Thresholds for Employment and Unemployment. A Spatial Analysis of German Regional Labour Markets 1992-2000

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Abstract. This paper investigates the laws of Verdoorn and Okun in order to determine thresholds for employment and unemployment in all Germany for the period 1992-2000. Disaggregated datasets for 180 German functional regions provide the basis for obtaining efficient estimates and spatial labour market characteristics. To capture cross-section dependencies, a spatial SUR model is built up utilizing the eigenfunction decomposition approach suggested by Griffith (1996, 2000). The results indicate that minimum output growth sufficient for a rise in employment is below the level needed for a simultaneous drop in the unemployment rate. If spatial effects are not controlled for, the thresholds seem to be markedly overrated.

Keywords: Threshold employment and unemployment, regional labour markets, spatial filtering techniques, spatial SUR analysis

JEL: C21, C23, E24, E32

1. Introduction

Changes in production and employment are closely related over the course of the business cycle. However, as exemplified by the laws of Verdoorn (1949, 1993) and Okun (1962, 1970), thresholds seem to be present in the relationship. Due to capacity reserves of the firms, output growth must exceed certain levels for the creation of new jobs or a fall in the unemployment rate. In order to assess the future development of employment and unemployment, these thresholds have to be taken into account. They serve as important guidelines for policymakers.

In contrast to previous studies, we present joint estimates for both the employment and unemployment threshold. Due to demographic patterns and institutional settings on the labour market, the two thresholds can differ, implying that minimum output growth needed for a rise in employment may not be sufficient for a simultaneous drop in the

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unemployment rate. Second, regional information is considered to a large extent. In particular, the analysis is carried out using a sample of 180 German regional labour markets, see Eckey (2001). Since the cross-sections are separated by the flows of job commuters, they correspond to travel-to-work areas. Labour mobility is high within a market, but low among the entities. As the sectoral decomposition of economic activities varies across the regions, the thresholds are founded on a heterogeneous experience, leading to more reliable estimates.

The contribution to the literature is twofold. First, to the best of our knowledge, no previous paper has investigated a similar broad regional dataset for the German economy as a whole before. By using a panel dataset, for each year information on the regional distributions around the regression lines as well as theirs positional changes is provided. Second, the methods applied are of new type. They involve a mixture of pooled and spatial econometric techniques. Dependencies across the regions may result from common or idiosyncratic (region specific) shocks. In particular, the eigenfunction decomposition approach suggested by Griffith (1996, 2000) is used to identify spatial and non-spatial components in regression analysis. As the spatial pattern may vary over time, inference is conducted on the base of a spatial SUR model. Due to this setting, efficient estimates of the thresholds are obtained.

The rest of the paper is organized as follows. In the next section (section 2), we review the laws of Verdoorn (1949, 1993) and Okun (1962, 1970), as they mark the cornerstones of the analysis. Both identify the threshold in terms of some lower bound of output growth. In Verdoorn's law, the growth rate is sufficient for an increase in employment, while in Okun's law, the focus is on a fall in the unemployment rate. Afterwards, the econometric methods are discussed (section 3). In section 4, the dataset is described. The empirical results are presented in section 5. The final part of the paper (section 6) concludes.

2. Threshold employment and unemployment

The law of Verdoorn (1949, 1993) states that faster output growth (y) will induce gains in labour productivity growth (p). Formally, the relationship

(2.1) $$p_t = \beta_0 + \beta_1 y_t \ , \ \beta_1 > 0$$

predicts increasing returns to scale if the Verdoorn coefficient β_1 turns out to be greater than 0, see Fingleton (2001). A positive, but declining slope parameter is reported in most empirical studies, see Harris and Lau (1998) and Léon-Ledesma (2000) for the UK and Spanish economy, respectively. Increasing returns may be explained by a variety of endogeneous growth models, see Aghion and Howitt (1998) for a survey.

A serious issue with Verdoorn's law lies in the ignorance of the role of capital, that can be substituted for labour. Because of the omitted variable problem, estimation of the parameters β_0 and β_1 from the relationship (2.1) seem to be biased. Suppose output is produced by a Cobb-Douglas technology,

(2.2) $\quad y_t = \tau + \eta\, l_t + \lambda\, k_t ,$

where l, k and τ are the growth rates of labour, capital and technology, respectively. Since employment growth is the difference between output and productivity growth, the relation

(2.3) $\quad p_t = \tau / \eta + [(\eta - 1)/\eta]\, y_t + (\lambda / \eta)\, k_t$

is implied. In general, the bias is proportional to the coefficient from regressing capital growth on output growth, see e.g. Greene (2003, pp. 148). However, the connection (2.1) between productivity and output growth can be defended, if capital growth equals output growth. This is in line with the stylised fact of a more or less constant capital-output ratio, see e.g. Jones (1998, pp. 12) and Maußner und Klump (1996, pp. 7). In this case, the parameters β_0 and β_1 are specified as $\beta_0 = \tau / \eta$ and $\beta_1 = (\eta + \lambda - 1)/\eta$, for which unbiased estimates can be obtained from Equation (2.1). The returns to scale parameter cannot be revealed form the Verdoorn coefficient β_1 without knowledge of the production elasticities. The constant β_0 corresponds with the rate of technological progress, divided by the production elasticity of labour.

Verdoorn's law was originally considered for the industrial sector. Since the service sector have become of increasing importance, the hypothesis should be examined using total output data. Due to the high correlation of output and productivity growth, however, spurious regressions can easily occur. If employment growth is constant, a perfect correlation between productivity and output growth would appear, which is not informative at all. This problem is avoided in a specification between employment (l) and output growth,

$$(2.4) \quad l_t = \alpha_0 + \alpha_1 y_t\,, \quad \alpha_0 = -\beta_0, \alpha_1 = 1 - \beta_1,$$

that has been already favoured by Kaldor (1975). A high correlation between productivity and output growth does not imply the same for employment and productivity growth. In the case of perfect correlation of the former variables, for example, the latter variables are not correlated at all. Thus, spurious regression arising from common trends driving productivity and output growth is avoided with Equation (2.4). Moreover, the best linear predictor of employment growth is given by a regression with the right-hand-side of Equation (2.4) as its systematic part.

A Verdoorn coefficient of 0.5 in (2.1) implies a marginal employment intensity α_1 of the same size in (2.4). This means that a 1 percent growth in output would stimulate employment by half a percent on the average. The underproportional reaction is due to efficiency gains, which can be realized more easily in periods of higher output growth. They may be traced to *inter alia* manpower reserves, increases in working hours and higher labour intensities.

The threshold of employment (y_E) indicates output growth for which employment is constant ($l_t=0$). In terms of the model parameters the threshold level y_E reads:

$$(2.5) \quad y_E = \frac{-\alpha_0}{\alpha_1}.$$

According to the parameter $-\alpha_0$, it is positively related to the rate of technological progress (τ) and negatively related to the production elasticity of labour (η). In addition, a higher marginal employment intensity (α_1) will reduce the threshold. Provided that output growth is above this bound, employment will be stimulated. If output growth falls beyond the threshold, losses in employment are expected on the average. In this case, output growth is not sufficient to compensate for the rise in productivity due to technological progress and employment shrinks. According to (2.4) and (2.5), the evolution of employment,

$$(2.6) \quad l_t = \alpha_1 (y_t - y_E),$$

depends on the deviation of actual output growth from the threshold level. Each percentage point of output growth above (below) the threshold comes along with positive (negative) employment reaction that is determined by the marginal employment intensity.

