Regional Unemployment Forecasts with Spatial Interdependencies

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Abstract

We forecast unemployment for the 176 German labour-market districts on a monthly basis. Because of their small size, strong spatial interdependencies exist between these regional units. To account for these as well as for the heterogeneity in the regional development over time, we apply different versions of an univariate spatial GVAR model. When comparing the forecast precision with univariate time-series methods, we find that the spatial model does indeed perform better or at least as well. Hence, the GVAR model provides an alternative or complementary approach to commonly used methods in regional forecasting which do not consider regional inter-dependencies.

1 Introduction

Forecasting the development in regional labour markets provides important information for political, institutional and economic agents for their respective planning processes. Previous studies focus on the future development of employment in small spatial units.[1] In our paper we predict unemployment for 176 German labour-market districts (*Agenturbezirke*) for three simulated forecast years (2004, 2005, 2006) with monthly data ending in the December of the pre-forecast year. Although the size of these districts varies, they are in general between NUTS 2 (*Regierungsbezirke*) and NUTS 3 (*Kreise*) regions. As a result of their small spatial size, it seems plausible that the economic development in a particular labour-market district is significantly influenced by neighbouring or close regional units. Such spatial dependencies are explicitly considered in this paper. More precisely, we integrate various spatial dependencies into a deterministic time-series model and compare the results with a simple deterministic as well as stochastic time-series approaches. We find that generally the spatial models indeed perform better or at least as well as the comparison models.

In recent approaches to regional forecasting, regional models are typically combined with methods from time-series econometrics. Some examples are provided by Magura (1998), Mayor et al. (2007) and Patuelli et al. (2006). These models focus on the industrial structure and intersectoral links, treating each region as an independent unit. However, new theories in regional science as well as empirical studies (see, for example, Fujita et al., 1999 or Behrens / Thisse, 2007) confirm the important role of regional interdependencies in the local economic development whereby commuting and the trade-flows of intermediary goods are deemed as the most relevant. Normally, these interdependencies are included in forecasts by taking unemployment in region i as a single variable, collecting these variables in a vector and then estimating a VAR model. Hence, the number of parameters which capture the spatial dependence grows quadratically in the number of regions. A VAR model therefore becomes intractable when forecasting many small regional units. Thus, although local economies are connected by many channels, hardly any regional forecasting study considers this aspect explicitly. Some notable exceptions are Beenstock / Felsenstein (2007), Longhi / Nijkamp (2007) and Kholodilin et al. (2007). Exploiting the information on spatial proximity may help to impose structure on the regional interdependence and make the system of regional equations solvable.

Figure 1 describes the spatial component of the connectivity between regions schematically. The development of region r is directly influenced by its neighbouring regions q and s and vice versa. In contrast, there is only an indirect interaction between the regions r and p. Within the regional interdependencies, there also exists a serial dimension which should be taken into consideration. On the one hand, it is possible that regions influence each other contemporaneously, i.e. $X_{T,s}$ effects $X_{T,r}$ and vice versa. On the other hand, the influence can have a time lag, e.g. $X_{T,r}$ is influenced by $X_{T-l,s}$. For example, a cyclical upturn in one region can lead through a higher

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[1] For a detailed overview about methods and mainly German studies see Hampel et al. (2007).

demand for input factors and higher incomes of commuters from neighbouring regions to a lagged upturn in the surrounding areas.
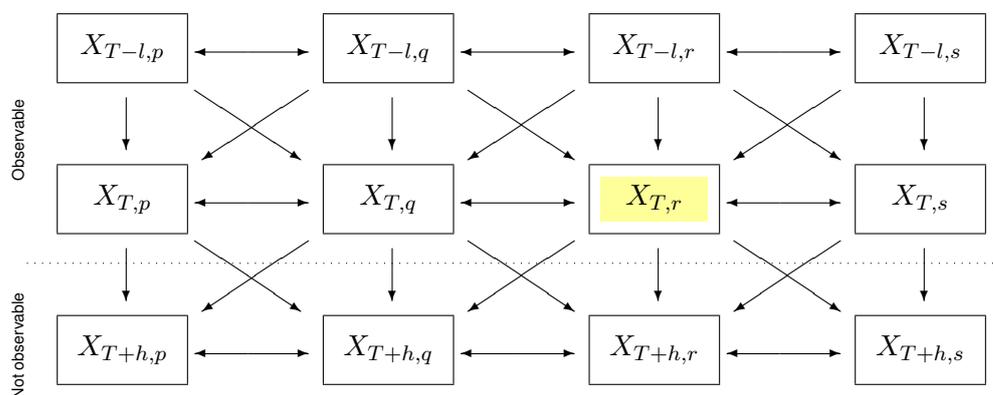

Figure 1: Possible Spatial and Serial Dependencies

The various intra- and interregional relations which are sketched in Figure 1 can be formally expressed by a model of the Global VAR (GVAR) type (cf. Pesaran et al., 2004):

$$y_{i,t} = \alpha_{i,1}y_{i,t-1} + \ldots + \alpha_{i,L}y_{i,t-L} + \pi_{i,0}y_{i,t}^* + \ldots + \pi_{i,L}y_{i,t-L}^* + \mu_{i,t} + u_{i,t}, \qquad (1)$$

where $y_{i,t}$ is the element of the dependent variable's vector Y_t which corresponds to region i at time t. $\mu_{i,t}$ represents the deterministic conditional mean of the data generating process of $y_{i,t}$. $u_{i,t}$ is an independently distributed stochastic disturbance. $y_{i,t}^* = \sum_{j=1}^{N} w_{i,j}y_{j,t}$ (with $w_{i,i} = 0$) denotes the weighted aggregate over those elements of the dependent vector Y_t which do not correspond to region i and N is the number of regions. $\alpha_{i,\ell}$ with $\ell = 1, \ldots, L$ are the parameters which describe the serial correlation within the panel i whereas $\pi_{i,0}$ represents the contemporaneous spatial autocorrelation and $\pi_{i,\ell}, \ell = 1, \ldots, L$ the space-time autocorrelation process.

Pesaran et al. (2004) employ exchange rates in their global VAR model to connect the regions in their international trade model. This can be criticised for two reasons. First, although the endogeneity of the weights $w_{i,j}$ is typically ignored in the GVAR literature (cf. Mutl, 2007), they are economically determined by some of the dependent variables within the model and need to be forecasted themselves. Second, economic theory provides various explanations for the connectivity of regional labour-markets, e.g. commuting flows, cross-regional input sharing, knowledge spill-overs and other sources of regional externalities. However they all have in common that their intensity depends on geographical proximity, e.g. contiguity or distance.[2]

The general GVAR formulation of equation (1) allows us to detect some of the implicit assumptions and restrictions which are typically made in spatial econometric analyses:

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[2] In addition, contiguity and physical distance have the advantage of being constant over time, i.e. they are known ex-ante and do not have to be forecasted themselves.

The limited degree of temporal dependence in space, and the homogeneity of the deterministic and stochastic processes.

