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Regional Unemployment Forecasting Using Structural Component Models With Spatial Autocorrelation

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Regional Unemployment Forecasting Using Structural-Component Models with Spatial Autocorrelation

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Abstract

Labour-market policies in Germany are increasingly being decided on a regional level. This implies that institutions have an increased need for regional forecasts as a guideline for their decision-making process. Therefore, we forecast regional unemployment in the 176 German labour-market districts. We use an augmented structural-component (SC) model and compare the results from this model with those from basic SC and autoregressive integrated moving average (ARIMA) models.

Basic SC models lack two important dimensions: First, they only use level, trend, seasonal and cyclical components, although former periods of the dependent variable generally have a significant influence on the current value. Second, as spatial units become smaller, the interdependence between them increases.

In this paper we augment the SC model for structural breaks, autoregressive components and spatial lags. Using unemployment data from the Federal Employment Services in Germany for the period December 1997 to December 2005, we first estimate basic SC models with components for structural breaks and ARIMA models for each spatial unit separately. In a second stage, autoregressive components are added into the SC model. Third, spatial autocorrelation is introduced into the SC model.

We test the quality of the models with simulated out-of-sample forecasts for the period January 2005 to December 2005. Our results show that the SC model with autoregressive elements is not superior to basic SC and ARIMA models in most of the German labour-market districts. The SC model with spatial autocorrelation performs better than the other models in labour-market districts which have a low seasonal span and a relatively high unemployment rate.

1 Introduction

Due to large differences in the regional labour-market performance in Germany, labour-market policy is increasingly taking place on a regional level. This implies that the local institutions have an increased need for regional forecasts as a guideline for their decision-making process. Of primary interest are the predicted local unemployment levels. These have important consequences when planning the required labour-market expenditures. For this reason, we focus on unemployment forecasts of the German labour-market districts (Agenturbezirke) for a forecast period of 12 months.

There is a large variety of time-series models which can potentially be used for our purposes. These models range from simple univariate models to complicated multivariate methods. However, it has often been shown (cf. for example the overview in Stock 2001) that simple methods perform nearly as well as more complicated ones. Further, as we forecast unemployment for 176 labour-market districts and want to compare the results amongst the districts, we need to apply standardised methods. Therefore, our focus is on two standard univariate methods: Box-Jenkins ((A)uto-(R)egressive-(I)ntegrated-(M)oving-(A)verage) models and structural component (SC) estimators. We forecast unemployment on a monthly basis using the two models as benchmarks. Then, we augment the SC model for autoregressive components and a spatial component. Using simulated out-of-sample forecasts we are then in a position to compare the augmented model with the basic benchmarks.

The paper is organised as follows: After a description of the data and the regional variation in unemployment in Germany, we provide an overview of different approaches to regional forecasting. Section 4 describes the applied forecasting methods ARIMA, basic SC models, SC models with autoregressive elements and SC models with spatial lags. The presentation and discussion of our results follows, before a conclusion ends the paper.

2 Data and Regional Variation in Unemployment in Germany

Forecasting unemployment for the whole of Germany provides relatively robust forecasts, but the explanatory power of such forecasts is low for the regional development of small spatial units as regional differences are not included. Due to regional conditions such as a different industry structure, qualification, wage level, or other sources of local labour-market development, forecasts for a smaller spatial unit can differ from national forecasts and even predict opposite results. Considering regional distinctions, we forecast unemployment on the basis of 176 German labour-market districts¹, which are, with the exception of Berlin and Hamburg, between NUTS 2 and NUTS 3 regions. However, before we present the results of our forecasts, we will first describe our data and the current unemployment situation in Germany with a special emphasis on the regional differences.

To analyse the current unemployment situation and to perform our forecasts, we use process data from the German Federal Employment Agency. This data currently covers all registered unemployed in 176 German labour-market districts on a monthly basis for the time period from December 1997 to December 2005.

¹ 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 for all periods. For this reason, the districts in Berlin were aggregated at all times to one district so that we forecast the regional unemployment levels for 176 and not for 178 districts.

According to the definition used by the German Federal Employment Agency, a person is unemployed if he or she:

- temporarily does not work or works less than 15 hours per week,
- is looking for a job which is subject to social-insurance contributions,
- is at the German Federal Employment Agency's disposal, i.e. can be placed if a suitable job-opening is found,
- is registered as unemployed at the German Federal Employment Agency,
- is under 65 years old and
- is not incapable of working because of illness.

This definition is slightly different to the "labour force concept" of the International Labour Organization (ILO) (see e.g. Eurostat 1996). According to the ILO, persons who are not registered as job-seekers or who are not entitled to unemployment benefits can be included as well. On the other hand, everybody who works one hour or more per week is not counted as unemployed. Thus, the number of unemployed in the sense of the ILO is often much lower than the number of registered unemployed at the German Federal Employment Services.

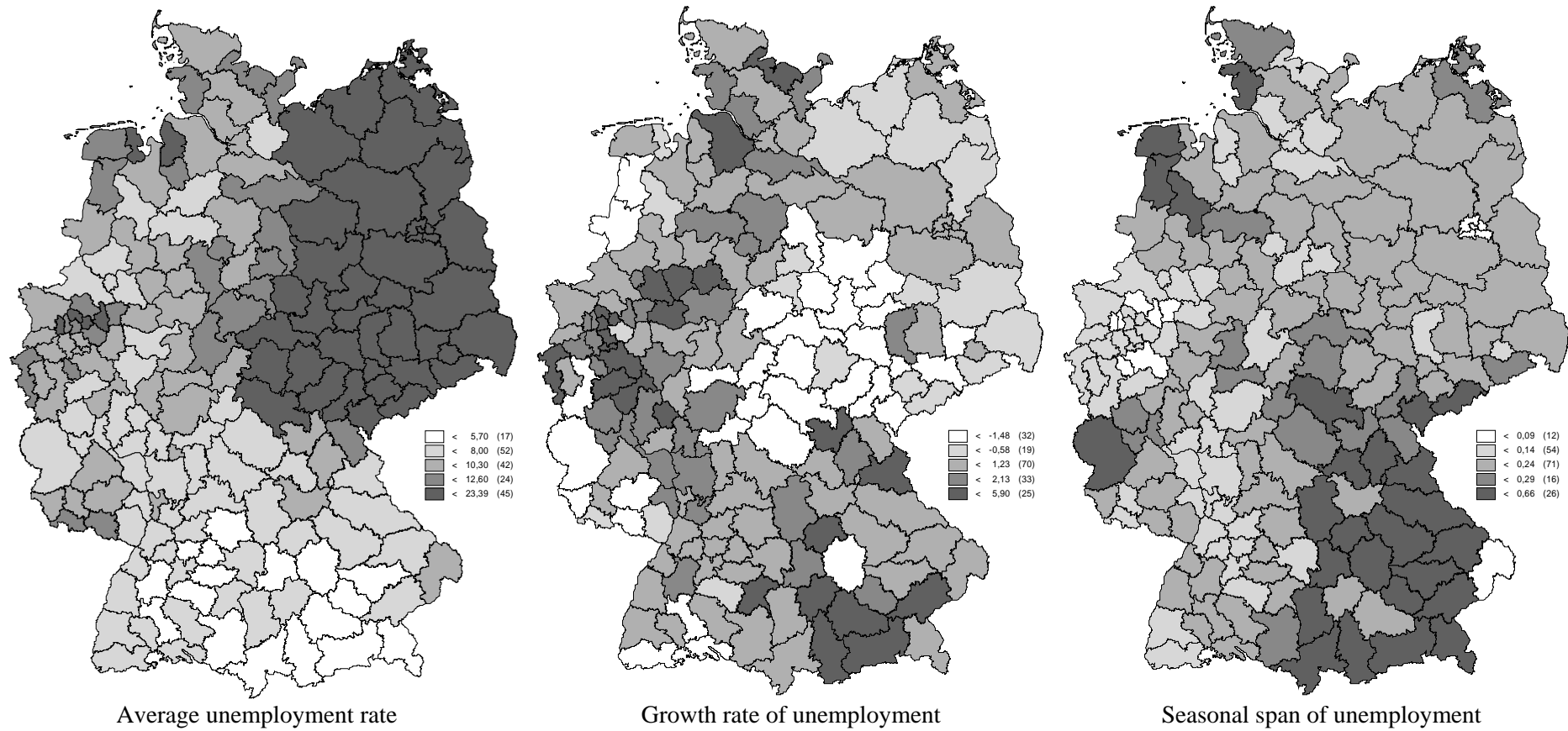
Due to substantial labour-market reforms based on a commission headed by Peter Hartz and hence the so-called "Hartz-Reforms", the scope of people who are officially counted as unemployed by the Federal Employment Agency changed considerably during our observation period. Since January 2005, former welfare recipients who are able to work (defined as being able to work for at least three hours per day) are counted as unemployed. Thus, for purely statistical reasons, the number of registered unemployed in Germany has substantially increased since then. Therefore, there is a structural break in our time series at this point in time. This break is most pronounced in western Germany and in urbanised labour-market districts. Although we control for this structural break, (the "Hartz-Effect") we cannot account for the modifications of the classification of unemployed and have to use the official data for our forecasts.

To illustrate regional differences in the development of unemployment in the 176 labour-market districts, Figure 1 shows the average unemployment rate, the average growth rate of unemployment and the seasonal span of unemployment.² The three maps simultaneously represent the basic elements of a time series: level, trend and season.

² The average growth rate of unemployment is calculated as the average of $\frac{Y_{Dec,t} - Y_{Dec,t-1}}{Y_{Dec,t-1}}$ for every year, where

$Y_{Dec,t}$ is the number of unemployed in December of year t . Our seasonal span is defined as the average of $\frac{Y_{max} - Y_{min}}{\bar{Y}}$ for every year, where Y_{max} is the maximum number of unemployed in the year, Y_{min} the minimum number and \bar{Y} the average number of unemployed in the year.