An increase of employment is often seen to go hand in hand with a simultaneous decrease of unemployment. However, demographic factors and institutional conditions of the labour market can weaken the relationship. For example, if population growth is accompanied by a similar rise in the labour force but an underproportional increase of employment, unemployment will accelerate. Also, structural developments like a rising female labour force participation rate have to be taken into account. Generally, more favourable institutional settings on the labour market can attract people from outside the labour force. Thus, a strong relationship between changes in employment and unemployment is suspended. In particular, the minimum output growth rate needed for a rise in employment may not be sufficient for a drop in unemployment. The threshold for the latter is estimated by means of Okun's law.

According to Okun (1962, 1970), a negative relationship between unemployment and output fluctuations exists. Due to rigidities like menu costs and efficiency wages, prices are temporarily fixed. As a consequence, firms tend to adjust output to aggregate demand in the short run. A rise in demand will stimulate production and employment, thereby lowering the unemployment rate. In particular, unemployment u will fall below its natural rate u^*,

(2.7) $$(u_t - u^*) = \delta_1 (y_t - y^*) \, , \, \delta_1 < 0 \, ,$$

if actual output growth is above its long run trend or potential y^*, that is driven by total factor productivity. Extended by a Phillips curve, the equation gives the aggregate supply curve of the economy. In this setting, u^* has to be interpreted as the unemployment rate that is consistent with an unchanged inflation rate. Also, the sacrifice ratio – the cumulative output loss arising from a permanent decrease in the inflation rate - can be assessed, see Cechetti and Rich (1999). The lower the Okun coefficient δ_1 in absolute value, the lower the responsiveness of unemployment to growth and the higher the income loss resulting from a policy of disinflation.

Due to labour market conditions like, for example, the unemployment benefit system, unemployment is presumably of higher persistence than employment. Hence, δ_1 is expected to be lower than the employment intensity (α_1) in absolute terms. Like the latter, δ_1 seems to be unstable and has increased in recent times, see Moosa (1997) and Lee (2000) for some empirical evidence. The stronger response of employment to output fluctuations may be caused by the productivity slowdown, stronger international competition, less legal protections of the employed and lower turnover costs, which encourage firms to reduce labour hoarding in periods of economic downturns. Assuming that potential output growth is roughly constant at least over sufficiently long intervals of time, the law can be rewritten,

(2.8) $\quad (u_t - u^*) = \delta_0 + \delta_1 y_t \ , \delta_1 < 0 \,,$

where the trend growth rate can be obtained from the intercept term. However, the gap specifications (2.7) and (2.8) of Okun's law are not directly suited for estimation. They involve unobservable variables, and there is no consensus on the proper procedure on how to identify them. In fact, a variety of filter techniques and trend decomposition methods exist, but they can lead to different conclusions. Therefore, the first difference (FD) specification of Okun's law,

(2.9) $\quad \Delta u_t = \gamma_0 + \gamma_1 y_t \ , \gamma_1 < 0 \,,$

may be more favourable for empirical reasons, see Okun (1970) and Prachowny (1993). In contrast to (2.8), the FD specification relates the change in the actual unemployment rate to actual output growth.

If actual output growth mets the threshold level (y_{U}), unemployment is equal to its natural rate, implying that its change is equal to 0. Plugging this condition into (2.8) or (2.9) shows that the threshold can be derived in terms of the model parameters. Specifically, the threshold for a drop in unemployment

(2.10a) $y_{\mathrm{U,GAP}} = -\delta_0 / \delta_1$

(2.10b) $y_{\mathrm{U,FD}} = -\gamma_0 / \gamma_1$

is supposed to decline, if the Okun coefficient rises in absolute value. In addition, a regressive trend growth rate can contribute to a reduction. Unemployment dynamics depend on the threshold according to

(2.11a) $(u_t - u^*) = \delta_1 (y_t - y_{\mathrm{U,GAP}})$,

(2.11b) $\Delta u_t = \gamma_1 (y_t - y_{\mathrm{U,FD}})$,

that is, unemployment will remain at its previous level if actual growth is just as high as the threshold for unemployment. For a drop of the unemployment rate output growth must exceed this level.

3. Spatially filtering and spatial SUR models

As the thresholds for employment and unemployment are estimated with regional data, dependencies between the cross-sections have to be taken into account. They may stem from common or idiosyncratic (region specific) shocks, which may generate spillovers among the cross-sections. Eventually, variables are spatially autocorrelated over the entities, and the particular pattern can bias the results, see Anselin (1988, pp. 58). Therefore, appropriate filters have to be employed in order to separate the spatial and non-spatial components of the series that enter the regression model.

At present, two approaches are available to identify spatial effects in the data, see Getis and Griffith (2002) for a recent survey. Getis and Ord (1992) have proposed a spatial distance statistic. It requires that all variables are positive and can be measured from natural origins. These conditions are not met in this study, as growth rates and changes of variables are involved. Thus, the eigenfunction decomposition approach suggested by Griffith (1996, 2000) is preferred. Here, filtering relies on a decomposition of Moran's *I* (*MI*) statistic

(3.1) $$MI = \frac{x'Wx}{x'x}$$

as a measure of the global spatial autocorrelation structure for a given variable. In particular, x holds the n observations of the variable under consideration, measured in deviations from the mean. W is an nxn-matrix of spatial weights, where the elements of each row sum up to 1, and n the number of regions, see Anselin (1988, pp.16) for a discussion. The W matrix stores the information on the geographic map patterns, and is derived from a binary contiguity matrix. The elements of the latter are equal to 1 for neighbourhood regions and 0 otherwise. Moran's I can be expressed as a weighted sum of the eigenvalues of the matrix

$$(3.2) \quad C = (I_N - \mathbf{1}\mathbf{1}'/N)W(I_N - \mathbf{1}\mathbf{1}'/N),$$

where I_N is the N-dimensional identity matrix and $\mathbf{1}$ a vector of ones, see Tiefelsdorf and Boots (1995) and Griffith (1996). The eigenvectors of the C-matrix are utilized to separate spatial from non-spatial components. Generally, spatial dependencies are represented by the system of eigenvectors, which identify distinct geographic map patterns. The non-spatial part of a variable is given by the OLS residuals of a regression of that variable on the significant eigenvectors, see Griffith (1996, 2000). Since the eigenvectors are both near-orthogonal and near-uncorrelated,[1] forward stepwise regression can easily applied for selection. Based on this approach, the model

$$(3.3) \quad y_t = \beta_0 + \beta_1 \cdot x_t^* + \sum_S \gamma_j \cdot \omega_j + v_t, \qquad t=1,2,\ldots,T,$$

can be estimated via OLS. Here, x^* refers to the non-spatial component of the regressor; the set S is formed by the relevant eigenvectors ω_j of C-matrix. Eigenvectors must represent substantial spatial autocorrelations in order to be considered as relevant. Griffith (2003, p. 107) suggests to assess substantial spatial autocorrelation on the basis of the ratio MI/MI_{max}, where $\mathrm{MI}_{\max}$ denotes the largest Moran coefficient of any eigenvector of the C-matrix. According to his qualitative classification we use a threshold value of 0.25 for the selection of candidate eigenvectors. As the linear combination of eigenvectors accounts for spatial dependencies, the errors are whitened.

