSE | 3208 | 4391 | 2202 | 2134 |
| MSE | 10289123 | 19282633 | 4850695 | 4554433 |
| BP | 0.12130 | 0.15402 | 0.01212 | 0.02469 |
| VP | 0.63364 | 0.67000 | 0.48124 | 0.45756 |
| CP | 0.24777 | 0.17858 | 0.50968 | 0.52075 |
| Theil's U | 1.01231 | 1.38582 | 0.69507 | 0.67350 |
| | | *Ex post* forecasts for the year 2001 | | |
| | FE | FE-1-9 | ML | ML-1-9 |
| MAE | 1249 | 1270 | 917 | 1051 |
| MAPE | 0.01558 | 0.01937 | 0.01547 | 0.01604 |
| RMSE | 2811 | 1895 | 1810 | 1995 |
| MSE | 7901367 | 3590168 | 3275144 | 3980244 |
| BP | 0.13708 | 0.05886 | 0.12090 | 0.20192 |
| VP | 0.49369 | 0.04749 | 0.00044 | 0.19968 |
| CP | 0.37188 | 0.89655 | 0.88137 | 0.60086 |
| Theil's U | 1.36249 | 0.91842 | 0.87720 | 0.96703 |
| | | *Ex post* forecasts for the year 2002 | | |
| | FE | FE-1-9 | ML | ML-1-9 |
| MAE | 736 | 1541 | 696 | 914 |
| MAPE | 0.01203 | 0.02106 | 0.01167 | 0.01298 |
| RMSE | 1194 | 2891 | 1213 | 1955 |
| MSE | 1424597 | 8355516 | 1472310 | 3823633 |
| BP | 0.11664 | 0.20610 | 0.10624 | 0.10825 |
| VP | 0.19107 | 0.54455 | 0.17436 | 0.56444 |
| CP | 0.69500 | 0.25179 | 0.72216 | 0.33006 |
| Theil's U | 1.18208 | 2.86279 | 1.20172 | 1.93660 |
| | | Average performance over the three periods | | |
| | FE | FE-1-9 | ML | ML-1-9 |
| MAE | 1097 | 1600 | 816 | 936 |
| MAPE | 0.01425 | 0.02130 | 0.01276 | 0.01340 |
| RMSE | 2404 | 3059 | 1742 | 2028 |
| MSE | 6538363 | 10409439 | 3199383 | 4119437 |
| BP | 0.12501 | 0.13966 | 0.07975 | 0.11162 |
| VP | 0.43947 | 0.42068 | 0.21868 | 0.40723 |
| CP | 0.43822 | 0.44231 | 0.70440 | 0.48389 |
| Theil's U | 1.18563 | 1.72234 | 0.92466 | 1.19238 |

Table 3: Spatial autocorrelation in employment across West German regions

| | Employment Levels | | Employment Growth | | Employment Changes | |
|---|---|---|---|---|---|---|
| Year | Moran's *I* | Probability | Moran's *I* | Probability | Moran's *I* | Probability |
| 1987 | 0.1223*** | 0.0006 | -- | -- | -- | -- |
| 1988 | 0.1221*** | 0.0006 | 0.0448 | 0.2063 | 0.1246*** | 0.0007 |
| 1989 | 0.1239*** | 0.0005 | 0.0670* | 0.0663 | 0.1579*** | 0.0000 |
| 1990 | 0.1254*** | 0.0004 | 0.0284 | 0.4049 | 0.1560*** | 0.0000 |
| 1991 | 0.1256*** | 0.0004 | 0.2960*** | 0.0000 | 0.1477*** | 0.0000 |
| 1992 | 0.1256*** | 0.0004 | 0.0068 | 0.7947 | 0.1268*** | 0.0005 |
| 1993 | 0.1237*** | 0.0005 | 0.1941*** | 0.0000 | 0.2266*** | 0.0000 |
| 1994 | 0.1221*** | 0.0006 | 0.2229*** | 0.0000 | 0.1969*** | 0.0000 |
| 1995 | 0.1250*** | 0.0005 | 0.0898** | 0.0158 | 0.0341 | 0.3085 |
| 1996 | 0.1263*** | 0.0004 | 0.0904** | 0.0152 | 0.0457 | 0.1845 |
| 1997 | 0.1271*** | 0.0004 | 0.1185*** | 0.0014 | 0.0729** | 0.0434 |
| 1998 | 0.1282*** | 0.0003 | 0.0818** | 0.0272 | 0.0483 | 0.1679 |
| 1999 | 0.1281*** | 0.0003 | 0.0445 | 0.2105 | 0.0981*** | 0.0063 |
| 2000 | 0.1252*** | 0.0004 | 0.1229*** | 0.0011 | 0.0460 | 0.1615 |
| 2001 | 0.1232*** | 0.0005 | 0.1777*** | 0.0000 | 0.1176*** | 0.0008 |
| 2002 | 0.1231*** | 0.0005 | 0.1504*** | 0.0001 | 0.1025*** | 0.0056 |