Figure 1: Average Unemployment Rate, Growth Rate and Relative Seasonal Span of Unemployment in Germany from 1998 to 2005



Source: Federal Employment Agency

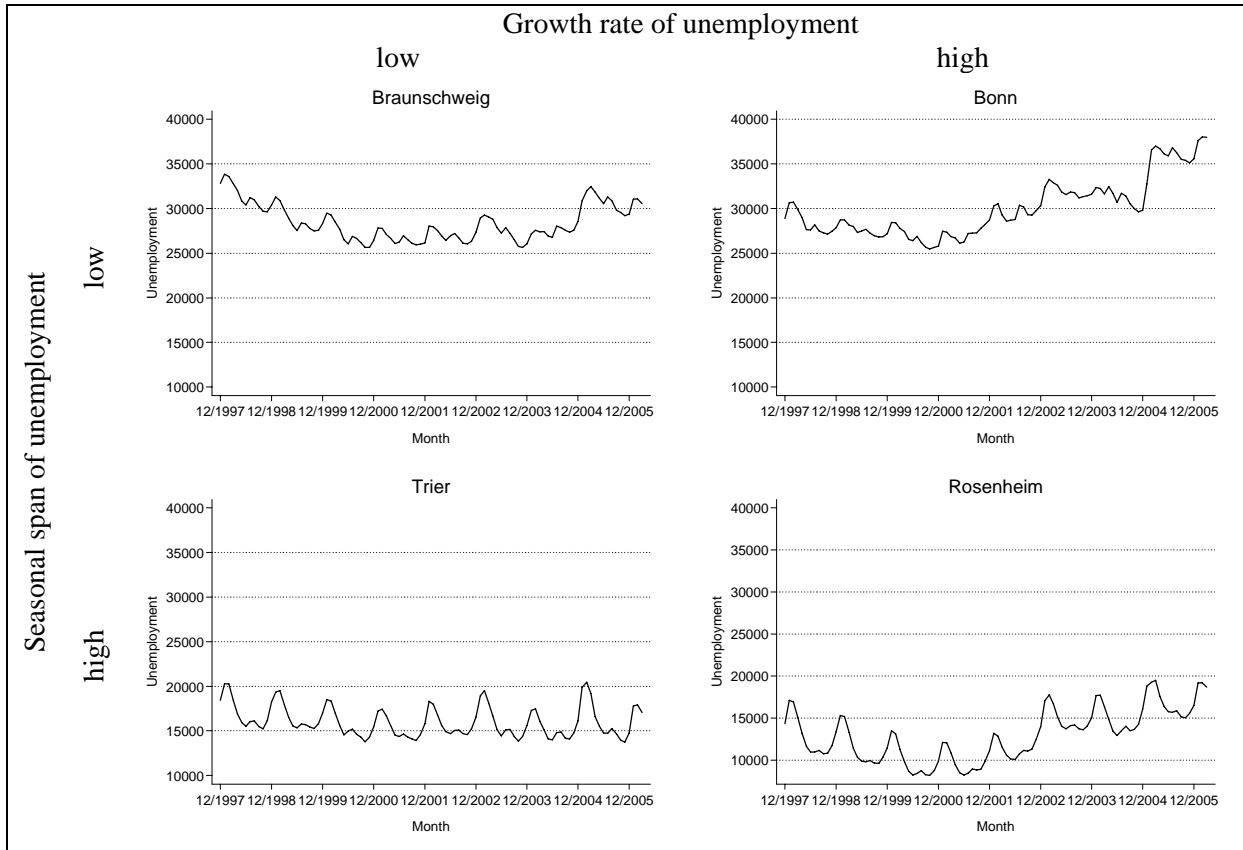
Typically, regional variation in unemployment is shown as differences between eastern and western Germany. However, as Figure 1 shows, this only holds for the average unemployment rate. The level of unemployment is much higher in the East than in the West. The average unemployment rate between 1998 and 2005 for eastern Germany amounts to 18.3 %. This is exactly 10 percentage points higher than in the West for the same time period. All eastern German labour-market districts have an unemployment rate of at least 12.6 %. Western German labour-market districts with relatively high unemployment rates are either adjacent to former East Germany, in the Ruhr area, Saarland or in the North. Relatively low unemployment rates can be found in southern Germany, more precisely in the south of Baden-Wuerttemberg and Bavaria.

The highest reduction in unemployment can be seen in the two eastern NUTS 1 regions Thuringia and Saxony-Anhalt. Unemployment in Ingolstadt in Bavaria, some labour-market districts in Hesse and some regions on the border to France has also declined. However, the negative growth rates of most of the eastern German labour-market districts should always be interpreted against the background of their high unemployment level. An increase in unemployment can be found in the south of Bavaria, in North-Rhine-Westphalia and along the coast of the North Sea.

Generally, urban labour-market districts have lower seasonal spans than rural areas. Often touristy regions and those where agriculture is important have high seasonal spans. Both can be mainly found along the coast of the East and North Sea, in East German low mountain ranges and in Bavaria. Comparing all three maps in Figure 1, large regional disparities become clearly visible. It can also be seen that labour-market districts which are located close to each other follow similar patterns, i.e. unemployment effects in neighbouring districts have an influence on the level of unemployment in the district being analysed. Thus, it can clearly be seen from Figure 1 that a general forecast for the whole of Germany is not sufficient for forecasting regional unemployment.

Figure 2 confirms these findings. It shows four labour-market districts with different combinations of growth rates and seasonal spans. Rosenheim, situated in the south of Bavaria, shows a high seasonal span with a positive growth rate of unemployment. A negative growth rate with a low seasonal span is observable in Braunschweig, a labour-market district near the Harz in Lower Saxony. Trier as a wine-growing region has a high seasonal span but a positive development of unemployment (i.e. negative growth rates of unemployment). A high growth rate of unemployment and a low seasonal span can be found in Bonn, the former capital of Germany. All in all, there is ample evidence that unemployment forecasts for Germany should be regionally differenced. Additionally, we find support that neighbourhood-effects are important when forecasting small regional units.

Figure 2: Different Combinations of the Growth Rate and Seasonal Span of Unemployment

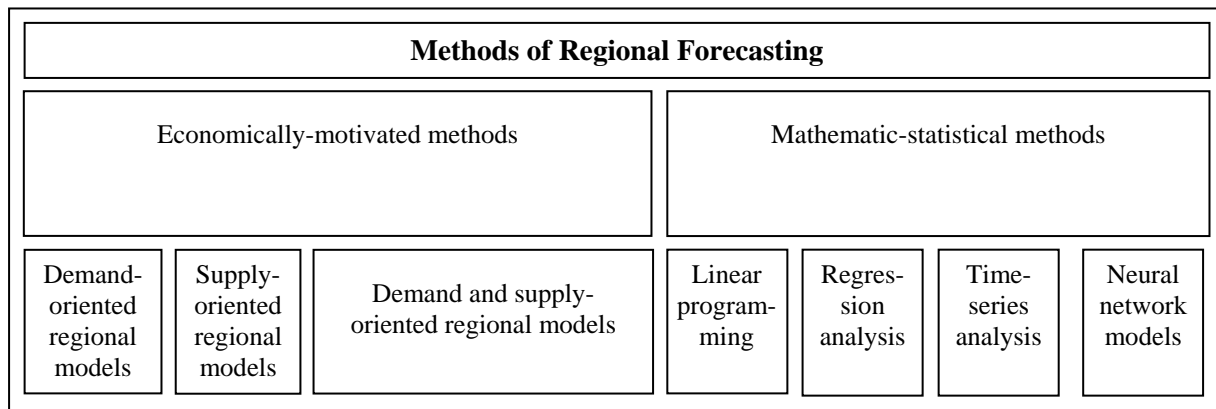


Source: Federal Employment Agency

3 Regional Labour Market Forecasts

Regionalised labour-market analyses are becoming more and more important, but the number of studies on regional forecasting is limited. Both, theoretical and empirical papers focus on employment rather than on unemployment. They can, however, also be applied to unemployment. Hence, in this section we present the theoretical background as well as some empirical specifications for forecasting regional employment. Figure 3 shows a taxonomy of regional employment forecasting methods.

Figure 3: Taxonomy of Methods of Regional Forecasting



Methods of regional employment forecasting can roughly be divided into two groups: economically-motivated and mathematical-statistical methods. The first group can be further divided into three sub-groups: demand-oriented, supply-oriented and demand and supply-oriented models. A well-known demand-oriented regional model is the economic-base-concept, which divides the regional economy in a base- (local needs serving sector) and a non-base sector (export sector). According to this concept, regional export activity is crucial for the regional growth process: The higher the local income from the export sector, the higher will be their demand for local products and services. For this reason, the economic base concept models the whole employment development as a function of the employment in the regional export sector. Developed in the 1950s, the economic base concept can in times of high import rates and complex economic relationships no longer be considered appropriate. The obvious shortcomings of this demand-based method have been described repeatedly (see e.g. Fritsch 1991) and the model has nowadays been abandoned as a forecasting tool for local employment (Jaeger 1996, 5).

Great importance for regional development is however still being attributed to determinants of production. In particular the Shift-Share-Analysis (SSA) as a supply-oriented model is widely-used to analyse regional employment pathways (for a German example of labour-market forecast with the SSA see Tassinopoulos 1996). The Shift-Share Approach interprets a variance in regional employment as a product of a structural (shift) and a local (share) component.³ The structural component shows how a region would develop if the regional employment growth in an industry was analogous to the national development of the corresponding industry. The local component is defined as a residuum that remains, if the actual variance was reduced by structural industrial influences. Infrastructure or the quality of the regional job offers for example can be among the factors hiding behind this share component. The conventional shift-share-method has often been criticised as it does not permit a model-assisted procedure, the observation of causality is problematic and it is not possible to incorporate additional exogenous variables (Blien and Wolf 2002). Nonetheless, the value of shift-share techniques as an analytical tool for regional science is generally considered as high, whereas many authors emphasise its problems as a forecasting tool (Tassinopoulos 1996, Bade 1991). Sweeney (2004) has generally criticised supply-oriented models for their implicit assumption of an infinitely elastic labour supply. He proposes a model which incorporates demographic forces into supply-oriented projections.

There are two concepts of demand and supply-oriented regional models. To assess the future performance of regional labour markets, the concept of labour-market accounts contrasts past developments of labour supply and demand. The difference between supply and demand is the resulting “labour market gap”, which has to be forecasted by separate estimations of the regional labour supply and demand developments. (as an example of a German labour-market account study, see Eltges et al. 1993, Eltges and Wigger 1994, Klaus and Maußner 1988, Eckey and Stock 1996). Due to its many disadvantages (see e.g. Jaeger 1996, 16-17), forecasting on the basis of this concept is associated with high uncertainty. The second concept in the category of demand-supply approaches is the regional input-output-analysis, an analytical tool to analyse inter-industry relations in a region. These relations depict how the output of one industry serves as an input of another one, and thereby makes one industry dependent on another both as customer of output and as supplier of inputs. Input-output models are widely used in economic forecasting to predict flows between sectors (see e.g. Rickman and Miller 2003, Schindler et al. 1997). Problems with this so called conditional forecast concept might occur when the assumption of constant coefficients is violated and not incorporated by trend estimations (Jaeger 1996, 20).

³ This structural component should not be mistaken with our time-series structural component.

Within the class of mathematic-statistical methods we include the method of linear programming, regression analysis, time-series analysis and the neural network approach. The mathematical method of linear programming is used to maximise or minimise a linear function under (linear) constraints (cf. Thoss and Kleinschneider 1982). The power of this method lies in considering forecast relevant information via restrictions, prediction floors and sensitivity analysis. However, wide knowledge about regional data and functional relations is required.