Note that the decomposition is required for each point t in time, as the spatial patterns may vary. Thus, (3.3) should be interpreted as a cross-section regression. However, dependencies also exist over time. For example, shocks arising in the regional labour mar-

[1] Although the standardisation of the weight matrix generally comes along with a loss of orthogonality and uncorrelatedness of the eigenvectors (Griffith, 1996), we make uniformly use of it because of its more natural interpretation, see Ord (1975). In our application it turns out, that nearly all correlations between the spatial components lie in a narrow range about zero.

kets do not diminish immediately. Instead of estimating unrelated equations in the style of (3.3) for different periods of time, a spatial SUR analysis is preferred. Contrary to the familiar SUR model, the system

$$
\begin{aligned}
& y_{1i} = \beta_0 + \beta_1 \cdot x_{1i}^{*} + \sum_{S_1} \gamma_{1j} \cdot \omega_j + \nu_{1i} \\
(3.4)\quad & y_{2i} = \beta_0 + \beta_1 \cdot x_{2i}^{*} + \sum_{S_2} \gamma_{2j} \cdot \omega_j + \nu_{2i} \\
& \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\
& y_{Ti} = \beta_0 + \beta_1 \cdot x_{Ti}^{*} + \sum_{S_T} \gamma_{Tj} \cdot \omega_j + \nu_{Ti}
\end{aligned}
$$

is formed by the time periods for all n spatial units ($i=1,2,\ldots,N$), see Anselin (1988, pp. 137). The sets $S_1, S_2, \ldots, S_T$ of eigenvectors may be composed of different elements. If the choice of spatial components for the sets S_t, $t=1,2,\ldots,T$, proves to be successful, the disturbances ν_{ti} will be contemporaneous uncorrelated:

(3.5) $Cov(\nu_{ti}, \nu_{tl}) = E(\nu_{ti} \cdot \nu_{tl}) = 0.$

Dependencies over time can be modelled by defining the NxN covariance matrix Σ,

(3.6) $\Sigma = E(\nu_t \cdot \nu_s') = \sigma_{ts} \cdot I_N,$

in which σ_{ts} denotes the covariance between the periods t and s, $t \neq s$, and ν_t an $Nx1$ vector of the disturbances in period t. With this the time-dependent autocorrelation structure of the spatial SUR system (3.4) is given by the $NTxNT$ covariance matrix

(3.7) $\Sigma^* = \Sigma \otimes I_N.$

Provided that $T < N$ the covariance matrix Σ^* can be estimated directly from the data.

As dependencies over time are taken into account, parameters are estimated more efficiently. In previous studies space-time models have been employed where spatial effects were captured in a restrictive way by first order autoregressive lags, see e.g. Beck and Katz (2001), Elhorst (2001) and Beck and Gleditsch (2003). Probably due to high computational demands empirical applications of the spatial SUR model are rarely to find. Exceptions are the works of Florax (1992) and Fingleton (2001). The advantage of Griffith's approach consists in allowing to set up the model straightforwardly with ordinary devices taken from regression analysis.

4. Regional labour markets and data

Threshold estimates are based on a sample of regional labour markets. As Eckey, Horn and Klemmer (1990) have pointed out, regions defined on behavioural settings are generally preferable over administrative units, as the latter may distort the economic conditions. Regional labour markets are defined on the basis of job commuters and correspond to travel-to-work areas.

Starting from 440 administrative districts (Kreise), Eckey (2001) constructed 180 regional labour markets of which 133 are located in the western and 47 in the eastern part of Germany. The three overlapping regions, i.e. regions that consist of both eastern and western districts, are mainly build from West German districts. Therefore, they are counted as West German regions.

While data on GDP and employment are available for administrative districts, the number of unemployed refer to labour market agencies (Dienststellenbezirke). Both classifications do not match with the borders of regional labour markets. Hence the data must be aggregated. On the average a regional labour market consists of 2.4 districts and 4.8 agencies.

The analysis is based on annual data. Nominal GDP and employed persons are obtained from the *Volkswirtschaftliche Gesamtrechnung der Länder* published by the Statistical state office of Baden-Württemberg. GDP is deflated by the regional GDP price indices, which are available at the state level. Growth rates of real GDP and employment are calculated in the continuous compounding form. Data on unemployment are taken from the *Amtliche Nachrichten der Bundesanstalt für Arbeit* which are edited by the Federal Employment Services.

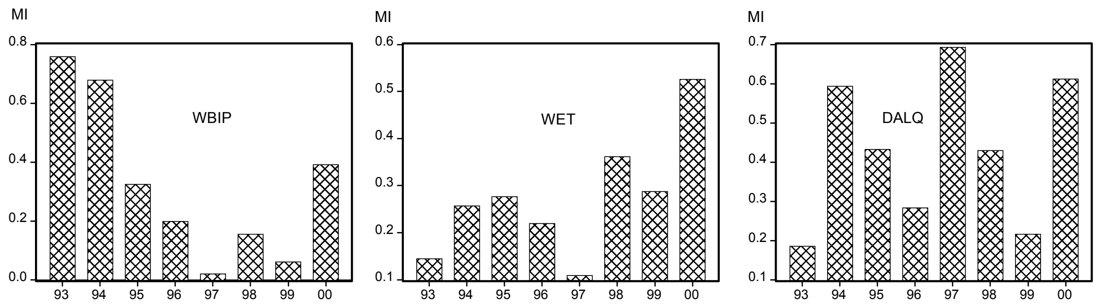
The sample runs from 1992 to 2000 and covers the recent experience of the German unification. Due to instabilities of the Verdoorn and Okun coefficients reported in most studies, reliable estimates of the thresholds demand a rather short time series dimension. As GDP is not available for 1993 on the district level, it has been interpolated by matching it with GDP on state level.

5. Spatial autocorrelation

In advance to estimation und testing Moran's *I* is computed as an overall measure for spatial autocorrelation for the variables considered. For the Okun relation, the FD specification is preferred, as it is based on observables. For all variables, the Moran coefficient fluctuates over time (see Figure 5.1). However, in most years spatial dependencies are striking in every case. With the exception of GDP growth in 1997 and 1999, Moran's *I* is significant at least on the 5 per cent level.[2]

As spatial autocorrelation varies over time, it will be not be removed by uniformly applying Griffith's filtering method to the variables over the entire sample period. This view is supported by the distinct map patterns in individual years. Although some common spatial components of the variables are at work over time, other eigenvectors of the *C* matrix change their significance from year to year. Hence, a varying spatial pattern has to be taken into account.

Figure 5.1: Moran's *I* of georeferenced variables



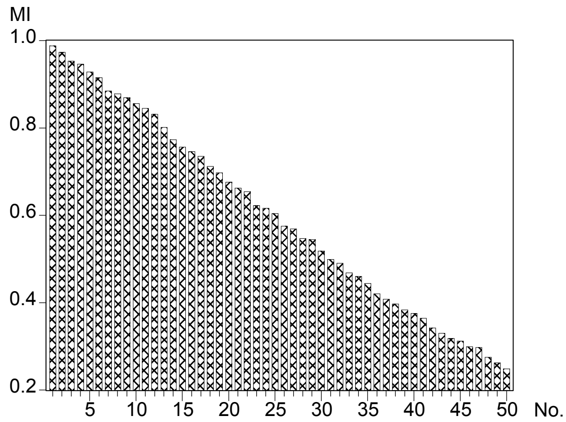
GDP growth Employment growth Unemployment (FD)

The spatial SUR model (3.4) presupposes that the explanatory variable is independent from the error term.[3] Thus GDP growth is pre-filtered to remove spatial effects. The growth rate of employment and the change of the unemployment rate are explained by the spatially filtered GDP growth rate and the map patterns of the endogeneous variables, that are extracted from the *C*-matrix. The spatial autocorrelations of the candidate

[2] The significance of Moran's *I* holds for both approaches randomisation and normal approximation.
[3] The issue of exogeneity of output in Verdoorn's hypothesis is addressed by Fingleton (2000) in a spatial lag model. Though the Hausman test provides some evidence for endogenous output, due to indeterminateness Fingleton favours output to be treated as exogenous.

eigenvectors for forming those map patterns are exhibited in Figure 5.2. MI_{max} takes a value of 0.988. According to the MI/MI_{max} criterion the number of relevant eigenvectors is restricted to 50.