First, from equation (1) it can be seen that there is the temporal dimension within the spatially dependent process described by $\pi_{i,\ell} y^*_{i,t-\ell}$. Many spatial econometric applications in forecasting (e.g. Kholodilin et al., 2007; Longhi / Nijkamp, 2007 and Baltagi / Li, 2004) just consider the contemporaneous spatial process, $\pi_{i,0} w_{i,\cdot} y_{\cdot,t}$. In contrast to this, Giacomini / Granger (2004), Arbia et al. (2007) and Hernandez-Murillo / Owyang (2006) omit the contemporaneous spatial lag and estimate only temporally lagged spatial dependence. Because none of the simultaneous forecasts is known in the future, only the predictor

$$\hat{y}_{i,T+h} = [I_N - diag_{i=1}^N(\pi_{i,0})W]^{-1}_{i,\cdot} \left[\mu_{\cdot,T} + \sum_{\ell=1}^L (\alpha_{\cdot,\ell} + \pi_{\cdot,\ell}W) y_{\cdot,T+h-\ell} \right]$$

can be computed. Kelejian / Prucha (2007)[3] show that typically this point forecast is less precise than the forecast $\hat{y}_{i,T+h} = \tilde{\mu}_{i,T} + \sum_{\ell=1}^L (\tilde{\alpha}_{i,\ell} + \tilde{\pi}_{i,\ell}W) y_{\cdot,T+h-\ell}$ where the contemporaneous spatial dependence is omitted and an incomplete model is estimated.

Second, all mentioned spatial econometric studies assume homogeneous coefficients over all regions. The advantage of this procedure is that the coefficient estimates will converge even for a small number of periods. However, the assumption of one homogenous process determining the development of all regions might not adequately capture the regional heterogeneity. Then, more precise forecasts eventually can be obtained by region-specific estimates, given that there are sufficient observations in time (cf. Baltagi, 2006).

In order to account for the spatial dependence and the regional heterogeneity in our forecasting procedures, we first estimate individually specified deterministic structural-component (SC) models for $\mu_{i,t}$. Then these are augmented either by the serially autoregressive or the space-time autoregressive process.[4]

The setup of the remaining paper is as follows: The look at the data in Section 2 provides support for the importance of modelling the spatially autoregressive processes. Further, we sketch the degree of the regional heterogeneity and hence the need for estimating region-specific coefficients. Section 3 describes the spatial GVAR forecasting procedures in detail. For comparison, we also estimate region-by-region ARIMA and Seasonal Holt-Winter (EWMA) models. The presentation and discussion of our results follows in Section 4 before a conclusion ends the paper.

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[3] Although Kelejian / Prucha (2007) discuss a strictly exogenous model of the form $(I - \rho W)y = X\beta + u$, their result should also hold for the pre-determined process $(I - \rho W)y = \mu + (\cdot)Y_L$.

[4] Due to the large number of possible parameters, including both serial and spatial autocorrelation at the same time as well as a high maximum lag length caused serious troubles in the computability of the estimators.

2 Regional Patterns of Unemployment in Germany

In this section we briefly describe the regional unemployment patterns in the 176 German labour-market districts.[5] With the exception of Berlin and Hamburg, these are between NUTS 2 and NUTS 3 regions.[6] For our analysis, we use record data from the German Federal Employment Agency. This data covers all registered unemployed in Germany on a monthly basis starting in January 1998 and ending in December 2006.

To demonstrate the regional heterogeneity, we decompose the unemployment development into the three basic elements of a time series: level, trend and seasonality. Figure 2 shows the average unemployment rate[7] which reflects the level, the growth rate[8] which represents the trend in the time series and the seasonal span[9].

The often emphasised differences between eastern and western Germany can only be found for the unemployment rate which is considerably higher in nearly all eastern labour-market districts. High unemployment rates in western Germany can be seen in the Ruhr Area, a traditional coalmining region and in some labour-market districts along the coast of the North Sea. Overall, the unemployment rates vary between 3.70 and 23.36 percent. The corresponding average number of unemployed in levels goes from 5,300 to 287,000. The ten labour-market districts with the lowest average unemployment levels have between 5,300 and 7,500 unemployed, the lowest decentile is below 9,000; the districts are spread all over Germany. Most labour-market districts with levels in the highest decentile, starting at 44,700 unemployed, often cover metropolises, even though some are rural areas in eastern Germany.

No differences between former West and East Germany can be seen for the growth rate and the seasonal span of unemployment. High positive growth rates, i.e. a strong increase in the number of unemployed, can be observed along the Middle and Lower Rhine (e.g. Cologne, Frankfurt) and around Munich. These rates reach maximum values of 3.95. The lowest growth rates are found in districts located in two east German Federal States Saxony-Anhalt (where unemployment is relatively high) and Thuringia (which shows a good performance among the eastern German labour-market districts) as well as in south-west German boarder regions where unemployment is low. The distribution of regional growth rates covers an interval of slightly more than eight percentage points. High unemployment rates but low seasonal spans can generally be observed in urbanised labour-market districts. Here, the

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[5] With the exception of Berlin, all forecasts are at this regional level. In Berlin the labour-market districts were reorganised spatially several times in recent years so that the data here was not available for all districts and periods. For this reason, we aggregate Berlin to one spatial unit.

[6] See `http://ec.europa.eu/comm/eurostat/ramon/nuts/introduction_regions_en.html` for a description of the NUTS classification system.

[7] Here we refer to the administrative unemployment rate (reported by the German Federal Employment Agency) which differs from the ILO standardised unemployment rate.

[8] This is defined as the average of $(Y_{Dec,\theta} - Y_{Dec,\theta-1})/Y_{Dec,\theta-1}$ for every year, where $Y_{Dec,\theta}$ is the number of employed in December of year θ.

[9] Defined as the average of $(Y_{max} - Y_{min})/\bar{Y}$ for every year, where Y_{max} is the maximum, Y_{min} the minimum and $\bar{Y}$ the average number of unemployed in the respective year.
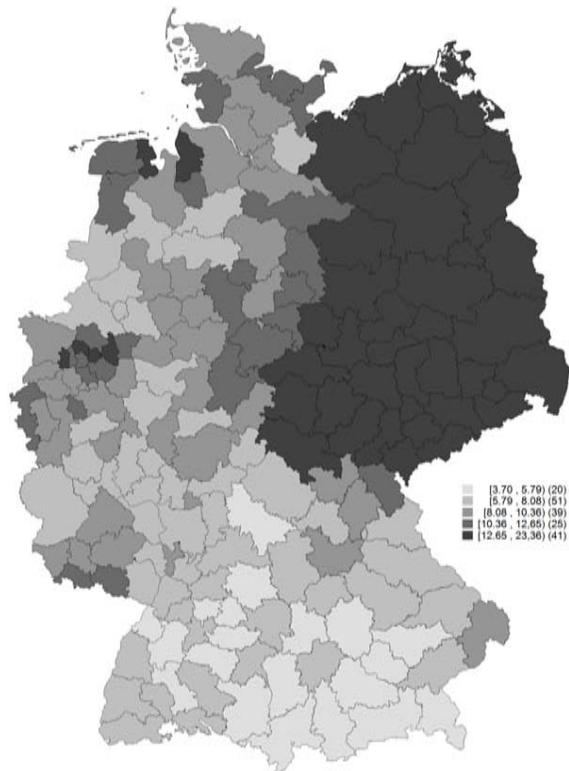
| | Unemployment Rate, 1998 – 2006 | Growth Rate, 1998 – 2006 | Seasonal Span, 1998 – 2006 |
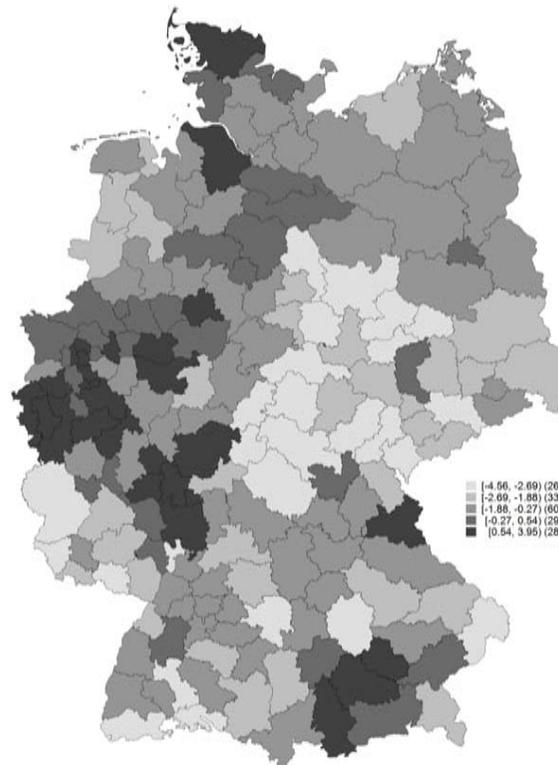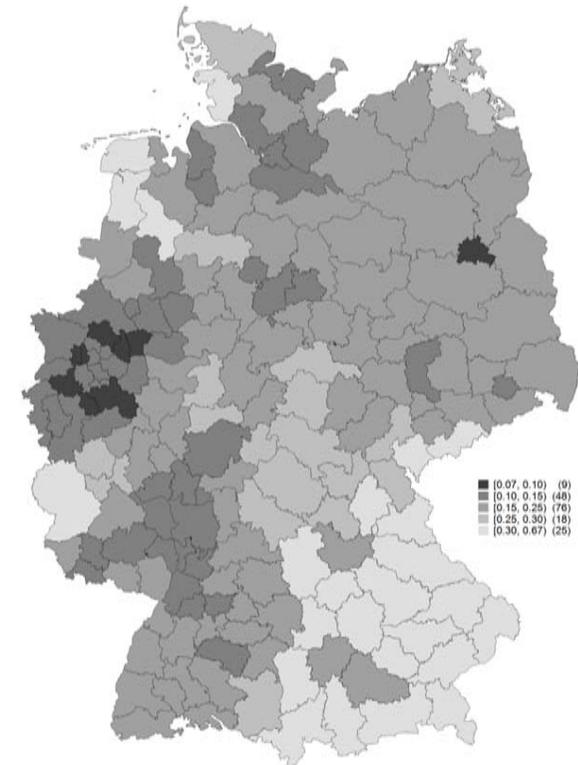
Number of labour-market districts in parenthesis
Source: Federal Employment Agency