Although the results of regression analysis for forecasting are not fully satisfactory (Jaeger 1996, 27), this method should be shortly described in particular with regard to its forecasting capacities. The basic purpose of a regression analysis is the determination of the dependence between a dependent variable and independent variables. An application of the regression analysis as an instrument for regional employment forecasting is often limited by narrow databases. In most cases, data is not collected or made public because of data-protection laws (see Hamm and Wienert 1989, 210). Further, in small spatial units there are influences that are not modelled in the normal range of the residuum so that regional forecasting with regression models is complicated (Jaeger 1996, 27) or can only perform well when the influences are considered respectively (for an example of a mixed approach of common extrapolation techniques and regression analysis see Oberhofer et al. 2000)

The most commonly used approach for (regional) forecasting, however, is time-series analysis. A good overview of time-series forecasting is given by De Gooijer and Hyndman (2005). Unlike regressions, time series analyses do not require any statements of causalities. These methods rather assess regularities in the time series and try to describe the data generating process by either deterministic or stochastic modelling. The simplest form of deterministic trend analysis and forecasting consists in exponential smoothing, a method where the forecast values are calculated from past data, whereas more actual data are incorporated with exponentially higher weights. Several authors have shown that exponential smoothing methods are surprisingly well predicting the near future (Satchell and Timmermann 1995, Chatfield et al. 2001). Other deterministic models strive to identify time-invariant structural components in a series, such as a level, trend or seasonal pattern (see De Gooijer and Hyndman 2005). Authors, who deal with such structural component models are Ray (1990), Harvey (1989) and Proietti (2000). The second way of analysing and forecasting time series is to model stochastic trends. A stochastic process can be based on autoregressive (AR) as well as on moving average (MA) components (see Section 4.1). Stochastic trend analyses, however, do not play a major role in regional labour market forecasting. Jaeger attributes this fact to the limits of forecasting horizon in ARIMA processes (Jaeger 1996, 31).⁴

A recent approach in the set of mathematic-statistical methods for Analysis and Forecasting Regional Employment has at least to be denoted here: Non-linear Neural Network Models (see for an example of German Labour Market Forecasts: Patuelli et al. 2006, partially in combination with Shift-Share-Analysis, Longhi et al. 2005). In contrast to traditional statistical models, they do neither require an identification process for the set of regressors employed, nor a specification of the relationship between dependant and independent variables. The technique essentially consists in modelling non-linear relationships among variables as inputs to a forecast, where the inputs are transformed through weighted combinations, substituted into one or more non-linear indicators. Whereas some authors

⁴ More common than univariate ARIMA models have been transfer functions (dynamic regression models) (see e.g. Weller 1989, Weller 1990) and multivariate (vector) ARIMA models in labour market forecasting. (see e.g. Patridge and Rickman 1998). However, parsimonious ARIMA models or transfer functions can still beat VARs, as Edlund and Karlsson (1993) show for Swedish unemployment rates.

report positive results from labour market forecasts using ANNs (Swanson and White 1997 as well as Stock and Watson 1998, who state that ANNs perform at least most slightly better than other time series techniques), others think that they are more powerful for financial variables than for labour market forecasts (for the reasons see amongst other Diebold 1998, 182).

As we have seen in this section, there have been various forecast studies for different German labour market regions (see Bruch-Krumbein et al. 1994, Eltges-Wigger 1994 and Klaus and Maußner 1988 for 18 Bavarian regions). Furthermore, some authors have completed studies for the whole of the German labour market regions, focussing on employment (Bade 1991, 1996, 1999, 2003 and Blien and Tassinopoulos 2001, Longhi et al. 2005, Patuelli et al. 2006). However, to our knowledge so far there have been no attempts to perform German labour-market forecasts with individually specified regional models, including e.g. spatial lag components. This gap is filled by the paper presented here.

4 Applied Forecast Methodology

In order to test which model we want to base our final forecast on, we first develop two univariate time-series models. These simple models often perform nearly as well as more complex methods. Here they are also used as reference models with which more complicated models can later be tested against. In a second step, the structural component model used here is extended to include autoregressive elements or spatial lags. Then, the results from the extended models can be compared with those from the simpler ones to test whether the forecast accuracy improves or not. In addition, it is important that the forecast results are comparable with each other. This means that we need to simultaneously forecast the unemployment levels of the 176 German labour-market districts. Hence, standardised methods are much easier to apply where the same basic assumptions are fulfilled in all districts. The disadvantage is that a certain degree of flexibility in modelling locally important labour-market processes is lost.

We use all data until and including December 2004 to run simulated out-of-sample forecasts for 2005 with which the performance of the models can be evaluated (see Section 5). Subsequently, the out-of-sample forecasts for 2006 are performed. To a large extent, the variable-selection procedure is automatised within standardised rules. We test which variables have a systematic influence and improve the model fit in each agency and include only these variables in the final regressions. In a last step, we check the final forecast specification to control for violations of the underlying assumptions of the respective models.

4.1 ARIMA-Forecast

Autoregressive-Integrated-Moving-Average (ARIMA) models are a standard procedure when forecasting time series. This so-called “Box-Jenkins” forecast method (see c.f. Box and Jenkins 1970 and Greene 2003) progresses in four steps:

- (1) In order for ARIMA-models to yield consistent results, it must first be ensured that the autoregressive process is stationary.
- (2) We test which previous periods are the most significant in explaining the current observation. This is done using the autocorrelation (AC) function for error correlation and the partial autocorrelation (PAC) values for the lagged dependent variable.

(3) After determining the possible autoregressive structures, we perform stepwise tests whether inclusion of these lags or errors into the regression improves a suitable selection criterion. Typically, for selection either measures of simulated forecast errors such as MSE or Information Criteria such as those of Akaike or Schwartz are used.

(4) When no additional lag diminishes the Selection Criterion, we test whether the residuals are white noise (Portmanteau-test), i.e., if the estimation has minimum variance. If the test is not rejected, we use the efficient estimate to forecast unemployment.

To extinguish seasonality first we use yearly differences of regional unemployment. On these we apply Augmented Dickey-Fuller tests for unit roots, cf. Bierens (2001); if the test indicates the presence of unit roots with and without a trend, we compute first (monthly) differences of the regional series, test this again and differentiate further until stationarity is achieved. A detailed description of the sequential procedure is given by Hassler (2000).

Let y denote the stationary series related to the observed time series Y . Then the model can be described by following ARMA equation:

$$y_t = \mu_t + \sum_{k=1}^p y_{t-k} \alpha_k + u_t \quad \text{with } u_t = \sum_{k=1}^q u_{t-k} \rho_k + \varepsilon_t \quad (1)$$

In most applications, all lags up to lag p (q) are included into the regression, where p (the number of AR-lags) and q (the degree of error correlation) are determined by an analysis of the correlogram. However, some lags might not provide relevant information about the development of the time series: One loses degrees of freedom without improving estimation, and particular in small samples would do better with restricting these coefficients to zero. Therefore we rank the lags according to their absolute PAC respective AC values and, starting with the highest, add them stepwise to the equation. This proceeding is denoted as “simple-to-general”.

Many studies conclude that lag selection building on Information Criteria performs better than other methods, see e.g. Inoue and Kilian (2006) or Stock (2001). Here, the decision whether a lag is maintained in the equation bases on the Corrected Akaike Information Criterion (AICC) which is defined as

$$AICC = \ln \sigma^2 + \frac{(T + k)}{T - k - 2} \quad (2)$$

where T is the number of observations, k the number of estimated parameters and σ the estimated standard deviation. This hardly known Information Criterion often yields more proper parameter selection than those of Akaike (AIC) or Schwartz (BIC): Typically the AIC leads to more variables than necessary while the BIC leads to underfitting, cf. Hurvich and Tsai (1989).

4.2 Basic Structural-Component Model

In the structural-components (SC) approach, it is assumed, unlike above, that there is a deterministic process which explains the endogenous variable. To this end, the observations are decomposed into a level, trend, business-cycle and seasonal component (see Harvey 2004, Ch. 2), i.e.:

$$Y_t = \mu_t + \gamma_t + \psi_t + \varepsilon_t \quad (3)$$

with

- μ_t level and trend component
- γ_t seasonal component
- ψ_t business-cycle component
- ε_t remaining stochastic error (irregular component)

Other components can be added if required.

Hence, this basic version of the model neither includes explanatory variables and effects of policy interventions nor, in contrast to the ARIMA-models, autoregressive processes (see Harvey 2004, Ch. 3 & 4).

Under the assumption that there is no damped trend, the system of level and trend component can be transformed into:

$$\mu_t = \mu_0 + \beta_0 t + \nu_t \text{ with } \nu_t \sim i.i.d.(0, \sigma_\nu(t)^2) \quad (4)$$

where μ_0 is the initial level, β_0 the slope parameter and ν_t the error term at time t . With a damped trend, the above equation becomes non-linear. Therefore, in addition to the linear trend, we also include a quadratic and cubic trend component.

The seasonal component can be model by adding dummies for each month (with the exception of one arbitrary month). Alternatively, in order to reduce the number of parameters which need to be estimated, it can be captured by various trigonometric functions whose length is defined by λ and amplitude by α and δ respectively– see Harvey (2004, Ch. 5.1):

$$\gamma_t = \sum_{j=1}^{\lfloor s/2 \rfloor} (\alpha_j \cos \lambda_j t + \delta_j \sin \lambda_j t) \quad \text{with} \quad \lambda_j = 2\pi j / s \quad (5)$$

Once the level, trend and seasonal component have been included, a first regression is run. All subsequent regressions contain only those variables which are significant at the 10 %-level. However, if multicollinearity between the trend components arises, the linear trend is kept and if the quadratic term is more significant than the cubic trend, it is kept and the cubic dropped, and vice-versa.

Economic theory differentiates between short-, medium- and long-term business cycles. Similarly to the seasonal figures, business cycles are modelled here by a cosines and sinus function. As the duration of a cycle in a labour-market district is unknown, its length is determined by the autocorrelation function of the residual in a regression without a cycle component. Thereby, we assume that the cycle length must be at least thirteen months to make sure that we are indeed capturing cycles and not just short irregular fluctuations. As the data for our simulated-out-of-sample forecasts only covers seven years, we can at best capture short-term cycles. If it turns out that both cycle components are insignificant, we test for joint significance and include the one with the (absolute) higher t-statistic. Once all (significant) components have been established, the full model can be regressed using standard OLS-regression techniques.

4.3 Structural Components with Autoregressive Elements

The aim of the structural-components method is to detect structural properties of time-series data. In contrast, autoregressive processes use the correlation structure of time lags. Both methods have their advantages: Especially for long time series, the structural-components method offers an appropriate instrument to capture recurring elements such as seasonal fluctuations or business cycles. Therefore, once a structure is detected, the forecasts are very robust and do not place much emphasis on short-term fluctuations. Autoregressive processes detect long-term structures differently. They represent time-series data by the special correlation structure observed in the past. By doing this, autoregressive methods do a good job in capturing short-term movements and are able to react quite flexibly to changes in the current data.