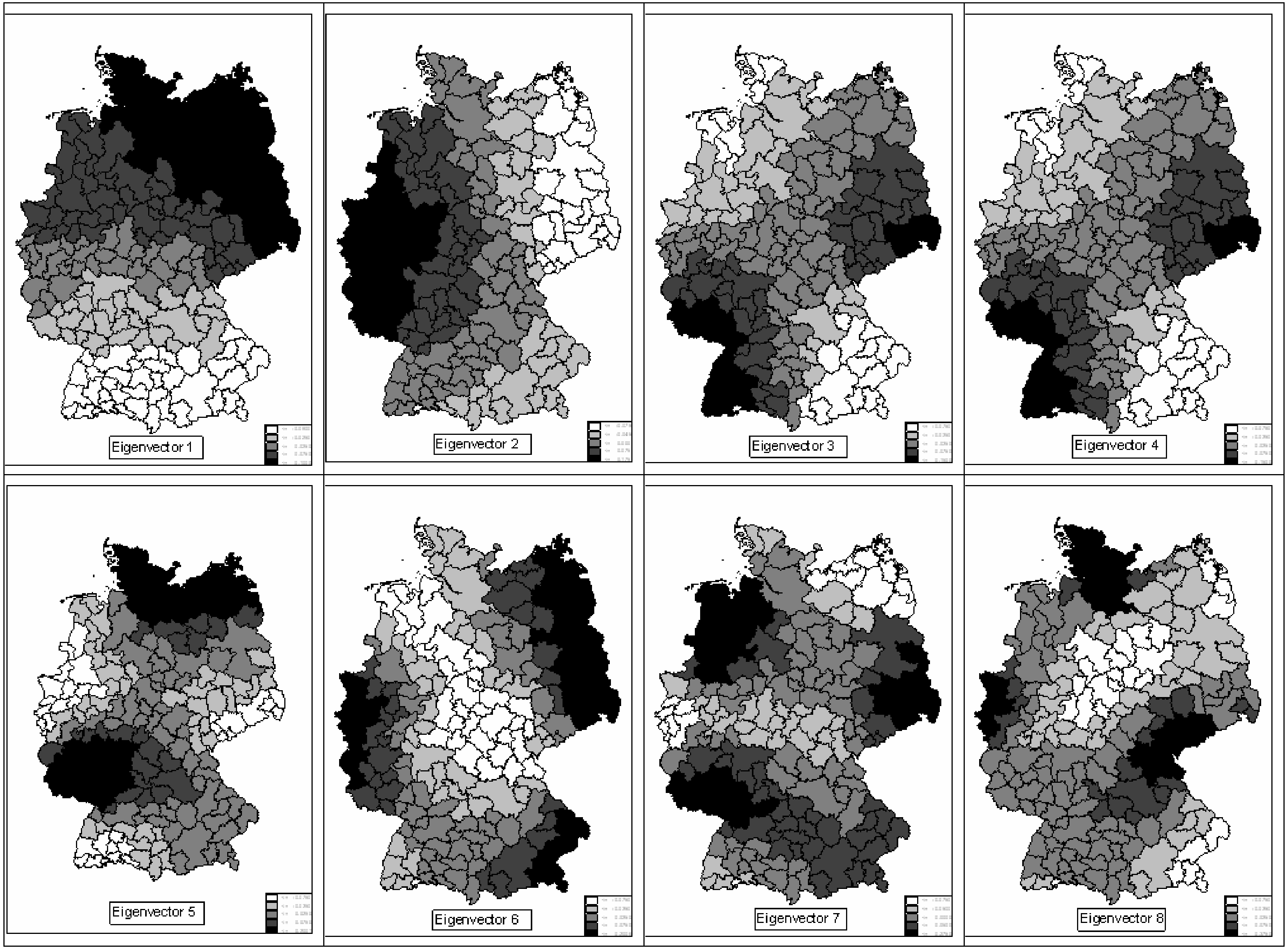
Figure 5.2: Moran's *I* of candidate eigenvectors



The map patterns of the eigenvectors corresponding to the eight largest eigenvalues of the C-matrix are portrayed in Figure 5.3. As expected there exist only a very limited number of clusters which increases with a decreasing degree of positive spatial autocorrelation. The clusters appear to lie on trend surfaces with positive or negative gradients depending upon the arbitrary chosen starting point. Obviously, a smooth transition from high-valued to low-valued clusters and *vice versa* takes place in the case of strong spatial autocorrelation. With a decreasing degree of positive spatial autocorrelation the map pattern becomes more speckled.

While eigenvectors extracted by principal component analysis may (PCA) have an economical significance, the eigenvectors of the C-matrix represent purely spatial components which may be accessible to a geographically interpretation (for methodical similarities between spatial filtering and PCA see Griffith, 2002, pp. 93). The map pattern of the eigenvector corresponding with the largest eigenvalue suggests itself to interpret the first spatial component as north-south component, since its trend surface shows a clear north-south inclination. Analogously, we can speak of the second spatial component as a west-east component. For the third and forth spatial component in each case two trend surfaces appear to exist: one having an east-west inclination in the northern and the other having an slope in the opposite direction in the southern part of the country. The

Figure 5.3: Map patterns of eigenvectors



fifth spatial component comprises a north-east trend as well as and a trend subsiding from an elevation at the northern border with France in all domestic directions. The sixth spatial component is marked by a central depression. This pattern also holds for the eighth component actually having two additional depressions at the north-eastern and south-eastern border. In the seventh component the central depression disappears, while two depressions are located at the northern and western border.

6. Estimation and testing results

As indicated by Moran's *I*, in almost all years the spatial correlations of the residuals from the spatial SUR model lie near-by zero (see Table 6.1). Only in one year the z value for Moran's *I* exceeds the quantile $z_{0.975}$ of the normal distribution that is usually used in a two-sided test of significance.[4] In contrast, the non-spatial GLS residuals are highly correlated. Revisions of the employment statistics led to a structural break in the late 1990s. Since April 1999 the minor employed are liable to the social security system. Their registration has brought a noticeably upward revision of the total number of employed. This is captured by means of time dummies.

Both coefficients of Verdoorn's law turn out to be significant with the correct sign. The spatial SUR model implies a threshold of 1.2% for employment. This level is in line with previous findings of Logeay (2001) and Walwei (2002), who report estimates in the range of 1-1.5%, on the base of time-series methods. The value of 2.9% implied by non-spatial GLS estimation overrates the threshold considerably.