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Spatial autocorrelation in the relative forecasting errors of the models in Table 2 (as measured by the Moran's *I* statistic

| | (1) FE | (2) FE-1-9 | (3) ML | (4) ML-1-9 |
|---|---|---|---|---|
| 2000 | 0.0748** | 0.0818** | 0.0698* | 0.0426 |
| Prob. | (0.0425) | (0.0274) | (0.0577) | (0.2332) |
| 2001 | 0.1148*** | 0.0604 | 0.1096*** | 0.0949** |
| Prob. | (0.0021) | (0.1002) | (0.0033) | (0.0107) |
| 2002 | 0.0325 | 0.1723*** | 0.0277 | 0.0429 |
| Prob. | (0.3538) | (0.0000) | (0.4220) | (0.2305) |

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Comparison of the non-spatial models' *ex post* forecasts in the 326 regions

| Statistical Indicator | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | | *Ex post* forecasts for the year 2000 | | | |
| | $FE^W$ | $FE^W$-1-9 | $ML^W$ | $ML^W$-1-9 | SEM | SEM-1-9 |
| MAE | 873 | 1826 | 835 | 860 | 591 | 564 |
| MAPE | 0.01099 | 0.02292 | 0.01114 | 0.01136 | 0.00986 | 0.00944 |
| RMSE | 2373 | 4033 | 2203 | 2147 | 897 | 854 |
| MSE | 5629641 | 16268604 | 4851938 | 4608754 | 805279 | 728655 |
| BP | 0.02688 | 0.16241 | 0.01215 | 0.02331 | 0.31960 | 0.18654 |
| VP | 0.51956 | 0.58878 | 0.48133 | 0.44873 | 0.18727 | 0.08304 |
| CP | 0.45655 | 0.25139 | 0.50956 | 0.53096 | 0.49523 | 0.73292 |
| Theil's U | 0.74880 | 1.27291 | 0.69515 | 0.67751 | 0.28320 | 0.26939 |
| | | | *Ex post* forecasts for the year 2001 | | | |
| | $FE^W$ | $FE^W$-1-9 | $ML^W$ | $ML^W$-1-9 | SEM | SEM-1-9 |
| MAE | 886 | 926 | 917 | 1047 | 534 | 614 |
| MAPE | 0.01485 | 0.01427 | 0.01547 | 0.01600 | 0.00874 | 0.01025 |
| RMSE | 1804 | 1857 | 1811 | 1998 | 850 | 911 |
| MSE | 3253780 | 3448667 | 3278526 | 3993201 | 721751 | 829994 |
| BP | 0.08304 | 0.01039 | 0.12057 | 0.19980 | 0.22498 | 0.31301 |
| VP | 0.00679 | 0.00141 | 0.00041 | 0.20017 | 0.20932 | 0.16413 |
| CP | 0.91299 | 0.99125 | 0.88173 | 0.60249 | 0.56809 | 0.52497 |
| Theil's U | 0.87433 | 0.90014 | 0.87765 | 0.96860 | 0.41179 | 0.44159 |
| | | | *Ex post* forecasts for the year 2002 | | | |
| | $FE^W$ | $FE^W$-1-9 | $ML^W$ | $ML^W$-1-9 | SEM | SEM-1-9 |
| MAE | 1166 | 1129 | 695 | 920 | 514 | 573 |
| MAPE | 0.0185 | 0.0180 | 0.0117 | 0.01313 | 0.00840 | 0.00885 |
| RMSE | 1946 | 1790 | 1212 | 1963 | 847 | 1043 |
| MSE | 3785102 | 3205296 | 1467973 | 3854350 | 717296 | 1088796 |
| BP | 0.3209 | 0.0562 | 0.1059 | 0.10678 | 0.18796 | 0.17969 |
| VP | 0.4153 | 0.0344 | 0.1738 | 0.55914 | 0.23298 | 0.45310 |
| CP | 0.2658 | 0.9123 | 0.7231 | 0.33683 | 0.58155 | 0.36973 |
| Theil's U | 1.9268 | 1.7731 | 1.1999 | 1.94436 | 0.83879 | 1.03342 |
| | | | Average performance over the three periods | | | |
| | $FE^W$ | $FE^W$-1-9 | $ML^W$ | $ML^W$-1-9 | SEM | SEM-1-9 |
| MAE | 975 | 1294 | 816 | 943 | 546 | 583 |
| MAPE | 0.01479 | 0.01840 | 0.01275 | 0.01350 | 0.00900 | 0.00951 |
| RMSE | 2041 | 2560 | 1742 | 2036 | 865 | 936 |
| MSE | 4222841 | 7640856 | 3199479 | 4152102 | 748108.8 | 882481.6 |
| BP | 0.14362 | 0.07634 | 0.07952 | 0.10996 | 0.24418 | 0.22642 |
| VP | 0.31390 | 0.20820 | 0.21851 | 0.40268 | 0.20986 | 0.23342 |
| CP | 0.54511 | 0.71831 | 0.70480 | 0.49009 | 0.54829 | 0.54254 |
| Theil's U | 1.18332 | 1.31539 | 0.92425 | 1.19682 | 0.51126 | 0.58147 |