Both properties are important for our purposes as we perform short to medium term forecasts with moderate sample sizes. Therefore, the combination of both methods seems adequate for improving the short-term behaviour of the forecasts without losing the long-term properties of the data-generating process.

The integration of autoregressive elements into the basic structural-components model is straight forward and can be written as:

$$Y_t = \mu_t + \gamma_t + \psi_t + \theta_t + \varepsilon_t, \quad (6)$$

where μ_t , γ_t , ψ_t and ε_t are defined as in Section 4.2 and θ_t represents the autoregressive component modelled as:

$$\theta_t = \sum_{i=1}^{I=26} \vartheta_i Y_{t-i}. \quad (7)$$

To work with a comparable lag-structure to the one chosen in the ARIMA approach and to capture at least influences of the last two years, the number of tested lags I , is set to a maximum of 26. Obviously, as in the ARIMA model, not all lags should be added in the final model.

Therefore, the starting point of the extended structural-components model is an estimation of the full model, which contains all components that have been used for forecasting as in Section 4.2 and the complete set of lags. The relevant lags are then determined by selecting all lags which are significant at the 10 %-level. We then test to see if any coefficients of the lag variables have values that are equal to or greater than one as on the one hand this would indicate that a past shock becomes more and more influential in the future. On the other hand, omitting this statistically significant variable leads to a potentially important information loss in the final regression. Therefore, in this case we run the regression once with all significant lags and once without the ones which have a coefficient which is greater or equal to one and then compare the results using a suitable error measure (see Section 5). Components that are insignificant in this regression are f-tested for joint significance. The final regression contains all significant components and, if their joint significance is indicated, in addition all insignificant structural components.

4.4 Structural Components with Spatial Interdependencies

Particularly, when forecasting variables in small areas, it seems plausible that the development of the dependent variable in neighbouring regions has an impact on the region being analysed. This can be due to the economic interdependencies between the regions. This relationship between neighbours can be described as a spatial autoregressive process. To model the spatial relation between regions we use a row normalised contiguity matrix. Because the simultaneous spatial lags are unknown in the forecast period, it is only possible to include the spatial lags of previous periods in the estimation, cf. Giacomini and Granger (2004).

Due to the reciprocal connection between regions, it is necessary to regress and forecast with panel techniques. To keep up the basic idea of the simple structural-component model, i.e. to account for the heterogeneous behaviour of regions, the data is written in block diagonal form. This allows for specific coefficients for each labour-market district, even for the spatial process parameters.

Hence, the model can be written as:

$$\vec{Y}_t = \vec{\mu}_t + \vec{\gamma}_t + \vec{\psi}_t + \vec{\xi}_t + \vec{\varepsilon}_t, \quad (10)$$

where $\vec{Y}_t = (Y'_{1t}, \dots, Y'_{Nt})'$ denotes the vector of unemployment at time t over all regions, and the components are defined analogously to above. The spatial component in region i , ξ_{it} , is defined as follows:

$$\xi_{it} = \sum_{\tau} \sum_{j=1}^N w_{ij} Y_{j,(t-\tau)} \kappa_{i\tau}, \quad \tau \in \{1, 12, 13\}. \quad (11)$$

where w_{ij} is the spatial weight. We include all components that were significant in the basic structural-components model. In addition, we include the one, twelve and thirteen months lagged values of the neighbours' average; pre-tests have shown that if any spatial components are significant then this happens with these lags. Therefore, it seems sufficient to use only these.

In the following section we introduce the accuracy measures used in this paper, show the results of the different approaches and discuss their strengths and weaknesses.

5 Results and Discussion

5.1 Accuracy Measures

In order to test how accurate the forecasts from the various models are we need some accuracy measure with which to test the results for the labour-market districts. A vast array of measures have evolved in the literature (see e.g. De Gooijer and Hyndman 2005, for a recent overview). Here, we calculate four different measures. First, we calculate the standard root mean square error (RMSE) as is common in the literature. The other three measures are all based on a comparison of the results of the simulated out-of-sample regression with the observed unemployment values in the labour-market districts. Thus, these measures are all based on the forecasted versus observed values in 2005. For this time period we then calculate the root mean square forecast error (RMSFE). Comparing this value with the RMSE we find that in general it is about three times higher. We then proceed by calculating the mean absolute

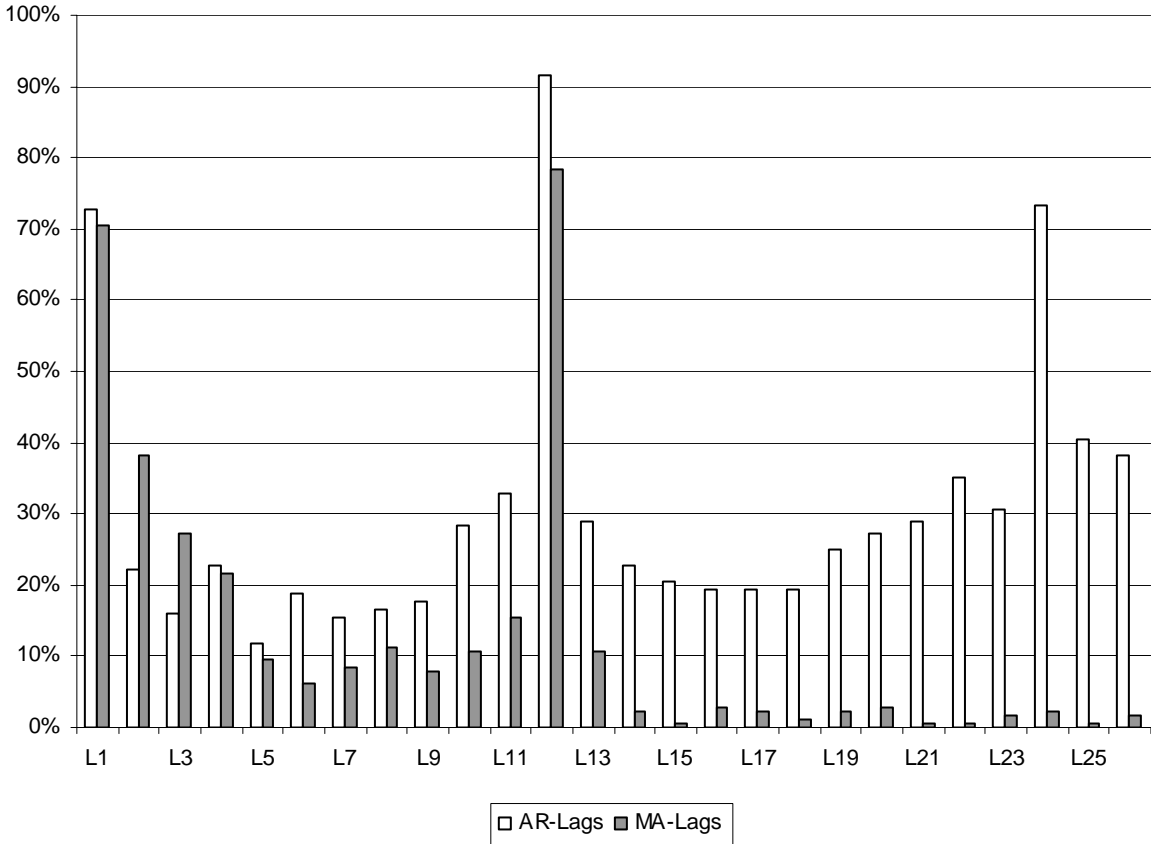
forecast error (MAFE). However, both the RMSFE and the MAFE have the disadvantage that they do not account for the different sizes of the labour-market districts in terms of the number of unemployed in the districts. Hence, districts with a relatively “large” number of unemployed will tend to have the largest errors. This can easily be accounted for by computing relative errors, i.e. by first dividing the absolute value of the forecast error by the total number of unemployed for each district and month and then calculating the mean of this value for each agency. We call this measure the mean absolute percentage forecast error (MAPFE). As it is this error which seems to best suit our purposes, we will only focus on it when presenting and discussing our forecast results. The MAPFEs for each district and model can be found in Table A. 1.

5.2 Results of the Models

ARIMA is a well-known method in modelling time-series data which is popular, fairly easy to implement and results in relatively low forecast errors, and hence in our paper serves as a reference model. The effort of modelling alternative, often more complicated methods, should then lead to better results in the form of lower forecast errors.

In our standardised ARIMA model selection, the time series are first checked for stationarity and differenced in season and furthermore in level if necessary. In nearly all labour-market districts (171), both differences are needed and only in five labour-market districts is the seasonal difference sufficient. Subsequently, the stepwise lag selection of autoregressive and moving-average terms follows. Despite the differentiation, the most frequently used autoregressive lags are the previous month and the typically seasonal lags of 12 and 24 months (see Figure 4). The one-month and two-year lag are selected in 73 % and the one-year lag even in 91 % of all cases. A second category of lags which was used in about 30-40 % of all labour-market districts are those around the one- and two-year lag (10, 11, 13, 20-23, 25, 26). The other autoregressive elements still are selected in roughly 10-20 % of the ARIMA estimations. Moving-average terms are added afterwards if they further improve the model fit. Thus, the moving-average terms add information that is not captured by the autoregressive elements. Here, the one and twelve period lagged errors are the ones most commonly chosen, with a frequency of 70 % and 78 %, respectively. The moving-average terms 2-4 are added in 20-40 % and those around the one-year lag still in 10-15 % of all cases. The terms after lag 13 were only used very rarely (maximum 3 %).