Figure 2: Average Unemployment Rate, Growth Rate and Seasonal Span of Unemployment in Germany, 1998 – 2006

seasonal fluctuation only amounts to 7 percent of the series. In contrast, particularly touristy regions and those where agriculture is important have relatively high seasonal spans of up to two thirds of the average unemployment within a year. Both touristy and agricultural dominated regions can be mainly found along the coasts of the Baltic and North Sea as well as in the South-East on the border to the Czech Republic.

The maps in Figure 2 show clusters with similar patterns. This suggests the presence of spatial correlation. Numerous indicators have been developed to test this. Here we use Moran's Index (cf. Moran, 1948 and Anselin, 1988):

$$MI = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{i,j}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{i,j} \frac{1}{N} \sum_{i=1}^{N}(y_i - \bar{y})^2} \qquad (2)$$

where $y_i(y_j)$ is the average unemployment level in region $i(j)$, $\bar{y}$ represents the national mean of y and $w_{i,j} = w_{i,j}^* / \sum_{j=1}^{N} w_{i,j}^*$ are the elements of the row-standardised contiguity matrix. Moran's I can be interpreted like a Durbin-Watson statistic where the serial AR1 correlation is replaced by a spatial AR1 correlation. Table 1 shows some descriptive statistics and Moran's I for the time-series elements. As can be seen in the map for the unemployment rate, there is significant spatial autocorrelation between the unemployment rates of the labour-market districts. Both other time-series elements also show highly significant Moran's I of 0.474 and 0.614, respectively. Further, while the unemployment rate and the seasonal span are relatively constant over the years, the growth rate is much more volatile with positive growth rates from 2002 until 2005 and negative rates in the other years.

Table 1: Descriptive Statistics (Average 1998 − 2006)

Variable	Mean	Std. Dev.	Min	Max	Moran's I
Unemployment rate	10.273	4.552	3.682	23.363	0.792***
Growth rate	-1.077	1.614	-4.564	3.954	0.474***
Seasonal span	0.201	0.102	0.075	0.659	0.614***

***Significant at the 1%-level.

Whereas we consider figures without dimension to underline the regional heterogeneity and the spatial correlation pattern, we base our forecasts directly on unemployment. For the estimation procedures it is important to use stationary time-series. The application of the proper filter to achieve stationarity is however a question of improving the forecast accuracy, cf. Franses (1991) or Osborn et al. (1999). We apply several tests for both unit roots at the zero frequency and seasonal unit roots in the region-specific series. Here, we report monthly HEGY-type tests, Augmented Dickey-Fuller (DF) tests for a unit root on the first lag, Dickey-Hasza-Fuller (DHF) tests for the seasonal unit root, and DF tests for seasonal unit roots, cf. Rodrigues / Osborn (1999). For the HEGY tests (Beaulieu / Miron, 1993 and Taylor, 1998) we show the number of not-rejected unit roots on the zero frequency, the occurrence of a unit root in at least one other frequency and the joint non-rejection of unit roots at all frequencies by the F_{2-12} and the F_{1-12} statistic. The tests on the levels Y_{it} are carried out considering seasonal dummies and a linear trend. In the first difference and the seasonal difference, the sea-

sonal mean is eliminated prior to the test, i.e. the tests are based on the single-mean hypotheses.

Table 2: Unit Root Tests, 1998 – 2006

Test procedure		$Y_{i,t}$	$\Delta^1(Y_{i,t} - \mu_{i,t})$	$\Delta^{12}Y_{i,t}$
		Districts where Unit roots are not rejected at the 10% level in the Series		
DF	$(1-L)$	174	11	59
DHF	$(1-L^{12})$	176	0	3
HEGY	π_1	175	64	21
	other freq.	162	153	142
	F_{2-12}	0	0	0
	F_{1-12}	0	0	0
DF	$(1-L^{12})$	0	0	0

The underlying test regressions are augmented by thirteen lags.

The conclusion from Table 2 is straightforward and coincides with the results from Dreger / Reimers (2005) for quarterly unemployment panel data. The regional series of monthly unemployment levels are not stationary. Even though the DHF statistics do not reject seasonal unit roots for all regions, these result from roots at the zero frequency. Joint unit roots at the seasonal frequencies can be rejected. Hence, the first difference filter seems adequate.

3   Forecast Methodology

3.1   The Spatial GVAR Model

As shown above, the series of the dependent variables – regional unemployment levels – are $I(1)$. Thus, we estimate the model in first differences to achieve stationarity and define

$$y_{i,t} = \text{Unemployment}_{i,t} - \text{Unemployment}_{i,t-1} \qquad .$$

In the following, we omit the contemporaneous spatial lag $\pi_{i0}y_{it}^*$ and rewrite the model from equation (1) as:

$$y_{i,t} = \alpha_{i,1}y_{i,t-1} + \ldots + \alpha_{i,L}y_{i,t-L} + \pi_{i,1}y_{i,t-1}^* + \ldots + \pi_{i,L}y_{i,t-L}^* + \mu_{i,t} + u_{i,t}. \qquad (3)$$

We model the deterministic part of this equation, μ_{it}, in the form of structural components: trend, seasonal figure, and business cycle. The trend is estimated by a flexible polynomial in time which is at least linear and at most a cubic trend. The seasonal figure is described by a combination of trigonometric functions of time, cf. Harvey (2004):

$$s_{i,t} = \sum_{j=1}^{(S/2)} (\gamma_{i,j}\cos\lambda_j t + \delta_{i,j}\sin\lambda_j t) \qquad \text{with } \lambda_j = \frac{2\pi j}{S}, \qquad (4)$$

where – with monthly data – $S = 12$ is the length of the seasonal figure and $\gamma_{i,j}, \delta_{i,j}$ are parameters to be estimated. The cycles generated by these sine and cosine functions show a length of minimum two and maximum twelve months.