The output elasticity of employment of 0.2 implies a rather weak reaction of employment to GDP growth. Factors like labour hoarding and adjustments of labour intensity have played a prominent role in the 1990s. It should be noted, however, that the elasticity has to be regarded as a result of variations occuring in the sample period (Figure 6.1). Both the intercept and the slope of the Verdoorn relation tend to vary from year to year. In 1993 the data exhibit even a negative relationship between the growth rates of GDP and employment for the entire regions.

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[4] For some difficulties with Moran's *I* in space-time models see Hooper and Hewings (1981).

Table 6.1: Verdoorn's law: estimation and testing results

	Non-spatial GLS estimation			Spatial SUR estimation		
	Coefficient		t-statistic	Coefficient		t-statistic
Output growth	0.1480		13.561	0.1906		12.434
Constant	-0.0044		-7.139	-0.0023		-4.426
D98	0.0129		13.749	0.0121		15.502
D99	0.0138		13.037	0.0126		13.128
D00	0.0143		13.510	0.0134		14.476
Empl. threshold	0.0294		7.543	0.0121		4.551
	R^2	SER	SSR	R^2	SER	SSR
	0.141	0.018	0.471	0.376	0.016	0.342

	Non-spatial GLS estimation	Spatial SUR estimation		
Year	Moran's *I* residuals (z values)	Moran's *I* residuals (z value)	Significant eigen-vectors	Moran's *I* spatial components
1993	0.403 (8,782)	-0.046 (-0,507)	1, 2, 4	0.966
1994	0.065 (1,589)	-0.007 (0,336))	1, 2, 8	0.976
1995	0.189 (4,158)	0.043 (1,703)	1, 2, 4, 12, 18, 29	0.897
1996	0.260 (5,633)	-0.031 (0,423)	2, 3, 6, 7, 11, 16, 17, 18, 22	0.844
1997	0.152 (3,326)	-0.050 (-0,603)	1, 2, 3	0.972
1998	0.369 (7,943)	0.016 (1,647))	1, 2, 3, 4, 6, 8, 10, 12, 25, 29	0.920
1999	0.323 (6,940)	0.069 (2,660)	1, 2, 3, 5, 8, 17, 23, 27, 28, 38	0.856
2000	0.491 (10,603)	0.038 (1,936)	1, 2, 3, 4, 7, 8, 14, 15	0.959

Notes: Non-spatial GSL estimation is based on the SUR model (3.4) without applying the spatial filtering approach. D98, D99, D00: Dummies for 1998, 1999 and 2000, R^2: coefficient of determination, SER: standard error of regression, SSR: sum of squared residuals

The high Moran coefficients of the linear combinations of the eigenvectors highlight the common spatial characteristics across neighbouring regions in all subperiods. According to the qualitative classification scheme introduced by Griffith (2003, p. 107), the *MI* scatterplot trend is pronounced in six years ($MI/MI_{max} \geq 0.9$). In 1996 and 1999 the MI/MI_{max} values indicate a conspicuous MI scatterplot trend. Figure 6.2 shows that both west-east and east-west trends of the spatial components dominate the map patterns with Verdoorn's law. The trend surfaces start in three years (1996, 1997, partly 1999) with a north-south stripe of high values along the western border. In other three years (1993, 1998, 2000) the trend is emanating inward from mounds in the north-west and south-east of the country.