Figure 4: Distribution of the Selected AR and MA-Lags in the ARIMA Estimates



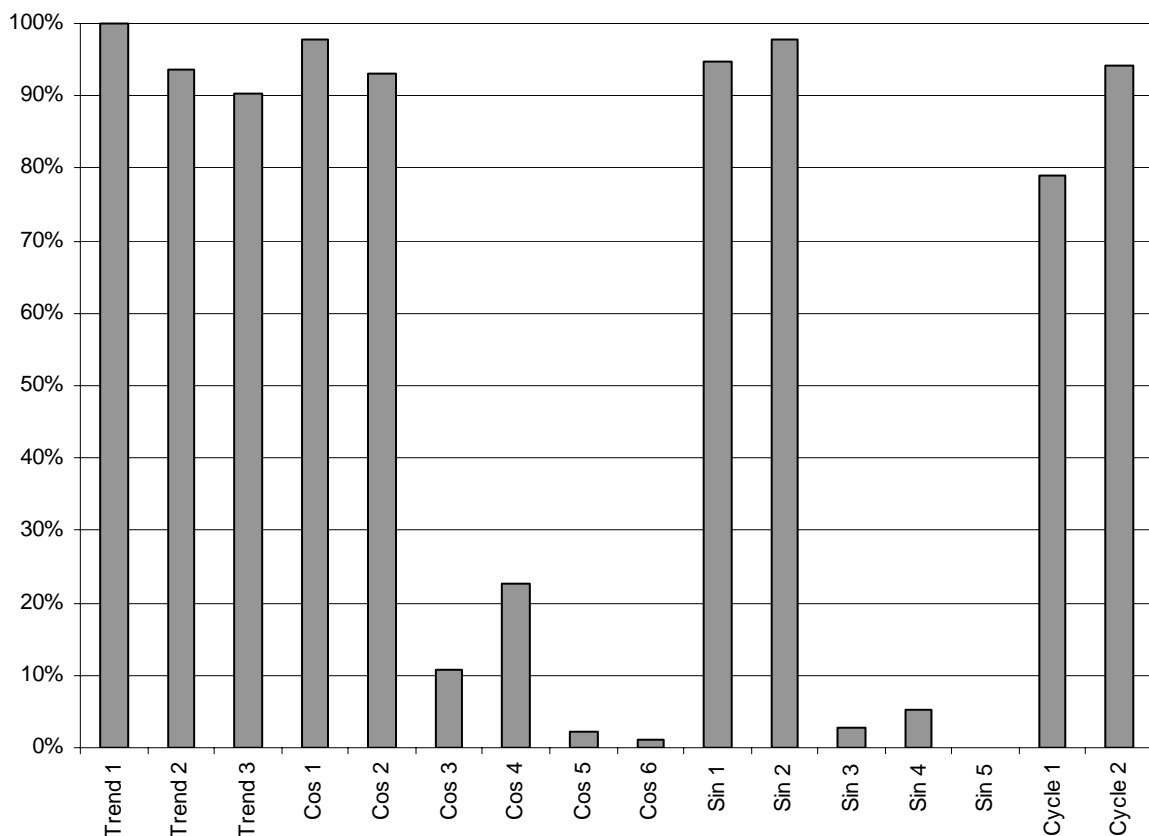
As Table 1 on page 22 shows, our ARIMA-models have an average MAPFE of 7.49 % across the 176 labour-market districts in the simulated out-of-sample forecasts. The best result was achieved for the labour-market district of Nordhausen, which had a MAPFE of only 1.56 %. By contrast, the prediction for Marburg deviates from the actual figures by 21.23 %. The result for Nordhausen was estimated with an only seasonally differenced time series containing the autoregressive lags 1, 2 and 5 and the moving-average lags 1, 2 and 3. For Marburg, the time series was differenced by season and level. The resulting model was fitted with AR-lags 11, 12, 17, 18, 21, 25, 26 and MA-lags 12 and 17. The standard deviation of 3.98 percentage points makes it possible to evaluate the accuracy of the predictions. According to this value, the confidence interval for one standard deviation, which contains about 2/3 of all values, ranges from 3.51 % to 11.47 %.

Interesting is also the spatial distribution of the forecast errors. Geographically concentrated patterns of lower (higher) MAPFEs indicate that the model fit better (worse) for these regions. The ARIMA predictions have relatively low MAPFEs in most of the eastern German labour-market districts and in Baden-Wuerttemberg. High prediction errors occur in the western North-Rhine-Westfalia, Rhineland-Palatinate, the southern Lower-Saxony and Hesse.

The basic SC model contains trend, season and business-cycle components. Due to the unique behaviour of the time series in each labour-market district, the composition of the chosen components differs between the labour-market districts. However, some components are more frequently used than others. The most important component is the linear time trend, which is kept by definition in every labour market district. Also the quadratic and cubic trend are kept in more than 90 % of the labour-market districts. The most commonly included seasonal components are the six and twelve month lasting

sinus and cosines functions which appear in about 95 % of all models. The length of the business-cycle component is modelled individually for each labour-market district and captures cycles with a length of at least 13 months. In 103 districts the cycle length is affected by the censoring (see Section 4.2) and is hence 40 months. In the remaining districts, the average length is 31 months. Two different types of business-cycles are used: one is modelled as a sinus and the other one as a cosines function. Hence, they are shifted in time but do not differ in length and amplitude. The sinus cycle is included in nearly 95 % and the cosines-cycle in more than 75 % of the 176 simulated out-of-sample estimations.

Figure 5: Selected Components in the Basic Structural Components Model



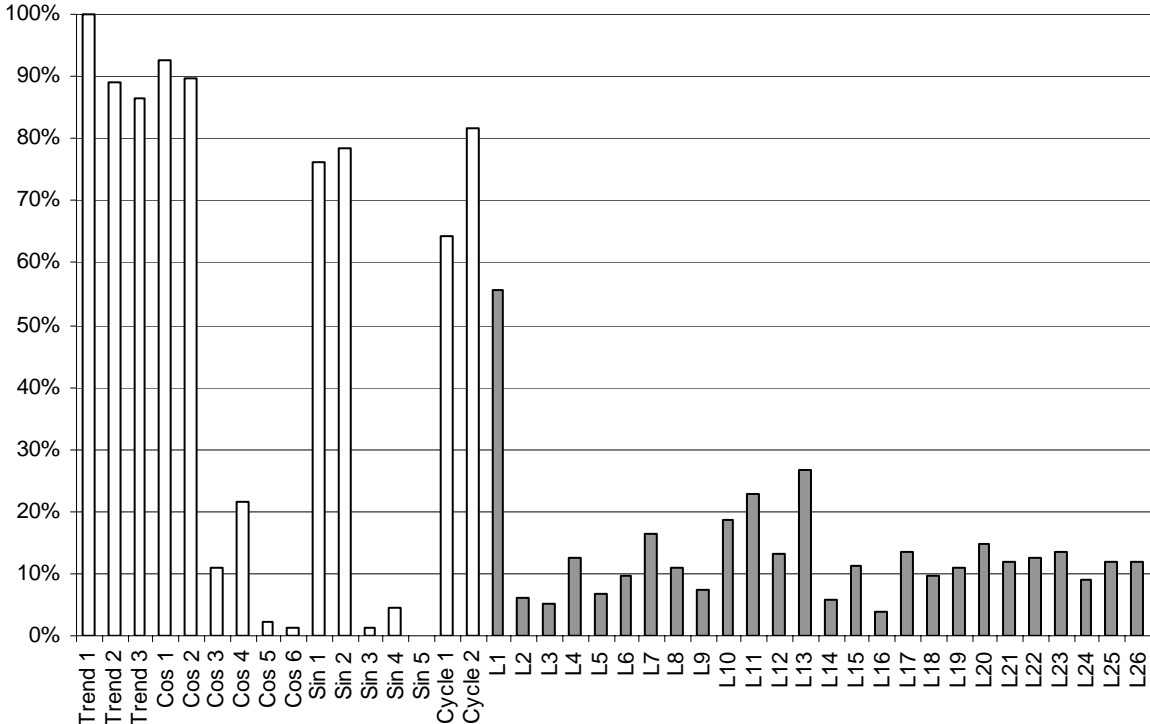
Trend 1: linear trend; Trend 2: quadratic trend; Trend 3: cubic trend; Cos t : year/ t -cycle; Sin t : year/ t -cycle; Cycle 1: cosines business-cycle; Cycle 2: sinus business-cycle

The evaluation of the basic SC model by the simulated out-of-sample forecasts shows a mean MAPFE of 8.57 %. The results also show a wide range in the calculated MAPFE. The best fit was achieved in Ludwigshafen with a MAPFE of 1.56 %, the highest value was observed in Goslar with 26.14 %. The models of both labour-market districts contain the same, and as shown above, quite commonly used structural components: the linear, quadratic and cubic trend, the six and twelve months lasting seasonal components and both cycles. The standard deviation over the 176 labour market districts is 4.52 percentage points, implying that 2/3 of all forecast errors are in a range between 4.04 % and 13.09 %. There are also differences in the spatial distribution of the MAPFEs. Basic SC models perform better in Mecklenburg-Vorpommern, Thuringia and the northern part of Brandenburg, all federal states situated in eastern Germany, whereas especially in Lower-Saxony, the Saarland and the northern part of the Ruhr area, the predictions are fairly poor.

In comparison to the ARIMA approach, only 71 (40 %) districts have a better fit. The average improvement of the MAPFE in these districts is 2.54 percentage points. On the other hand, not only are the results worse in 60 % of the districts, the average increase of the error measure is also higher and amounts to 3.52 percentage points. An improvement can mainly be found in labour-market districts situated in the Lower-Saxony and Saxony-Anhalt, whereas the basic SC model is worse than ARIMA, in districts near the border to France and Belgium, in Hesse and in the north eastern part of Mecklenburg-Vorpommern on the border to Poland.

As described in Section 4.3, we augment the basic SC model for autoregressive elements to improve the short-term adjustment of the time series. By doing this, some structural components that are significant in the basic model, become insignificant and are dropped. In general, the same components play a dominant role, but are included less often than in the basic model. The cubic and quadratic trends are still used in nearly 90 %, the full-year and half-year seasonal components appear in about 75 % and 90 % of all cases, respectively. The sinus business-cycle is included in nearly 82 % and the cosines business-cycle in more than 64 % of the 176 simulated out-of-sample models. Thus, the trend and cosine components are dropped about 4, the sinus components about 18 and the business-cycle components about 14 percentage points more often than in the basic model. The dropped components are partly replaced by the added autoregressive component. Clearly, the most frequently used lag is the first one, which is included in more than 55 % of all districts. Also the lags around the twelfth lag (lags 11 and 13) are included in one fifth of all cases. Other frequently selected lags are the periods 4 and 7 month and those around two years in the past which are included in roughly 10-20 % of all models.

Figure 6: Selected Components and AR-Lags in the Structural Components Model



Trend 1: linear trend; Trend 2: quadratic trend; Trend 3: cubic trend; Cos *t*: year/*t*-cycle; Sin *t*: year/*t*-cycle; Cycle 1: cosines business-cycle; Cycle 2: sinus business-cycle; L*t*: Lag *t*

Surprisingly, the SC model with autoregressive elements has a rather high mean MAPFE of 18.17 %. This is nearly 10 percentage points higher than in the basic model. The fits range from 2.14 % in Stralsund up to 79.20 % in the labour-market district Verden. In the Stralsund forecast, the commonly used structural components as mentioned above and additionally the lags 1, 2, 6, 8, 10, 13, 17, 19, 22, 23, 24, 25 and 26 are used, whereas for Verden, the 12-months cosines and the cosines-business-cycle are dropped and only the lags 3, 15, 19, 20, 22 and 24 are additionally included. The standard deviation over the 176 labour-market districts is with 14.84 percentage points more than 3 times higher than in the basic model. Equivalently, the one-standard-deviation-interval is much larger and ranges between 3.33 % and 33.01 %. Geographically, the SC model with autoregressive components seems to fit better for the eastern and central parts of Germany, but worse for the southern and northern parts of the country.