As the economic activity in a region often has a cyclical component, we also use two trigonometric functions to model potential business cycles. As the duration of a cycle in a labour-market district is unknown, its length is determined by the peaks in the autocorrelation function of the residual in a regression where only constant, linear trend and seasonal figure are included. Thereby we assume that the cycle length must be at least thirteen months. Hence, the business-cycle functions are similar to equation (4), with the exception that now $j = 1$ and $\lambda_j < \frac{2\pi}{12}$. In the specification of the deterministic part of the model we proceed by subsequently running OLS regressions on the components. Linear trend, season, business cycle, quadratic and cubic trend are included stepwise and, to guarantee parsimonious specification, those new coefficients are restricted to zero which are not significant at the 5%-level. A maximum of 16 coefficients per region have to be estimated for the deterministic part; the actual number c is usually smaller than this.

With regard to the stochastic part of equation (3), we estimate, forecast and compare four different models:

1. In the purely deterministic Structural Components model (SC), the (serially and space-time) autoregressive part is omitted, i.e. the coefficients $\alpha_{i,\ell}$ and $\pi_{i,\ell}$, $(\forall i \in \{1, \ldots, N\}, \ell \in \{1, \ldots, L\})$ are restricted to zero.

2. In the Structural Components model with serially autoregressive elements (SCAR), the space-time autoregressive coefficients $\pi_{i,\ell}$ are restricted to zero whereas the $\alpha_{i,\ell}$ are estimated.

3. Alternatively, the serial autoregressive process can be omitted (i.e. $\alpha_{i,\ell} = 0$) and only the spatial autoregressive process is estimated in addition to the deterministic structural components. However, there exist several ways to model the connectivity of regions (cf. Haining, 2003, p.74–85), i.e. to define the spatial weights $w_{i,j}$; here we apply two of them.

   (a) Typically regions are connected more intensely the shorter the distance between them is. Hence, distance based connectivity weights are generated by functions which decrease with distance. We apply a simple inverse exponential scheme with the distance $d_{i,j}$ between the centres of region i and j measured in kilometers:

$$w_{i,j}^* = \begin{cases} e^{-d_{i,j}} & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases}. \tag{5}$$

   Note that this weight is positive for any distance even though it converges towards zero as distance becomes "large".

(b) In contrast, neighbourhood is a dichotomous concept: Either regions are neighbours (resulting in an interrelation between them), or they are not. Here we use the definition of contiguity and use an indicator variable which takes the value 1 if the regions have a common border:

$$w_{i,j} = I_i \quad \text{(Common border between regions } i \text{ and } j) \tag{6}$$

In the following, we abbreviate the spatially autoregressive structural components model that is based on contiguity with SCSARC and the distance-based model with SCSARD. We apply row-normalised weights $w_{i,j} = \frac{w_{i,j}^*}{\sum_{j=1}^N w_{i,j}^*}$ in both spatial models where the weights add up to 1 for each row of the connectivity matrix.

Typically the inclusion of a large number of lags leads to many insignificant parameters and also to rather imprecise forecasts. Hence, we try to estimate the model parsimoniously while still capturing a high maximum lag L. To this end, we determine the bivariate correlation of the lagged stochastic variables with the residual of the pure SC model and add these lags subsequently to the estimation, sorted by the absolute value of correlation and starting with the highest. In each step, we keep the newly included lag in those regions where the t-statistics are significant at the 5% level, run a new regression and maintain these significant lags if we find an improvement of the corrected Akaike Information Criterion AIC_c (cf. Hurvich / Tsai, 1989).[10] The maximum tested lag length is 26 in the SCAR model (as well as in the following ARIMA estimations) and 13 in the spatially autoregressive models, a compromise between considering a sufficiently long time horizon (roughly two years) and not losing too many observations. The lower number of lags in the spatial models is solely due to the very long extra estimation time needed for each additional lag.

In our case, per region we have c coefficients to estimate the mean μ_{it}, $p \leq L$ coefficients to estimate the serial correlation and $q \leq L$ coefficients for the spatially autocorrelated (SAR) process. I.e., the maximum number of coefficients is $(c + 2L)N$. This is significantly larger than $N + p + q$ as the number of coefficients which are estimated by Hernandez-Murillo / Owyang (2006)[11], but smaller than the $(c + LN)N$ coefficients which are estimated in a completely unrestricted VAR model.

3.2 Comparison Models

Autoregressive integrated moving average (ARIMA) models are a standard procedure when forecasting time series. We implement this model according to an adapted Box-Jenkins forecast method (cf. Box / Jenkins, 1970). To remove seasonal effects, we first use yearly differences of regional employment. These are tested for unit roots

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[10] Many studies conclude that lag selection based on information criteria results in more precise forecasts than other methods, see e.g. Inoue / Kilian (2006) or Stock (2001).

[11] To our knowledge, the most flexible spatial econometric approach is provided by Hernandez-Murillo / Owyang (2006), who estimate N mean coefficients, p AR lags and q SAR lags.

and further monthly differentiated until stationarity is achieved. $\Delta^S y_{it} = y_{i,t} - y_{i,t-S}$ is the seasonal difference of the stationary series $y_{i,t}$, i.e. the monthly changes in the unemployment levels. Seasonal patterns are eliminated by setting $S = 12$. Then the model can be described by the following ARMA equation:

$$\Delta^S y_{i,t} = \mu_{i,t} + \sum_{k=1}^{p} \Delta^S y_{i,t-k}\,\alpha_k + u_{i,t} \qquad \text{with } u_{i,t} = \sum_{k=1}^{q} u_{i,t-k}\rho_k + \epsilon_{i,t} \qquad (7)$$

In selecting the lags, we proceed as in the stochastic part of the SC model. Thus, only a small set of lags is included in the final forecast although the maximum lag order is high.

Many models from the family of Exponentially Weighted Moving Averages (EWMA) have proven to forecast with a high accuracy, cf. Stock (2001); hence, they are adequate as benchmark models. As our series have a remarkable and regular seasonal figure (up to 60 % of the variation, see Section 2), we apply the additive seasonal Holt-Winters estimator (cf. Chatfield / Yar, 1988) because it seems most suitable to the observed time-series characteristics.

4   Results

In comparing the performance of the spatial models with the others amongst the differently sized labour-market districts, looking at the mean squared forecast error is not appropriate because it does not take these differences into account. For our purposes, it is important to explicitly eliminate the size of the districts. Therefore, the focus here is on the mean absolute percentage forecast error (MAPFE) which is defined as:

$$MAPFE_{i,\theta} = \frac{1}{12} \sum_{h=1}^{12} \frac{|\hat{y}_{i,T+h} - y_{i,T+h}|}{y_{i,T+h}} \times 100 \qquad (8)$$

where $\theta \in \{2004, 2005, 2006\}$ denotes the year for which the simulated out-of-sample (SOOS) forecast was performed and T is the December in the year prior to the respective SOOS-year.