Figure 6.1: Verdoorn's law: scatterplots with regression lines

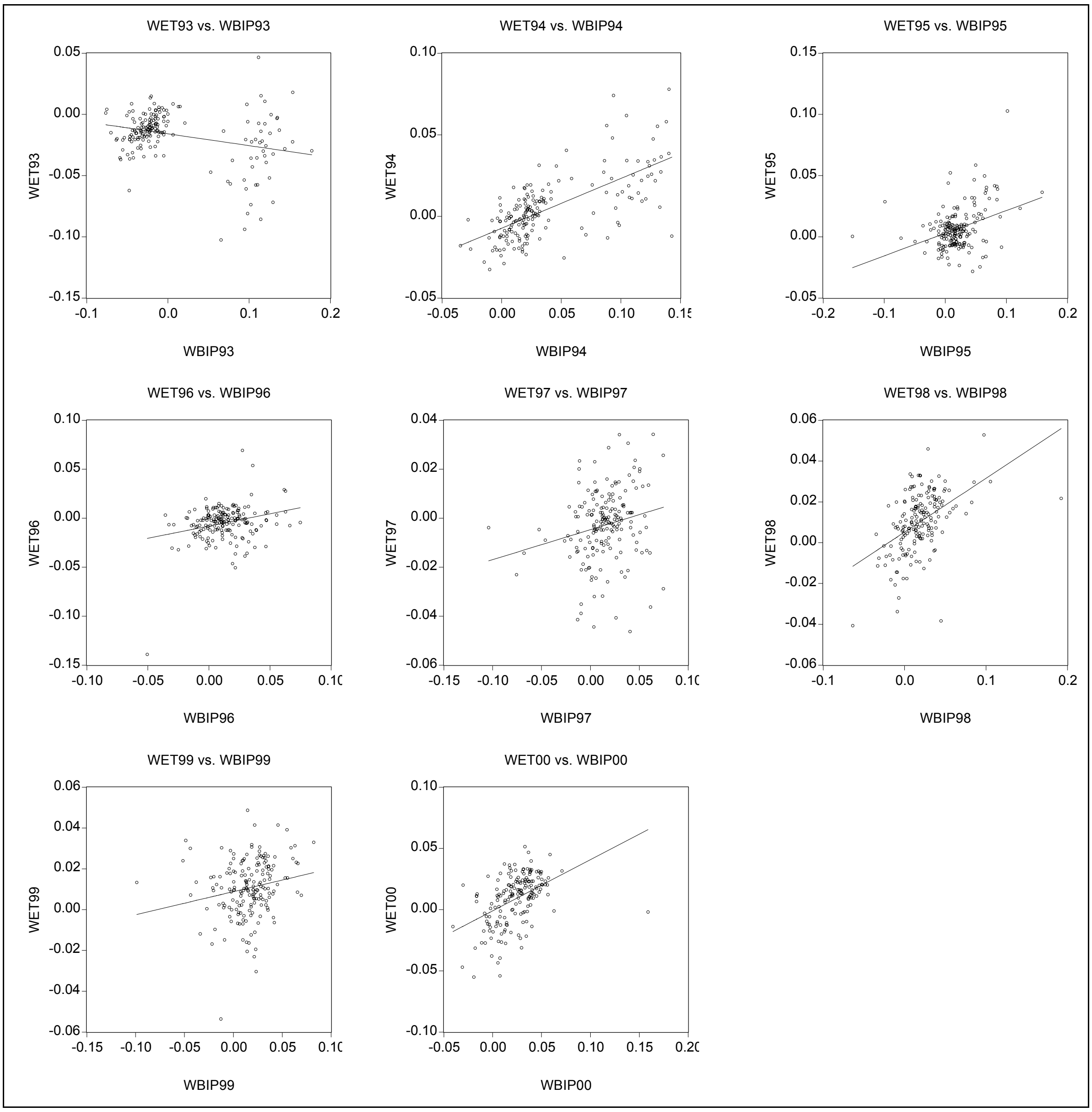


Figure 6.2: Verdoorn's law: map patterns of spatial components

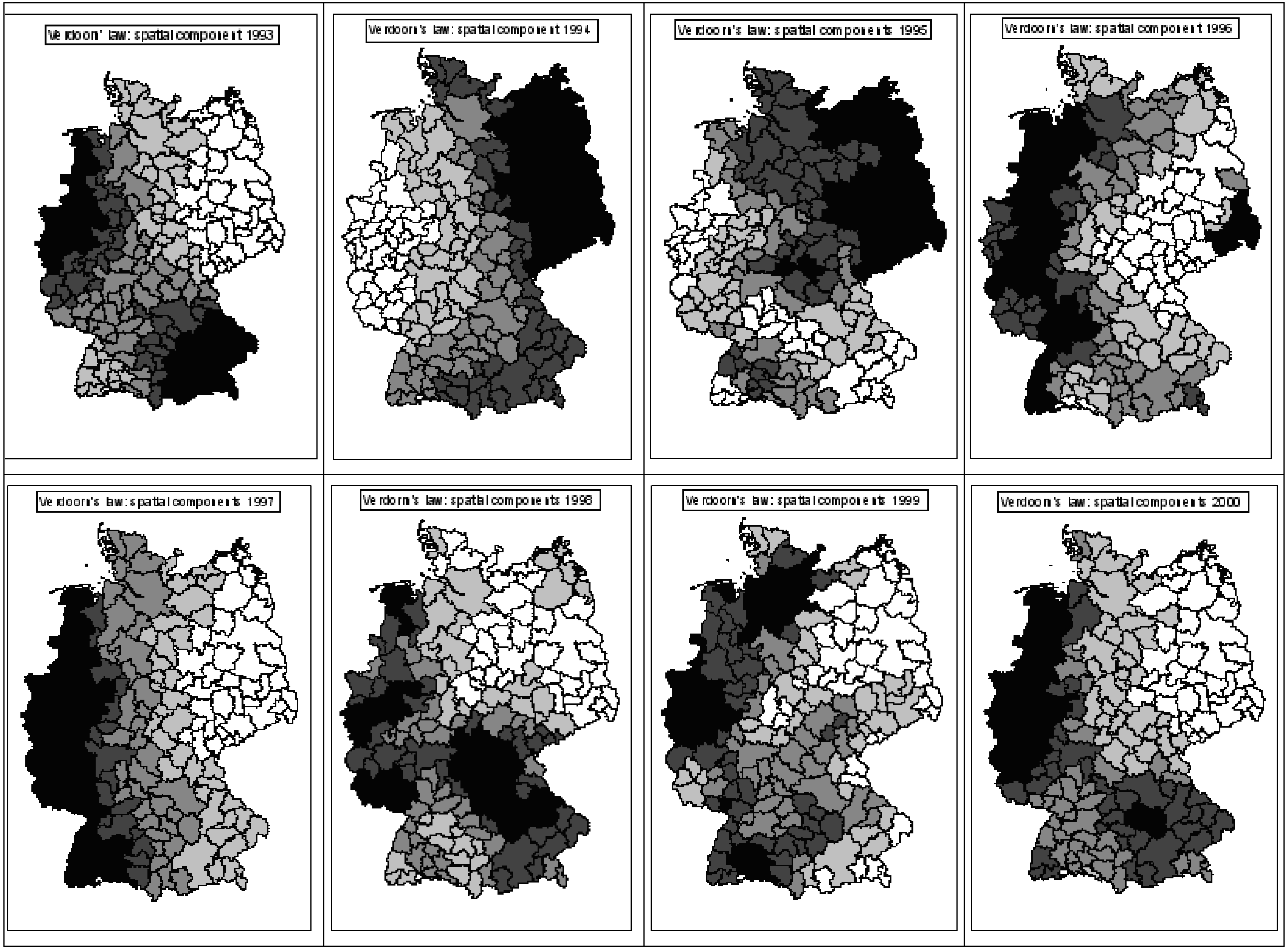


Table 6.2: Okun's law: estimation and testing results

	Non-spatial GLS estimation			Spatial SUR estimation		
	Coefficient		t-statistic	Coefficient		t-statistic
Output growth	-0.0510		-11.336	-0.0453		-9.032
Constant	0.0020		11.036	0.0010		7.781
D93	0.0996		16.862	0.0157		29.453
D00	-0.0090		-26.983	-0.0055		-18.740
Unempl. threshold	0.0401		10.946	0.0219		6.125
	R^2	SER	SSR	R^2	SER	SSR
	0.305	0.010	0.133	0.524	0.008	0.091

	Non-spatial GLS estimation	Spatial SUR estimation		
	Moran's *I* residuals (z value)	Moran's *I* residuals (z value)	Significant eigen-vectors	Moran's *I* spatial components
1993	0.180 (4,043)	0.002 (1,278)	2, 4, 7, 12, 14, 16, 21, 22, 27, 33, 36, 37	0.702
1994	0.518 (11,199)	0.043 (2,201)	1, 2, 3, 5, 6, 7, 10, 12, 14	0.965
1995	0.375 (8,081)	0.081 (2,851)	1, 2, 3, 4, 7, 10, 13, 31	0.938
1996	0.321 (6,931)	0.020 (1,374)	1, 2, 3, 9, 10, 16, 17	0.949
1997	0.693 (14,756)	0.061 (3,230)	1, 2, 3, 4, 6, 7, 14, 21, 25, 29, 31, 32, 33, 34, 35, 38, 39	0.891
1998	0.402 (8,645)	0.025 (1,237)	1, 2, 6, 9, 10, 23, 25, 40	0.802
1999	0.236 (5,114)	0.026 (1,878)	6, 8, 10, 13, 14, 16, 17, 26, 27, 28, 33	0.721
2000	0.559 (12,058)	0.024 (2,136)	1, 2, 3, 4, 5, 7, 17, 19, 22, 24, 25, 28, 33, 38	0.939

Notes: Non-spatial GSL estimation is based on the SUR model (3.4) without applying the spatial filtering approach. .D93, D00: Dummies for 1993 and 2000, R^2: coefficient of determination, SER: standard error of regression, SSR: sum of squared residuals

Table 6.2 reports the results of the FD specification of Okun's law. The law is supposed to hold over the entire sample period. However, although all coefficients are significant with the expected signs, their magnitude appear to be very low. Due to persistence effects, unemployment does not react very much in response to a change in the growth rate.

Again, the average does not reflect the variations during the sample period (Figure 6.3). In half of the years of the sample period the Okun relation is practically suspended. However, the spatial SUR estimate of the implied unemployment threshold of 2.2% for the entire sample period proves to be highly significant. It is broadly in line the finding of Schalk and Untiedt (2000) who established a decline of the unemployment threshold by 2 percentage since the 70s. On the contrary, Walwei's (2002) estimate lies close to the non-spatial GLS threshold of 4.0% that seems to be overrated as spatial effects are not controlled for.