Compared with the results of the basic estimations, the MAPFE of the autoregressive approach is higher in 134 (76 %) labour market regions and only lower in 42 (24 %) cases. For those districts where the AR-model is better, the MAPFE improves by 3.45 percentage points. On the other hand, if the results are poorer, the MAPFE increases by 13.69 percentage points on average which explains the high rise in the total average MAPFE. The districts in which the forecast errors increase are mainly situated in the southern federal states Baden-Wuerttemberg, Bavaria, Hesse, Saarland and Rhineland-Palatinate. In eastern and northern Germany the results are ambiguous.

As described in Section 4.4, we augment the basic SC model to account for spatial interdependencies across labour-market districts. Therefore, a panel approach needs to be applied. Thus, the following results have two sources of variation in comparison to the basic model: the change of the estimation technique and in addition the spatial component. To calculate the effect of the change in the estimation procedure, we also estimate a panel model with only the basic components. In the spatial-lag estimations we always only add the spatial lags of order 1, 12 and 13 which represent the weighted influence of the neighbouring districts of the previous month, the same month in the previous year and the previous month in the previous year.

The results for the basic model estimated with the panel approach show a MAPFE of 12.10 %, implying that the change of the estimation technique causes an additional forecast error of 3.54 percentage points. Compared to the forecast estimated separately per district, the average MAPFE is 0.42 percentage points higher and amounts to 8.98 %, but in relation to the simultaneous estimation of the basic SC model over all districts, the MAPFE decreases by 3.12 percentage points.

By including a geographical component in which unemployment in one labour-market district also depends on its neighbours' development, the forecasts and thereby the calculated MAPFEs should become more even across the regions. This is confirmed in the results where the standard deviation of the MAPFE decreases from 4.52 percentage points in the basic model to 4.13. The results in the spatial model range from 2.21 % in Wittenberg to 24.11 % in Weißenburg. The spatial model fits best for Thuringia, and Saxony, but rather poorly for Bavaria and the southern North-Rhine-Westphalia.

In comparison to the basic model, the results are better for Lower-Saxony and large parts of Saxony, but worse for nearly all southern and north-eastern German labour-market districts. In total, the predictions for 70 (40 %) labour-market districts improve and the other 106 (60 %) worsen in their MAPFE. The mean improvement is 3.47 % and hence roughly as high as in the autoregressive model. However,

if the predictions are worse than in the basic case, the forecast errors increase by only 2.99 percentage points on average.

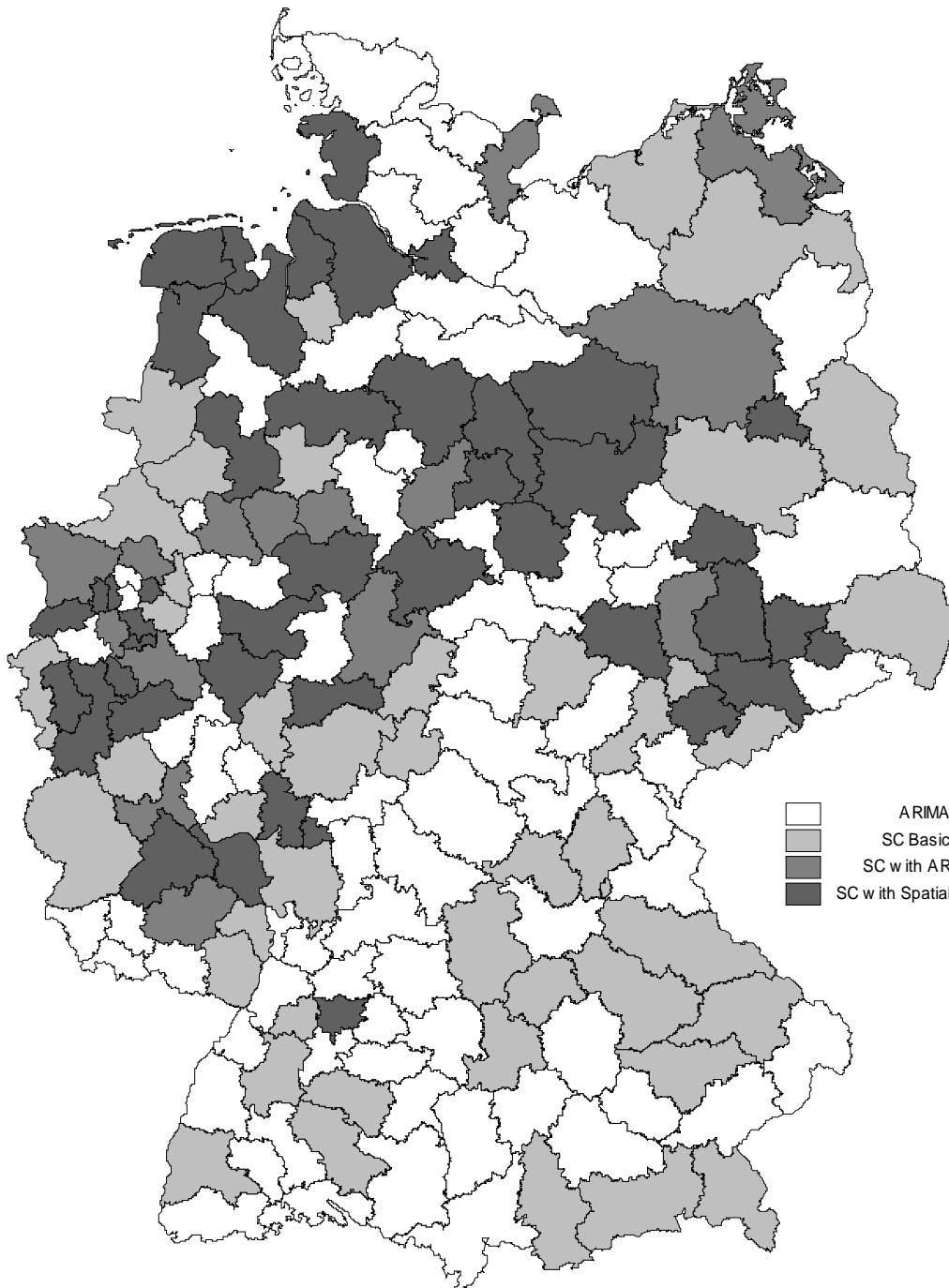
Table 1: Results of the Simulated Out-of-Sample Forecasts

		ARIMA	Basic SC	SC with AR	SC with Spatial
Mean		7.49	8.57	18.17	8.98
Standard deviation		3.98	4.52	14.84	4.13
Minimum		1.56	1.56	2.14	2.21
Maximum		21.23	26.14	79.20	24.11
Comparison with basic SC	Better than basic SC	105 (59.66 %)		42 (23.86 %)	70 (39.77 %)
	Worse than basic SC	71 (40.34 %)		134 (76.14 %)	106 (60.23 %)

5.3 Comparison of the Models

Compared with the distribution measures of the calculated MAPFE, ARIMA seems to be the best model: the reference model has the lowest average, minimum and maximum MAPFE, as well as the lowest standard deviation. However, looking at each district separately shows the heterogeneity of the results. Figure 7 shows the model with the best forecast (lowest MAPFE) for each labour-market district.

Figure 7: Spatial Distribution of the Best Models



In total, ARIMA still is the best model in 73 labour-market districts (41 %). The basic SC model and SC with spatial components each fit best in 44 cases (25 %), whereas the SC model with AR components yields the minimum MAPFE in only 15 districts (9 %). Hence, the SC model in its different variations has the lowest MAPFE in 103 labour market districts (59 %). In the southern and central parts of Germany, i.e., in the federal states Baden-Wuerttemberg, Bavaria, Saarland and Thuringia, with one exception (Ludwigsburg in Baden-Wuerttemberg), ARIMA or the basic SC model fit best. In the northern federal states Lower-Saxony, Schleswig-Holstein and in Saxony-Anhalt, ARIMA and SC with spatial components are superior to the other models. The only exceptions are Bremen, Hildesheim and Lübeck, where the basic SC and the SC with AR model fit better. In all other federal states

the results are mixed. Obviously, there are regional factors which correspond with the fit of the models. Therefore, we calculated bivariate correlations between factors which might potentially have an influence on the model fit and the 0/1-vectors, containing a one if the model performs best and zero otherwise. The correlation coefficients are shown in Table 2.

Table 2: Correlation of the Best Model and Possible Determining Factors

	ARIMA	Best model		
		Basic SC	SC with AR	SC with Spatial
Growth rate of unemployment	-0.0723	0.0350	0.1413	-0.0551
Seasonal span of unemployment	0.0430	0.1920*	-0.1296	-0.1766*
Average unemployment rate	-0.1082	-0.0832	0.0729	0.1792*
Hartz-Effect	-0.0860	-0.1161	0.1295	0.1450
Dummy Hartz-Effect	-0.1174	0.0950	0.0934	-0.0289

* Significant at the 5 %-level

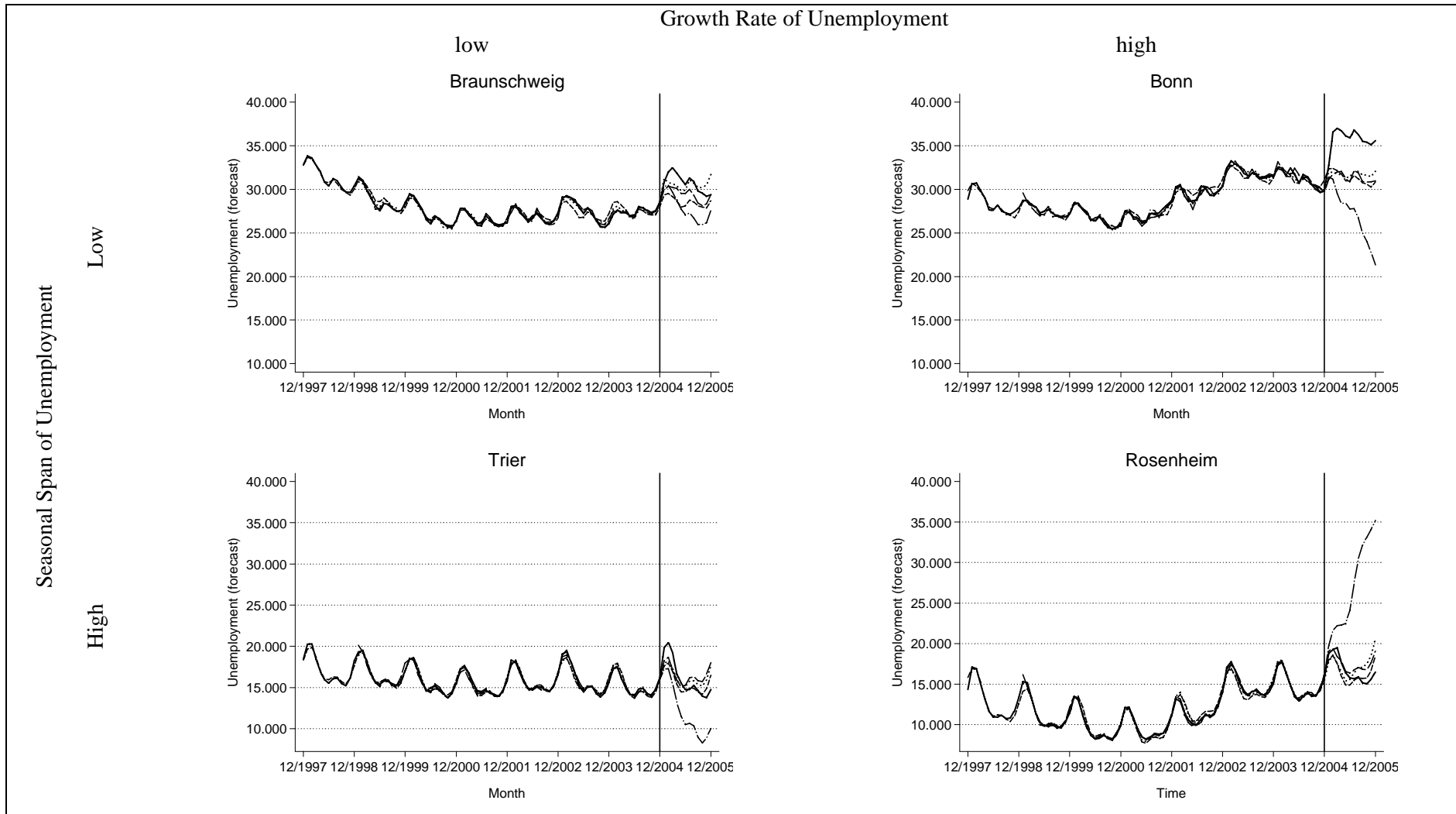
The growth rate of unemployment does not show a significant correlation with any model vector, indicating that all models fit equally well (poorly) irrespective of the growth rate. The seasonal span in contrast is significantly correlated with the performance of the basic SC model and the SC model with spatial components, but with a different sign. This means, that the basic SC model fits significantly better in labour market districts with a high seasonal span, whereas the SC with spatial components performs better forecasts in districts with a low seasonal span. A reason for this could be that the seasonal span is typically lower in urbanised districts where generally higher interdependencies (e.g. a larger number of commuters) between these districts and their neighbours are observed.