4.1   Overview of the Results of the Models

As can be seen from Table 3, all models lead to relatively high-quality forecasts given the fact that – due to the small spatial units being analysed here and the pronounced seasonal and cyclical time series – there is both a large variation in the level of unemployment within as well as between labour-market districts over time. With the exception of the EWMA model in 2005 and the ARIMA forecast in 2006, the mean MAPFEs are always well below ten percent. In fact in 2004, the two spatial models both have average MAPFEs of only slightly over four percent and the lowest standard

Table 3: Mean Absolute Percentage Forecast Errors 2004 – 2006

	2004				2005				2006			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
EWMA	6.07	6.25	0.67	58.87	10.64	5.29	1.79	31.12	8.04	4.44	1.50	30.69
ARIMA	4.26	3.05	0.64	22.70	7.64	3.96	2.02	22.56	10.19	6.51	1.62	31.23
SC	4.49	3.04	0.48	14.57	8.23	4.51	1.33	30.78	8.37	4.64	1.70	25.09
SCAR	4.83	3.54	0.92	21.94	8.16	4.56	1.06	32.42	8.21	4.72	1.70	25.09
SCSARC	4.01	2.60	0.54	14.05	8.14	4.56	1.22	31.78	8.51	4.94	1.86	24.95
SCSARD	4.08	2.73	0.56	13.92	8.20	4.56	1.39	31.69	8.32	4.72	1.71	24.91

deviations and maximum errors of all models. The forecasting error of 4.01% for the SCSARC model in 2004 means a deviation of approximately 176,000 unemployed relative to the real unemployment value (4,381,000). The overall highest average MAPFE calculated for the EWMA model in 2005 stands for nearly 517,000 unemployed relative to a base of 4,861,000.

Further, compared to 2004, a high increase of the MAPFEs of all models in 2005 is noticeable. The forecast error is often twice as high as in 2004. This strong increase is a result of a new method of counting the unemployed in the course of large labour-market reforms in Germany.[12] Firstly, since then the former welfare recipients who are able to work are counted as unemployed. Secondly, it took several months before the software used by the communities was completely compatible with that used by the Federal Employment Agency. Therefore, for the first few months in 2005, the unemployment figures had to be at least partly estimated in some regions. Both these facts mean that there is likely to be much more disturbance in the data in 2005. However, standard time-series models as well as our augmentations are not contrived to consider such structural breaks. The MAPFEs in 2006 stay at nearly the same high level as in 2005. This is due to the fact that for the SOOS period in 2006, the applied data end in 2005. Additionally, a trend reversal as an implication of the economic upturn at the end of 2005 leads to less precise forecasts. This can especially be seen in the ARIMA model, i.e. the model in which the autoregressive structure of the data plays a decisive role. For this model, the forecast error increases sharply relative to 2004 and 2005.

Noting that not all regions are affected by the statistical reorganisation and the overall positive economic environment to the same extent, the variation of the MAPFEs is quite large. The most precise forecast is found for a SC model in 2004, representing a small labour-market district in Lower-Saxony. Given the 23,200 unemployed, our forecast differs by only 100 (0.48%). At the other extreme, the highest MAPFE of 58.87% results in the EWMA model in 2004. This is calculated in a similarly small (30,805 unemployed) district, but one with a much more pronounced seasonal influence in Saxony.[13] As the focus of this paper is on the spatial models' specification, we examine their results in more detail.

4.2 The Results of the Spatial Models in Detail

Spatial dependencies clearly play an important role in our forecasts. In 2004 and 2005, spatial lags are included in the final regressions in roughly 70 percent of the

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[12] The German labour-market districts responded to this structural break heterogeneously. Hence, a simple adjustment to this break is not sufficient. More complex adjustment methods would require external information which is not included in the univariate setting.

[13] Generally, rural and seasonally dependent regions have very imprecise EWMA forecasts. Our model underestimates the seasonal component as its span sharply declines in the 2004 SOOS-period. This leads to the fact that the other components are relatively more important with the result that almost a simple exponential smoothing model is calculated and in every treated region the predicted number of unemployed decreases from month to month.

labour-market districts. In 2006, however, they are less important as they only influence the final regressions in roughly 55 percent of the SCSARC regressions and 40 percent in the SCSARD regressions. This seems to be due to the large labour-market reforms mentioned above which may have changed the former relations or decreased the signal-to-noise ratio resulting in less clear dependence relations.

Figure 3 shows which spatial lags are included how often in the spatial contiguity and distance models. It can again be seen that there are large differences between 2006 and the other two years. In the forecast for 2006 only the very short-term lags of up to two (three) months in the SCSARD (SCSARC) case are selected. This also reflects the structural break due to the German labour-market reforms in 2005. In the other two years on the other hand, in both spatial models also the one-month spatial lag, additionally in the SCSARC model the six-month and in the SCSARD model the two-month spatial lag, respectively, most often have a significant influence on the forecast and lead to an improvement of the AIC_c. The spatial lags for eight and ten months in the past play no role in the SCSARC models. The spatial models where the distance is used to calculate the weight matrix show a slightly different spatial lag inclusion. In 2004 only the five-month spatial lag is not in the model. For 2005 a slightly surprising spatial lag selection is found: all tested spatial lags are included in the model with the exception of the six and twelve-month spatial lag. Overall, spatial lags are more often included in the SCSARC models, presumably because the contiguity based weighting scheme considers only the close-by regions whereas the distance based scheme considers all although the weight of distant regions is small. Especially in spatially large districts, the relatively long distance even to neighbouring districts automatically leads to a lower weight of and hence lower potentially significant influence than is the case in the contiguity model.