## FIGURES

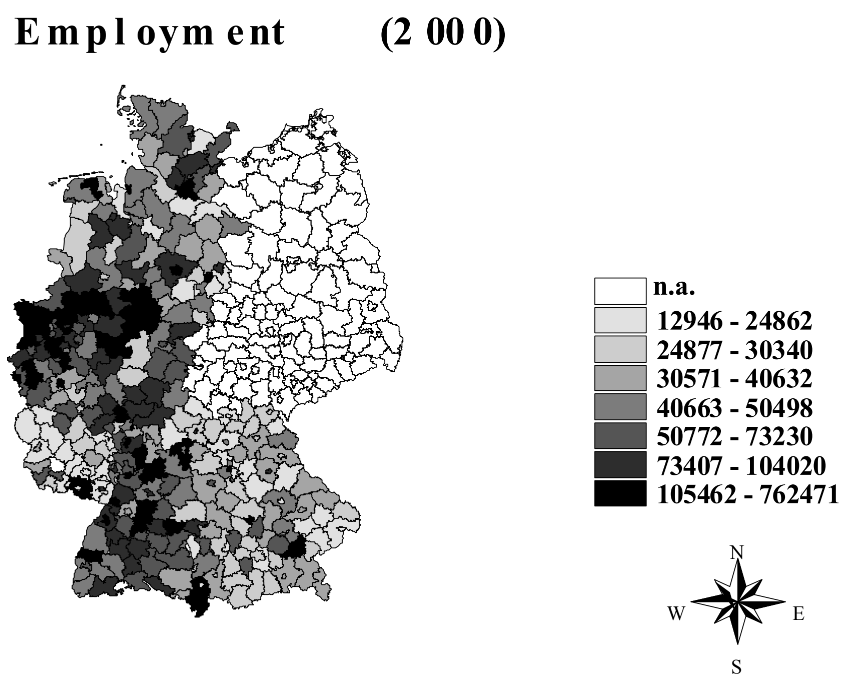


Figure 1: Employment levels in West German regions