Figure 6.3: Okun's law: scatterplots with regression lines

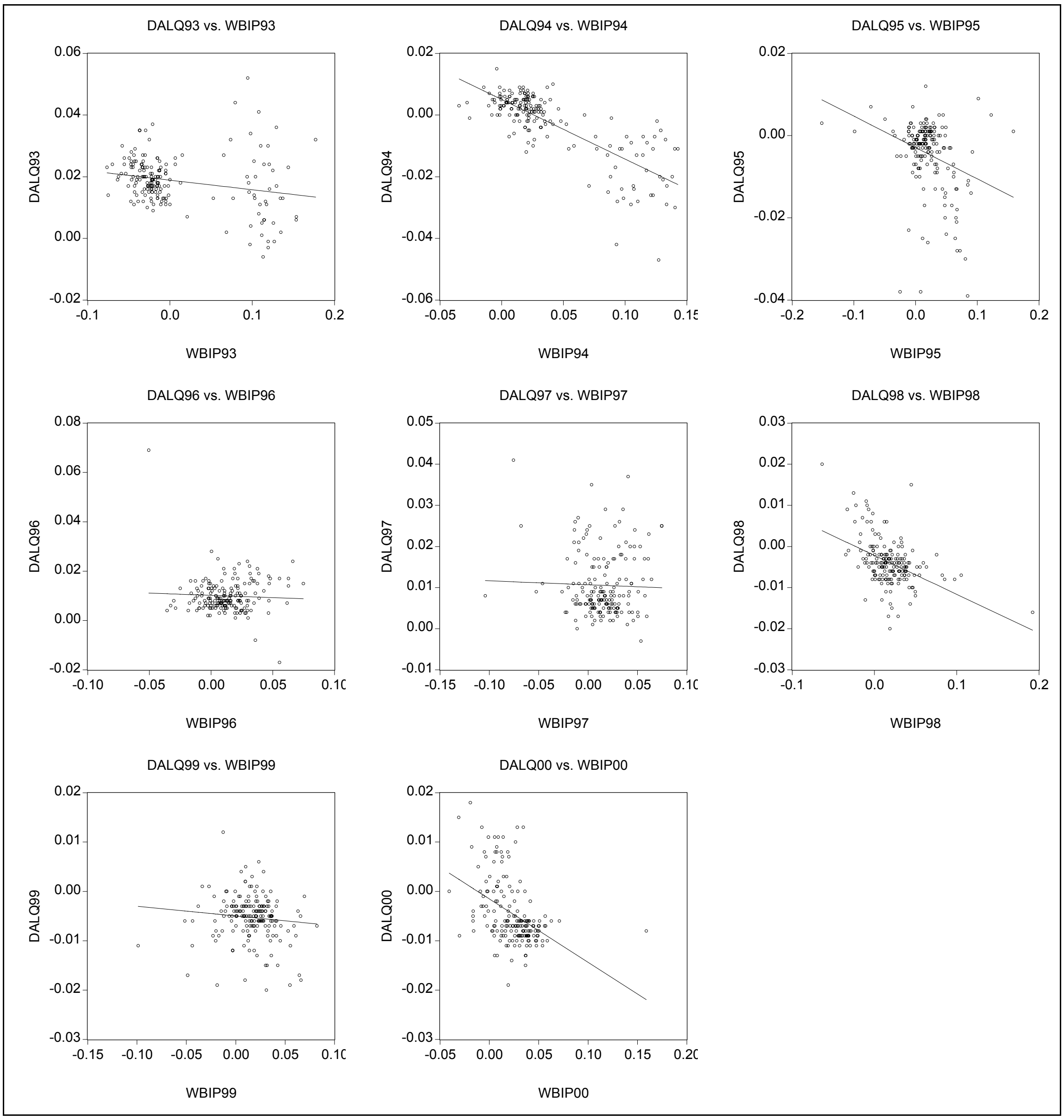
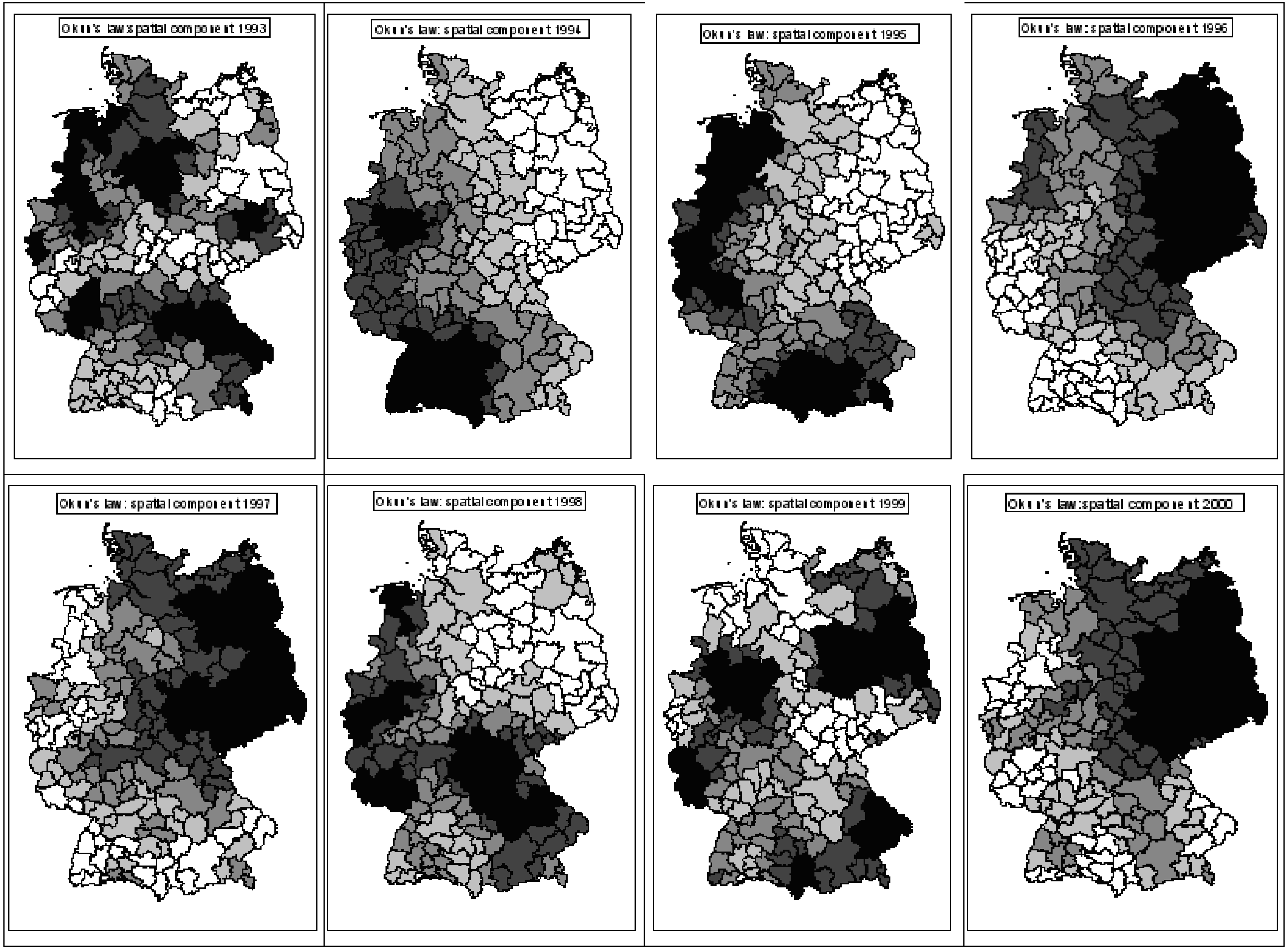


Figure 6.4: Okun’s law: map patterns of spatial components



As with Verdoorn's law the spatial effects can be splitted into common components and map patterns. From Moran's *I* it becomes obvious that the spatial components capture the largest part of the cross-section dependencies present in the change of the unemployment rate. On the average, the spatial correlations of the residuals are reduced by a factor of about 12 by spatial SUR estimation compared with non-spatial GLS estimation. In six out of eight subperiods Moran's *I* of the spatial SUR residuals lies close to zero (< 0.05).