Figures 4 and 5 show in which regions the spatial dependencies are the most important, i.e. how many different spatial lags were included in the final regression for a particular labour-market district. The more spatial lags included in the final estimation, the darker is the colouring of the district. As above, the spatial pattern in 2006 in both models differs from that in the previous two SOOS periods. In 2004 and 2005 it is the larger cities where the spatial lags have the most influence. There are two explanations for this: First, unemployment changes in these cities are very likely to also drag the development in neighbouring or nearby regions. This means that the developments in these neighbouring regions all point in the same direction and hence become jointly significant. The neighbouring districts themselves are however not only influenced by the close large city but also by other (smaller) labour-market districts in the vicinity which might be undergoing a different development. Hence in this case, the regional influences are ambiguous so that the spatial lags are not significant or do not improve the model fit enough to improve the AIC_c. Second, the share of employees working in the service sector relative to the industrial sector is higher in cities. The economic situation in the service sector, at least to the extent that it provides local non-tradeable services, depends on the performance of the industrial sector in the periphery. Therefore, a downturn (upturn) in the periphery is likely to
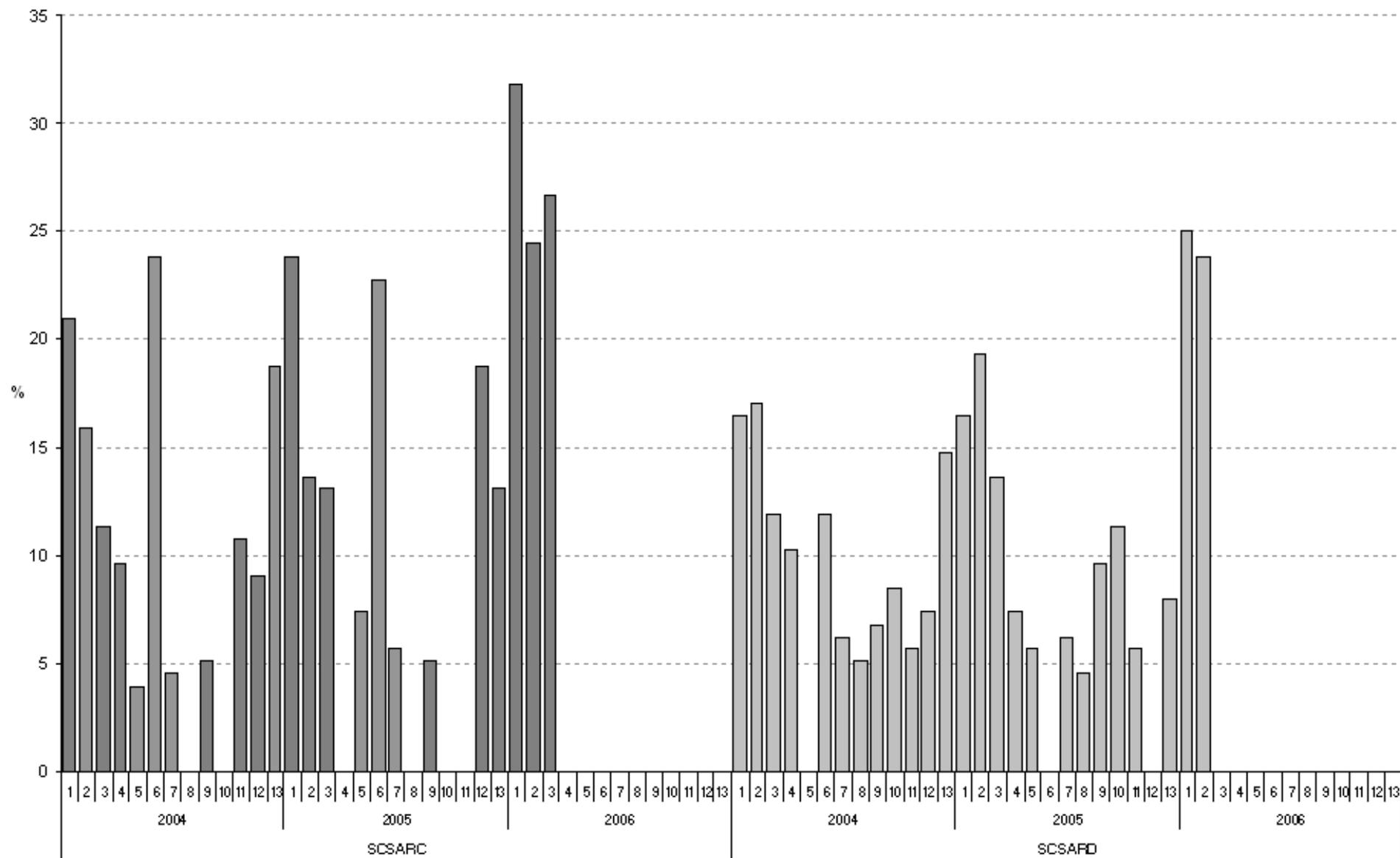
Figure 3: Inclusion of Spatial Lags in the Forecasts: Share of Regions where $\pi_{i,\ell}, \ell = \{1, \ldots, 13\}$ is significantly different from zero

2004   2005   2006
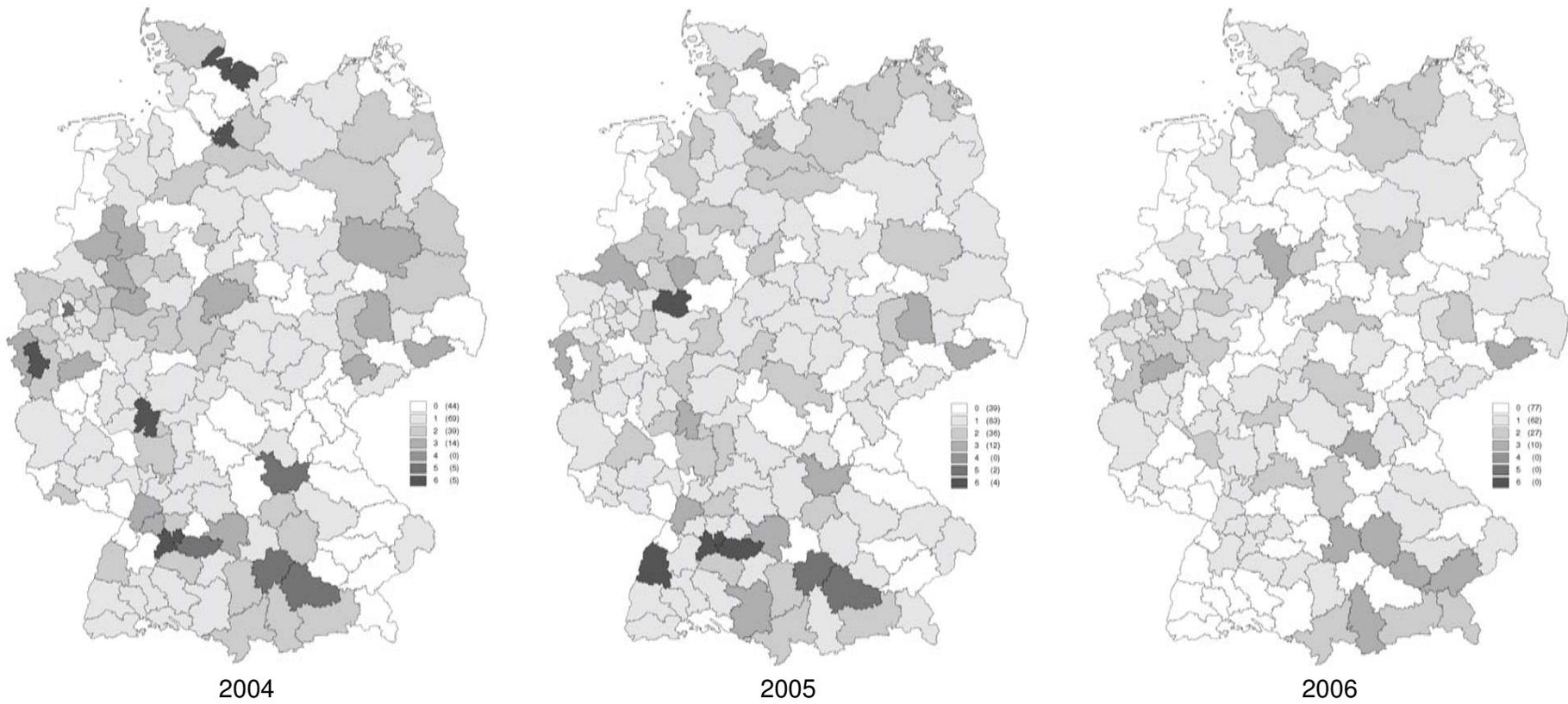
Number of labour-market districts in parenthesis