Testing the level of unemployment, we used the average unemployment rate, which is significantly positive related only with the SC model with spatial components, showing that this model works better than the other models if a labour-market district suffers from high unemployment. As already discussed in Section 2, the data since 2005 additionally counts the welfare recipients as unemployed and is therefore not directly comparable with the data in previous years (“Hartz-Reform”). Therefore, we estimated a “Hartz-Effect” and calculated the corresponding time-series which is corrected for this effect, but neither the dummy nor the effect itself show a significant correlation with our models. This corresponds with the expectations for these coefficients, because the effect is not covered by the data used for the simulated out-of-sample estimation. These findings also allow us to use our calculated error measures, as the correlation results show no bias in the model fits due to the “Hartz-Effect”.⁵

⁵ We also calculated the Hartz-corrected time-series for all 176 labour market districts by adjusting the original data for the estimated Hartz-effects and computed the corrected MAPFEs. We expected all average forecast errors to decrease significantly, but only the MAPFE of the Basic SC model decreased slightly, whereas the MAPFEs of the other models increased by more than one percentage point.

The variables for which we calculated correlations with the models are equivalent with the characteristics of time-series (level, trend, season) already motivated in Figure 1. In Figure 2 we observed four labour market districts with strong differences in the growth rate and the seasonal span of unemployment. To check the derived correlation results, we take another look at those time-series and the predictions of our models in Figure 8.

Figure 8: Unemployment Forecasts for Different Combinations of Growth Rate and Seasonal Span of Unemployment



Source: Federal Employment Agency

Unemployment
 ARIMA
 SC Basic
 SC with AR
 SC with Spatial

The positive correlation of the basic SC model and the seasonal span of unemployment suggests that the districts with a high seasonal span can be forecasted best with the basic SC model as is indeed the case. Trier as well as Rosenheim both have the lowest MAPFEs of 6.49 % and 5.97 %, respectively, if predicted with the basic SC model. The second best model in Trier is SC with spatial components with a considerably higher MAPFE of 8.71 %. The second lowest MAPFE in Rosenheim is estimated by ARIMA, which is only 0.66 percentage points higher. The same holds for the negative correlation between SC with spatial components and the seasonal span of unemployment: SC with spatial components has the best fit in Braunschweig (MAPFE: 3.23 %) and Bonn (MAPFE: 11.25 %), and the MAPFEs are slightly more than one percentage point lower than the ARIMA results. Looking at the level component, i.e., the average rate of unemployment, those labour-market districts in which SC with spatial components is best, should be associated with high unemployment rates. This is only true for Braunschweig with an average unemployment rate of 11.45 %, but does not hold for Bonn, which shows a relatively low rate of only 7.09 %.

6 Conclusion

In this paper we estimate unemployment with different time-series models for all (176) labour-market districts in Germany. As the conditions in these districts are very heterogeneous, we need to employ individual models which capture the local labour-market conditions. We do this by testing which variables have a systematic influence and improve the model fit in each agency and including only these variables in the final regressions. By doing this, we are in a position to systematically compare the selected models in both their explanatory factors and model fit.

We measure the frequencies of the chosen factors and are able to observe the typical model structures of ARIMA and the various SC models. We find that ARIMA models often contain the 1st, 12th and 24th AR-lag; these lags obviously have a high explanatory power. The most frequently selected MA-lags were the first and twelfth. Basic SC models perform relatively well if all trend components, the full and half-year sinus and cosines seasonal components and the two cyclical components are included. Adding autoregressive elements often leads to the inclusion of the first lag and to the exclusion of some of the components used in the basic SC model.

We evaluate the models using simulated-out-of-sample forecasts for 2005 and calculating different accuracy measures for this time period. Overall, ARIMA estimations result in the lowest average, minimum and maximum MAPFE and the lowest standard deviation. However, which model fits best depends on which region is being analysed and corresponds to the local structural characteristics. Our findings show that the basic SC model achieves the best results in districts with a high seasonal span. However, if the season span is relatively low, e.g. in urbanised districts, the SC model which is augmented by spatial interdependencies performs best. The spatial SC model also leads to good forecasts in districts with relatively high unemployment rates.

These findings show that if unemployment forecasts are required on a small regional level, it is extremely important to first individually select the model according to the specific regional characteristics. Second, the variables included in the selected model also need to be adapted to the local labour-market conditions.

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Appendix

Table A. 1: Accuracy Measures

Labour-Market District	Mean Average Percentage Forecast Error (MAPFE)					Best Model
	ARIMA	Structural Components				
		Basic	with AR	Panel	with Spatial	
031 AA Neubrandenburg	11.21	6.54	10.27	12.17	8.08	Basic
032 AA Rostock	7.18	4.88	11.89	13.86	8.94	Basic
033 AA Schwerin	2.67	5.99	15.52	7.56	5.17	ARIMA
034 AA Stralsund	7.48	4.85	2.14	10.86	8.67	with AR
035 AA Cottbus	5.17	10.30	6.85	13.08	13.07	ARIMA
036 AA Eberswalde	3.49	4.89	4.55	6.68	12.30	ARIMA
037 AA Frankfurt (Oder)	9.66	9.64	11.57	10.61	15.94	Basic
038 AA Neuruppin	4.47	4.85	3.63	11.96	9.31	with AR
039 AA Potsdam	5.25	4.99	6.45	6.33	8.56	Basic
042 AA Dessau	2.71	3.61	7.60	3.81	4.84	ARIMA
043 AA Halberstadt	4.81	7.54	7.51	13.26	3.50	with Spatial
044 AA Halle	5.41	6.07	7.30	5.88	6.31	ARIMA
045 AA Magdeburg	9.88	12.22	18.36	7.24	14.73	Panel
046 AA Merseburg	6.84	7.26	12.88	4.97	4.88	with Spatial
047 AA Sangerhausen	7.72	9.34	13.75	12.93	13.32	ARIMA
048 AA Stendal	7.30	10.14	8.53	4.26	8.99	Panel
049 AA Wittenberg	3.45	2.40	5.44	5.64	2.21	with Spatial
070 AA Altenburg	5.81	1.61	4.22	16.42	8.03	Basic
071 AA Annaberg-Buchholz	7.78	2.83	18.21	10.28	8.83	Basic
072 AA Bautzen	8.16	3.09	12.86	7.61	5.54	Basic
073 AA Chemnitz	5.03	6.03	3.18	4.78	2.57	with Spatial
074 AA Dresden	6.25	6.01	10.59	2.75	5.26	Panel
075 AA Leipzig	4.79	8.72	3.82	4.31	7.34	with AR
076 AA Oschatz	5.17	4.72	5.93	16.04	3.72	with Spatial
077 AA Pirna	2.02	19.00	16.47	5.90	9.55	ARIMA
078 AA Plauen	2.23	21.67	7.03	7.41	4.21	ARIMA
079 AA Riesa	2.70	10.10	3.24	3.09	2.70	with Spatial
092 AA Zwickau	5.42	7.93	11.83	4.12	3.50	with Spatial
093 AA Erfurt	7.45	5.10	20.15	8.71	6.79	Basic
094 AA Gera	4.44	2.88	4.37	11.38	8.71	Basic
095 AA Gotha	2.07	6.90	3.94	9.97	3.85	ARIMA
096 AA Jena	2.93	6.23	3.32	13.26	4.52	ARIMA
097 AA Nordhausen	1.56	22.60	3.67	4.34	4.16	ARIMA
098 AA Suhl	1.73	2.67	8.65	18.52	7.65	ARIMA
111 AA Bad Oldesloe	5.42	6.92	18.24	10.86	7.36	ARIMA
115 AA Elmshorn	5.98	7.08	44.80	9.39	8.21	ARIMA
119 AA Flensburg	5.44	11.52	10.84	5.88	5.57	ARIMA
123 AA Hamburg	6.25	8.19	18.74	5.67	4.94	with Spatial
127 AA Heide	9.00	12.69	36.15	8.04	11.59	Panel
131 AA Kiel	2.82	4.41	28.39	5.50	5.92	ARIMA
135 AA Lübeck	18.12	14.86	12.54	12.58	14.48	with AR
139 AA Neumünster	2.90	7.12	15.67	7.85	9.39	ARIMA
211 AA Braunschweig	4.24	7.05	9.57	3.59	3.23	with Spatial
214 AA Bremen	14.64	11.42	13.18	23.52	13.60	Basic
217 AA Bremerhaven	18.77	21.32	28.90	10.51	14.61	Panel
221 AA Celle	11.10	22.43	71.69	11.81	9.13	with Spatial
224 AA Emden	5.07	3.97	8.15	3.65	3.76	Panel
227 AA Goslar	19.89	26.14	26.09	19.90	20.90	ARIMA