Figure 6.4 exhibits that again both west-east and east-west trends dominate the map patterns of the spatial components. With Okun's law the Moran scatterplot trends are pronounced ($MI/MI_{max} \geq 0.9$) in five years. For 1998 the MI/MI_{max} value indicates a strong MC trend and for 1993 and 1993 noticeable MC trends. It is conspicuous that the east-west trend inclinations run considerably smoother than the declining trend surfaces. In the latter case always several moulds in the western part of the country can be located.

The difference between the unemployment and employment threshold is noticeable. The gap is likely to be attributed to the growth of the working population, mainly due to a perceptible rise in the participation rate of women, which increased by 1.1 percentage points in the sample period (Statistisches Bundesamt, 2003). Also, the unemployment benefit system has to be considered. In periods of economic upturns new jobs are partially filled with people from outside the labour force. Thus, employment is affected, while unemployment is eventually stable. In case of downturns, job losses will imply a simultaneous rise in unemployment to receive financial support.

7. Conclusions

In this paper, we have estimated thresholds of output growth needed for a rise in employment and a fall in the unemployment rate for the unified Germany on the base of the laws of Verdoorn and Okun. A spatial analysis of 180 German regional labour market regions reveals that the relations between employment, unemployment and production may be distorted by strong spatial dependencies. To capture spatial autocorrelations a feasible spatial SUR techniques is proposed. It turns out that minimum output growth sufficient for a rise in employment is below the level which is needed for a drop in the unemployment rate. Especially, the employment and unemployment thresholds are assessed by bounds of about 1.2 and 2.2 percent, respectively. The ordering is related both to demographic changes and institutional settings on the labour market, such as the working of the unemployment benefit system. However, these numbers are only rough guidelines for the policymakers, as the estimates are hardly stable even in shorter periods of time.

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References

Aghion, P., Howitt, P. (1998): Endogeneous growth theory, MIT Press, Cambridge.

Anselin, L. (1988): Spatial Econometrics: Methods and Models, Dordrecht, Kluwer Academic Publishers.

Attfield, C.L.F., Silverstone, B. (1998): Okun's law, Cointegration and gap variables, Journal of Macroeconomics 20, 625-637.

Beck, N., Gleditsch, K. (2003), Space is more than geography, Discussion Paper, Department of Political Science, University of California, San Diego.

Beck, N., Katz, J.N. (2001), Nuisance vs. substance: specifying and estimating time-series-cross-section models, Political Analysis 6, 1-36.

Cechetti, S., Rich, R.W. (1999): Structural estimates of the U.S. sacrifice ratio, Federal Reserve Bank of New York, Staff Paper 71.

Eckey, H.-F. (2001), Der wirtschaftliche Entwicklungsstand in den Regionen des Vereinigten Deutschlands, Volkswirtschaftliche Diskussionspapiere Nr. 20/01, Universität Kassel, Fachbereich Wirtschaftswissenschaften, Kassel.

Eckey, H.-F., Horn, K. and Klemmer, P. (1990), Abgrenzung von regionalen Diagnoseeinheiten für die Zwecke der regionalen Wirtschaftspolitik, Bochum.

Elhorst, J.P. (2001), Dynamic Models in Space and Time, Geographical Analysis 33, 119-140.

Fingleton, B. (2000), Spatial econometrics, economic geography, dynamics and equilibrium: a third way?, Environment & Planning A32, 1481-1498.

Fingleton, B. (2001): Equilibrium and economic growth: Spatial econometric models and simulations, Journal of Regional Science 41, 117-147.

Florax, R. (1992), The University: A Regional Booster? Economic Impacts of Academic Knowledge Infrastructure, Aldershot, Ashgate, Hants.

Freeman, D.G. (2001): Panel tests of Okun's law for ten industrial countries, Economic Inquiry 39, 511-523.

Getis, A., Griffith, D.A. (2002): Comparative spatial filtering in regression analysis, Geographical analysis 34, 130-140.

Getis, A. Ord, J.K. (1992): The analysis of spatial association by use of distance statistics, Geographical Analysis 24, 189-206.

Griffith, D. (1996), Spatial autocorrelation and eigenfunctions of the geographic weights matrix accompanying geo-referenced data, The Canadian Geographer 40, 351-367.

Griffith, D.A. (2000), A linear regression solution to the spatial autocorrelation problem, Journal of Geographical Systems 2, 141-156.

Griffith, D. (2003), Spatial autocorrelation and spatial filtering, Springer, Berlin, New York.

Harris, R., Lau, E. (1998): Verdoorn's law and increasing returns to scale in the UK regions, 1968-91: Some new estimates based on the cointegration approach, Oxford Economic Papers 50, 201-219.

Hooper, P. and Hewings, G. (1981), Some Properties of Space-Time Processes, Geographical Analysis 13, 203-223.

Jones, C.I. (1998), Introduction to Economic Growth, Norton, New York.

Kaldor, N. (1975): Economic growth and the Verdoorn law – A comment on Mr. Rowthorn’s article, Economic Journal 85, 891-896.

Lee, J. (2000): The robustness of Okun's law: Evidence from OECD countries, Journal of Macroeconomics 22, 331-356.

León-Ledesma, M.A. (2000): Economic Growth and Verdoorn's law in the Spanish regions, 1962-91, International Review of Applied Economics 14, 55-69.

Logeay, C. (2001), Labour Market in Downturn, Economic Bulletin 12/2001, Deutsches Institut für Wirtschaftsforschung (DIW), Berlin.

Maußner, A. and Klump, R. (1996), Wachstumstheorie, Springer, Berlin, New York.

Moosa, I. (1997): A cross-country comparison of Okun's coefficient, Journal of Comparative Studies 24, 335-356.

Okun, A.M. (1962): Potential GNP: Its measurement and significance, American Statistical Association, Proceedings of the Business and Economic Statistics Section, 98-104.

Okun, A.M. (1970): The political economy of prosperity, WW Norton & Company, New York.

Ord, K. (1975), Estimation Methods for Models of Spatial Interaction, Journal of the American Statistical Association 70, 120-126.

Pons-Novell, J., Viladecans-Marsal, E. (1999): Kaldor’s law and spatial dependence: Evidence from the European regions, Regional Studies 33, 443-451.

Prachowny, M.F.J. (1993): Okun's law: Theoretical foundations and revised estimates, Review of Economics and Statistics 75, 331-336.

Rowthorn, R.E. (1979): A note on Verdoorn’s Law, Economic Journal 89, 131-133.

Schalk, H.J. and Untiedt, D. (2000), Wachstum und Arbeitslosigkeit. Empirische Befunde und wirtschaftspolitische Optionen für die Bundesrepublik Deutschland, Bonn.

Tiefelsdorf, M., Boots, B. (1995), The exact distribution of Moran's I, Environment and Planning A27, 985-999.

Verdoorn, P.J. (1993): On the factors determining the growth of labour productivity, Italian Economic Papers 2, 59-68. Originally published: Verdoorn, P.J. (1949), Fattori che regolano lo sviluppo della produttivita del lavoro, L'Industria 1, 3-10.

Walwei, U. (2002), Labour Market Effects of Employment Protection, IAB Labour Market Research Topics 48, Institut für Arbeitsmarkt- und Berufsforschung der Bundesanstalt für Arbeit, Nürnberg.