Figure 4: Inclusion of Spatial Lags in the SCSARC Model, 2004 – 2006

2004	2005	2006
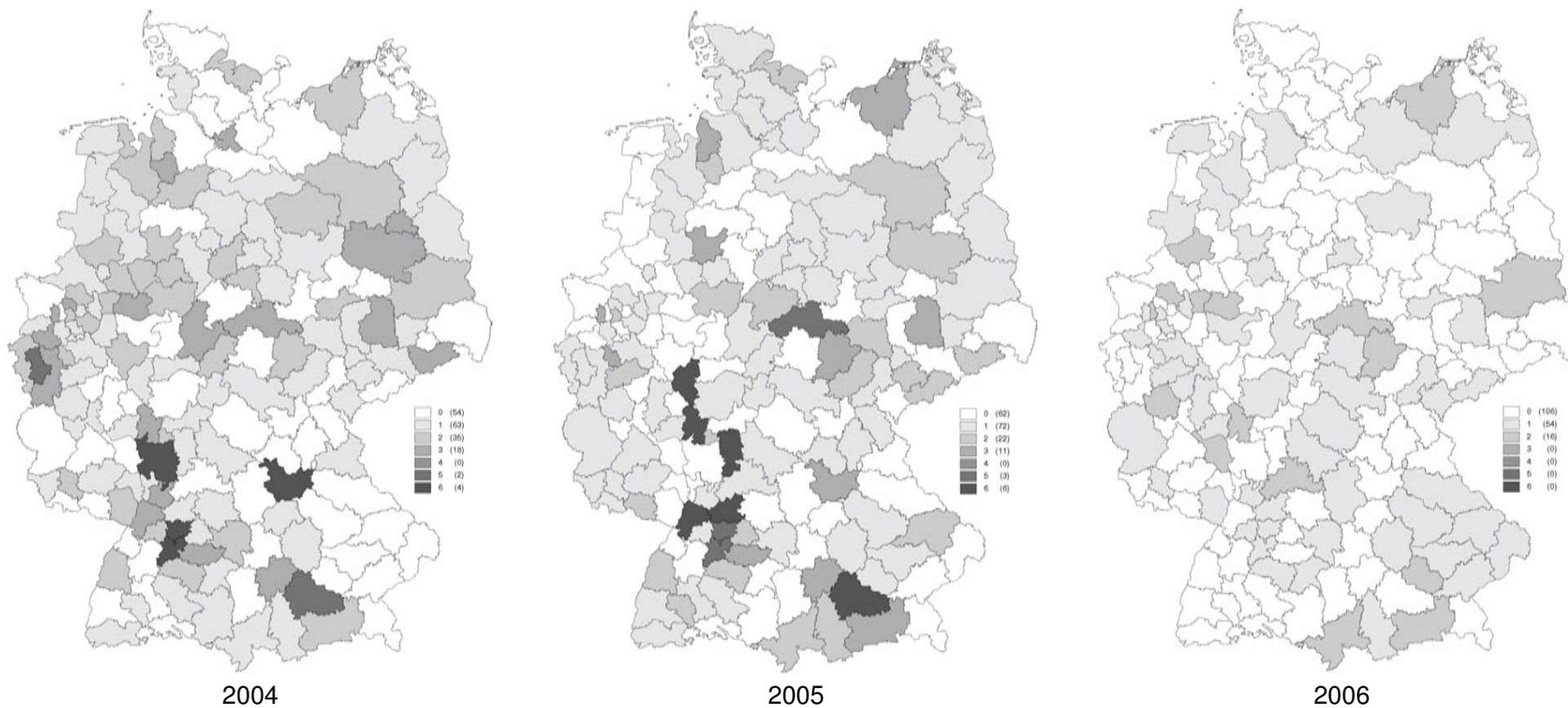
Number of labour-market districts in parenthesis

Figure 5: Inclusion of Spatial Lags in the SCSARD Model, 2004 – 2006

negatively (positively) effect the number of unemployed in the service sector located in the "central city".

Tables 4 and 5 show that – with the exceptions of the ARIMA and SCAR in 2005 and the EWMA and SCAR in 2006 – the number of labour-market districts whose MAPFE improves (i.e. decreases) by using spatial GVAR models is higher than where it leads to a poorer MAPFE. Further, the average percentage-point change is usually larger for the improvements than it is for those labour-market districts where the forecast errors are higher in the spatial models.

We run Diebold-Mariano tests (Diebold / Mariano, 1995) to see whether the spatial models lead to a significant improvement in the forecast for an agency or not.[14] This test compares two forecasts of the same variable by testing the null hypothesis of equal accuracy in forecast performance. A forecast of a spatial model is denoted as better (worse) if the null hypothesis is rejected and the model has the lower (higher) mean squared forecast error.

The Diebold-Mariano test also highlights the fact that the spatial models often lead to better forecasts than the other models. The spatial models are significantly better in 8 out of 12 cases. Significantly worse forecasts of the SCSARC and SCSARD models solely arise in 2005 and 2006. The pattern for the two spatial models is identic. In 2005 the ARIMA and the SCAR model do indeed perform significantly better and in 2006 the EWMA and the SCAR forecasts are more precise. Although the lag selection (see Figure 3) is different between the SCSARC and SCSARD model, a look at the performance of these models at the level of labour-market districts shows only marginal differences between the two spatial alternatives. Per year, in at most 13 of the 176 labour-market districts is one spatial model more accurate than a certain comparison model when the forecast of the other spatial model was less precise.

5   Conclusion

In this paper we forecast unemployment for all 176 labour-market districts in Germany. We explicitly consider the spatial interdependence which may arise between them. Due to this large number of regions, we use a spatial GVAR model. In one spatial model, the SCSARC model, the effect of all neighbouring districts on the district being analysed is accounted for. In a second spatial model (SCSARD), the role of all other districts is analysed whereby the potential influence of a district declines with increasing distance from the district which is being analysed.

With regard to the structure of the interregional dependence in space and time, two conclusions can be made. First, the selection of the included spatial autoregressive lags differs between the SCSARC and the SCSARD model. While the distance-based, continuous spatial connectivity scheme shows no certain time structure, in

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[14] We also applied the modified Diebold-Mariano test as proposed by Harvey et al. (1997). This did not lead to different results from those in the original test.

Table 4: Comparison of SCSARC Results with other Models using the Diebold-Mariano Test

| | 2004 | | | | 2005 | | | | 2006 | | | |
	EWMA	ARIMA	SC	SCAR	EWMA	ARIMA	SC	SCAR	EWMA	ARIMA	SC	SCAR
No. of districts with improvement	108	94	100	112	112	73	93	87	81	107	88	81
No. of districts with decline	68	82	76	64	64	103	83	89	95	69	88	95
Average percentage-point change:												
of improved	-5.03	-2.59	-1.59	-2.01	-6.47	-3.79	-0.90	-1.12	-4.00	-5.39	-0.94	-1.52
of declined	2.65	2.44	0.98	1.28	3.97	3.64	0.87	1.04	4.28	4.07	1.22	1.86
significantly better forecasts	82	68	72	78	84	47	48	45	46	72	60	59
significantly worse forecasts	36	48	47	42	18	49	46	51	50	33	63	58
no significant differences	58	60	57	56	74	80	82	80	80	71	53	59

Table 5: Comparison of SCSARD Results with other Models using the Diebold-Mariano Test

| | 2004 | | | | 2005 | | | | 2006 | | | |
	EWMA	ARIMA	SC	SCAR	EWMA	ARIMA	SC	SCAR	EWMA	ARIMA	SC	SCAR
No. of districts with improvement	108	90	102	113	108	73	90	84	86	106	91	80
No. of districts with decline	68	86	74	63	68	103	86	92	90	70	85	96
Average percentage-point change:												
of improved	-5.03	-2.59	-1.59	-1.90	-6.47	-3.79	-0.90	-1.19	-3.79	-5.66	-1.06	-1.80
of declined	2.65	2.44	0.98	1.32	3.97	3.64	0.87	1.15	4.16	3.87	1.02	1.71
significantly better forecasts	84	64	85	83	85	43	51	49	48	74	61	61
significantly worse forecasts	33	45	50	43	20	50	52	56	49	35	59	54
no significant differences	59	67	41	50	71	83	73	71	79	67	56	61

the dichotomous SCSARC model, particularly the almost simultaneous one- to three-month lags, the half-year and the one-year lag are most relevant. Second, the regional pattern is similar for the two spatial models. Spatial lags are mainly included in the forecasts for urbanised regions and central cities.

We evaluate the models using simulated out-of-sample forecasts for three years. The forecast errors are in the range of between four and ten percent. Compared to the average seasonal variation of nearly 20 percent (with a maximum of 67 percent), a forecast error of about 4 to 10 % is clearly small. As to our knowledge there is no unemployment forecasting study for small spatial units in Germany, the forecast quality can only be evaluated by looking at employment forecasts: The number of employees is nearly seven times higher than that of the unemployed. Hence, the above mentioned forecast error of four to ten percent in unemployment corresponds to the same number of people as an employment forecasting error of 0.6 to 1.4 %. Other employment forecasting studies for Germany reach considerably higher errors of about 0.7 to 4 %. Therefore, we conclude that the forecast quality of all our models is very high.

In the majority of the 176 regions, the forecasts are slightly more accurate when accounting for spatial dependencies. Only in less than one third of the regions are the spatial forecasts less precise than those of the comparison models. Hence, the two spatial models are often equally or more accurate than the comparison models. Because none of the models is known to be outperformed ex-ante, supposedly a combination of the different forecast approaches in which the model results are pooled to one forecast might further improve the overall accuracy.

References

Anselin, Luc (1988): *Spatial Econometrics: Methods and Models*, Dortrecht: Kluwer Academic Publishers.

Arbia, Giuseppe/ Bee, Marco/ Espa, Giuseppe (2007): Aggregation of Regional Economic Time Series with Different Spatial Correlation Structures, Department of Economics Working Papers 20/2007, University of Trento.

Baltagi, Badi H. (2006): Forecasting with Panel Data, Discussion Paper 25, Deutsche Bundesbank.

Baltagi, Badi H./ Li, Dong (2004): Prediction in the Panel Data Model with Spatial Correlation, in: Anselin, Luc/ Florax, Raymond J. G. M./ Rey, Sergio J. (Eds.) *Advances in Spatial Econometrics*, Heidelberg and New York: Springer, chap. 13, pp. 283–295.

Beaulieu, J. Joseph/ Miron, Jeffrey A. (1993): Seasonal Unit Roots in Aggregate U.S. Data, *Journal of Econometrics*, 55, pp. 305–328.

Beenstock, Michael/ Felsenstein, Daniel (2007): Spatial Vector Autoregressions, *Spatial Economic Analysis*, 2, pp. 167–196.

Behrens, Kristian/ Thisse, Jacques-Francois (2007): Regional Economics: A New Economic Geography Perspective, *Regional Science and Urban Economics*, 37, pp. 457–465.

Box, George. E.P./ Jenkins, Gwilym M. (1970): *Time Series Analysis: Forecasting and Control*, San Francisco: Holden-Day.

Chatfield, Chris/ Yar, Mohammad (1988): Holt-Winters Forecasting: Some Practical Issues, *The Statistician*, 37, 2, pp. 129–140.

Diebold, Francis X./ Mariano, Roberto S. (1995): Comparing Predictive Accuracy, *Journal of Business and Economic Statistics*, 13, 3, pp. 253–263.

Dreger, Christian/ Reimers, Hans-Eggert (2005): Panel Seasonal Unit Root Tests: Further Simulation Results and an Application for Unemployment Data, *Allgemeines Statistisches Archiv*, 89, 8, pp. 321–337.

Franses, Philip H. (1991): Seasonality, Non-stationarity and the Forecasting of Monthly Time Series, *International Journal of Forecasting*, 7, pp. 199–208.

Fujita, Masahisa/ Krugman, Paul R./ Venables, Anthony J. (1999): *The Spatial Economy. Cities, Regions, and International Trade*, Cambridge (MA), London: The MIT Press.

Giacomini, Raffaella/ Granger, Clive W. J. (2004): Aggregation of Space-Time Processes, *Journal of Econometrics*, 118, 1-2, pp. 7–26.

Haining, Robert (2003): *Spatial Data Analysis. Theory and Practice*, Cambridge, New York (NY): Cambridge University Press.

Hampel, Katharina E./ Kunz, Marcus/ Schanne, Norbert G./ Wapler, Rüdiger/ Weyh, Antje (2007): Regional Employment Forecasts with Spatial Interdependencies, Discussion Paper 02/2007, IAB.

Harvey, Andrew C. (2004): Forecasting with Unobserved Components Time Series Models, in: Elliott, Graham/ Granger, Clive W. J./ Timmermann, Allan (Eds.) *Handbook of Economic Forecasting*, Amsterdam et al.: Elsevier, chap. 7, pp. 327–412.

Harvey, David/ Leybourne, Stephen/ Newbold, Paul (1997): Testing the Equality of Prediction Mean Squared Errors, *International Journal of Forecasting*, 13, 2, pp. 281–291.

Hernandez-Murillo, Ruben/ Owyang, Michael T. (2006): The Information Content of Regional Employment Data for Forecasting Aggregate Conditions, *Economic Letters*, 90, pp. 335–339.

Hurvich, Clifford M./ Tsai, Chih-Ling (1989): Regression and Time Series Model Selection in Small Samples, *Biometrika*, 76, 2, pp. 297–307.

Inoue, Atsushi/ Kilian, Lutz (2006): On the Selection of Forecasting Models, *Journal of Econometrics*, 130, 2, pp. 273–306.

Kelejian, Harry H./ Prucha, Ingmar R. (2007): The Relative Efficiencies of Various Predictors in Spatial Econometric Models Containing Spatial Lags, *Regional Science and Urban Economics*, 37, pp. 363–374.

Kholodilin, Konstantin A./ Siliverstovs, Boriss/ Kooths, Stefan (2007): Dynamic Panel Data Approach to the Forecasting of the GDP of German Länder, Discussion Paper 664, Deutsches Institut für Wirtschaftsforschung (DIW), Berlin.

Longhi, Simonetta/ Nijkamp, Peter (2007): Forecasting Regional Labour Market Developments under Spatial Autocorrelation, *International Regional Science Review*, 30, 2, pp. 100–119.

Magura, Michael (1998): IO and Spatial Information as Bayesian Priors in an Employment Forecasting Model, *Annals of Regional Science*, 32, 4, pp. 495–503.

Mayor, Matías/ López, Ana Jesús/ Pérez, Rigoberto (2007): Forecasting Regional Employment with Shift-Share and ARIMA Modelling, *Regional Studies*, 41, pp. 543–551.

Moran, Patrick A. P. (1948): Some Theories in Time Series: II. The Significance of the Serial Correlation Coefficient, *Biometrika*, 35, 3-4, pp. 255–260.

Mutl, Jan (2007): Consistent Estimation of Global VAR Models, `http://www.wiwi.uni-frankfurt.de/profs/binder/mutl/papers/gvar_01_2007.pdf`, 23.11.2007.

Osborn, Denise R./ Heravi, Saeed/ Birchenhall, Chris R. (1999): Seasonal Unit Roots and Forecasts of Two-digit European Industrial Production, *International Journal of Forecasting*, 15, pp. 27–47.

Patuelli, Roberto/ Reggiani, Aura/ Nijkamp, Peter/ Blien, Uwe (2006): New Neural Network Methods for Forecasting Regional Employment. An Analysis of German Labour Markets, *Spatial Economic Analysis*, 1, pp. 7–30.

Pesaran, M. Hashem/ Schuermann, Til/ Weiner, Scott M. (2004): Modeling Regional Interdependencies using a Global Error-Correcting Macroeconometric Model, *Journal of Business and Economics Statistics*, 22, 2, pp. 129–162.

Rodrigues, Paulo M. M./ Osborn, Denise R. (1999): Performance of Seasonal Unit Root Tests for Monthly Data, *Journal of Applied Statistics*, 26, 8, pp. 985–1004.

Stock, James H. (2001): Forecasting Economic Time Series, in: Baltagi, Badi. H. (Ed.) *A Companion to Theoretical Econometrics*, Malden (MA): Blackwell Publishers, chap. 27, pp. 562–584.

Taylor, Robert (1998): Testing for Unit Roots in Monthly Time Series, *Journal of Time Series Analysis*, 19, 3, pp. 349–368.

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