Labour-Market District	Mean Average Percentage Forecast Error (MAPFE)					Best Model
	ARIMA	Structural Components				
		Basic	with AR	Panel	with Spatial	
231 AA Göttingen	8.70	10.06	10.84	5.43	7.40	Panel
234 AA Hameln	6.06	9.49	11.35	8.73	8.96	ARIMA
237 AA Hannover	12.97	25.61	31.40	15.59	18.09	ARIMA
241 AA Helmstedt	10.52	14.69	43.67	5.63	6.03	Panel
244 AA Hildesheim	13.63	19.81	12.39	13.34	13.25	with AR
247 AA Leer	4.16	8.76	5.85	4.09	4.50	Panel
251 AA Lüneburg	2.47	8.45	59.67	3.06	3.19	ARIMA
254 AA Nienburg	13.21	16.17	36.34	7.75	8.17	Panel
257 AA Nordhorn	5.67	5.13	27.01	8.79	8.92	Basic
261 AA Oldenburg	14.00	12.98	24.23	7.10	10.04	Panel
264 AA Osnabrück	8.57	11.97	6.71	5.52	6.13	Panel
267 AA Stade	12.84	15.44	20.93	11.91	11.75	with Spatial
271 AA Uelzen	5.44	10.30	9.20	9.83	9.37	ARIMA
274 AA Vechta	7.50	15.59	12.34	8.88	8.77	ARIMA
277 AA Verden	6.24	7.32	79.20	7.00	6.98	ARIMA
281 AA Wilhelmshaven	12.99	14.96	12.22	11.68	12.25	Panel
311 AA Aachen	13.96	7.69	8.50	24.35	12.62	Basic
313 AA Ahlen	6.13	8.99	4.64	5.23	7.30	with AR
315 AA Bergisch Gladbach	11.86	6.52	3.01	18.13	10.80	with AR
317 AA Bielefeld	7.38	6.38	3.73	10.66	8.93	with AR
321 AA Bochum	14.34	10.67	20.87	7.32	8.57	Panel
323 AA Bonn	12.30	12.45	24.49	3.40	11.25	Panel
325 AA Brühl	11.48	10.35	39.39	4.19	13.03	Panel
327 AA Coesfeld	4.50	3.93	12.95	11.71	7.63	Basic
331 AA Detmold	4.33	15.50	3.94	5.35	6.81	with AR
333 AA Dortmund	11.10	6.04	6.15	6.64	8.47	Basic
335 AA Düren	9.09	7.21	7.75	5.82	8.61	Panel
337 AA Düsseldorf	13.39	8.32	8.08	24.58	12.13	with AR
341 AA Duisburg	13.13	11.73	36.94	8.57	10.49	Panel
343 AA Essen	11.91	18.79	17.11	16.36	17.72	ARIMA
345 AA Gelsenkirchen	7.93	10.01	11.92	11.20	10.57	ARIMA
347 AA Hagen	7.26	4.52	8.41	18.31	5.59	Basic
351 AA Hamm	3.62	4.28	8.84	5.98	4.99	ARIMA
353 AA Herford	5.23	4.45	23.77	11.96	6.79	Basic
355 AA Iserlohn	4.67	6.29	16.79	12.93	7.51	ARIMA
357 AA Köln	5.43	5.93	12.05	4.44	10.31	Panel
361 AA Krefeld	6.23	3.72	13.36	5.21	3.31	with Spatial
363 AA Meschede	12.44	11.36	26.03	3.87	10.47	Panel
365 AA Mönchengladbach	3.09	5.03	4.01	6.65	5.84	ARIMA
367 AA Münster	5.02	9.03	6.23	10.54	6.05	ARIMA
371 AA Oberhausen	11.97	10.43	24.13	19.89	9.51	with Spatial
373 AA Paderborn	4.39	8.82	5.36	4.33	7.82	Panel
375 AA Recklinghausen	7.64	10.25	6.59	12.23	10.70	with AR
377 AA Rheine	4.37	3.76	13.14	8.30	9.77	Basic
381 AA Siegen	9.12	12.89	8.79	6.47	12.11	Panel
383 AA Soest	3.48	10.77	13.36	4.20	6.31	ARIMA
385 AA Solingen	3.56	3.21	5.39	6.90	3.04	with Spatial
387 AA Wesel	16.71	8.37	6.07	17.00	8.70	with AR
391 AA Wuppertal	13.23	10.06	40.06	6.35	10.23	Panel
411 AA Bad Hersfeld	14.11	5.01	18.19	12.19	6.80	Basic
415 AA Darmstadt	8.23	3.34	6.61	20.60	5.97	Basic
419 AA Frankfurt	10.33	8.14	32.53	23.81	4.41	with Spatial
423 AA Fulda	9.24	8.85	11.75	10.79	9.62	Basic
427 AA Gießen	17.78	6.20	17.36	6.27	7.01	Basic

Labour-Market District	Mean Average Percentage Forecast Error (MAPFE)					Best Model
	ARIMA	Structural Components				
		Basic	with AR	Panel	with Spatial	
431 AA Hanau	5.73	8.04	7.14	7.06	8.58	ARIMA
435 AA Kassel	14.49	12.72	7.64	22.93	16.05	with AR
439 AA Korbach	5.44	9.53	15.57	15.23	9.89	ARIMA
443 AA Limburg	4.66	7.03	7.68	7.30	8.91	ARIMA
447 AA Marburg	21.23	19.51	27.94	11.56	14.51	Panel
451 AA Offenbach	11.24	8.07	11.52	18.59	6.42	with Spatial
455 AA Wetzlar	6.09	5.57	7.29	17.89	5.79	Basic
459 AA Wiesbaden	11.90	7.05	9.63	22.42	9.64	Basic
511 AA Bad Kreuznach	8.42	6.03	15.22	5.18	3.74	with Spatial
515 AA Kaiserslautern	6.01	6.52	4.40	6.06	5.19	with AR
519 AA Koblenz	19.22	14.41	12.84	27.59	19.46	with AR
523 AA Ludwigshafen	2.21	1.56	2.79	4.53	2.49	Basic
527 AA Mainz	6.62	7.00	13.23	6.24	7.78	Panel
531 AA Mayen	6.82	5.70	15.26	6.17	5.90	Basic
535 AA Montabaur	5.28	8.60	35.64	9.87	9.96	ARIMA
539 AA Neunkirchen	5.30	7.40	8.63	8.28	8.11	ARIMA
543 AA Landau	7.18	5.90	62.27	9.43	6.46	Basic
547 AA Neuwied	5.76	7.39	8.25	11.19	7.74	ARIMA
551 AA Pirmasens	9.05	12.37	15.51	12.61	11.89	ARIMA
555 AA Saarbrücken	7.46	11.01	19.83	8.05	10.02	ARIMA
559 AA Saarlouis	5.02	12.19	16.63	22.38	15.26	ARIMA
563 AA Trier	9.83	6.49	27.62	8.71	8.28	Basic
611 AA Aalen	3.43	10.49	27.55	21.84	15.14	ARIMA
614 AA Balingen	10.12	4.81	25.27	13.23	7.11	Basic
617 AA Freiburg	8.80	5.38	14.87	8.02	9.36	Basic
621 AA Göppingen	8.30	10.19	39.74	17.01	9.64	ARIMA
624 AA Heidelberg	3.53	6.53	7.90	14.47	4.18	ARIMA
627 AA Heilbronn	5.61	8.48	28.78	15.92	7.69	ARIMA
631 AA Karlsruhe	2.69	6.01	22.44	17.67	6.27	ARIMA
634 AA Konstanz	4.96	5.29	10.33	17.35	6.99	ARIMA
637 AA Lörrach	6.06	7.94	8.78	21.85	10.59	ARIMA
641 AA Ludwigsburg	4.78	4.56	23.16	13.44	3.98	with Spatial
644 AA Mannheim	5.39	7.97	14.45	7.96	8.55	ARIMA
647 AA Nagold	5.93	4.41	18.35	16.91	4.43	Basic
651 AA Offenburg	3.15	6.67	33.92	19.76	4.13	ARIMA
654 AA Pforzheim	3.45	1.83	3.29	19.29	3.11	Basic
657 AA Rastatt	3.84	6.04	12.00	9.86	6.36	ARIMA
661 AA Ravensburg	5.03	7.11	21.86	15.20	8.47	ARIMA
664 AA Reutlingen	3.25	2.56	37.89	19.14	3.59	Basic
667 AA Rottweil	6.60	7.34	17.78	20.70	8.06	ARIMA
671 AA Waiblingen	4.35	5.40	18.16	11.17	4.85	ARIMA
674 AA Schwäbisch Hall	2.96	5.53	20.70	28.23	16.75	ARIMA
677 AA Stuttgart	7.43	11.76	18.90	8.68	13.58	ARIMA
681 AA Tauberbischofsheim	5.66	7.87	44.76	20.08	10.21	ARIMA
684 AA Ulm	5.22	7.21	7.56	11.11	7.69	ARIMA
687 AA Villingen-Schwenningen	3.91	7.52	34.56	31.53	9.67	ARIMA
711 AA Ansbach	10.90	8.91	9.72	14.53	20.64	Basic
715 AA Aschaffenburg	7.34	7.52	49.07	17.82	7.95	ARIMA
719 AA Bamberg	6.98	3.12	5.52	14.41	7.80	Basic
723 AA Bayreuth	6.71	2.36	47.55	15.90	14.55	Basic
727 AA Coburg	5.49	8.92	18.30	23.33	15.24	ARIMA
731 AA Hof	4.45	7.40	22.42	16.41	5.36	ARIMA
735 AA Nürnberg	5.30	8.55	13.02	19.09	12.31	ARIMA
739 AA Regensburg	8.75	6.18	19.85	14.17	12.59	Basic

Labour-Market District	Mean Average Percentage Forecast Error (MAPFE)					
	ARIMA	Structural Components				Best Model
		Basic	with AR	Panel	with Spatial	
743 AA Schwandorf	7.92	7.42	10.86	15.35	14.90	Basic
747 AA Schweinfurt	5.87	5.97	30.28	10.17	6.93	ARIMA
751 AA Weiden	7.51	12.62	23.75	9.01	10.77	ARIMA
755 AA Weißenburg	13.75	12.29	29.56	25.48	24.11	Basic
759 AA Würzburg	9.11	10.38	40.62	16.31	11.57	ARIMA
811 AA Augsburg	8.15	9.18	8.52	22.88	11.32	ARIMA
815 AA Deggendorf	11.37	7.73	42.31	12.71	13.49	Basic
819 AA Donauwörth	5.43	5.21	26.23	10.81	13.93	Basic
823 AA Freising	16.81	17.32	28.05	42.20	24.08	ARIMA
827 AA Ingolstadt	4.87	7.24	5.95	20.89	9.85	ARIMA
831 AA Kempten	7.68	9.72	70.03	25.95	15.78	ARIMA
835 AA Landshut	7.92	7.80	17.09	13.49	10.07	Basic
839 AA Memmingen	6.99	7.68	62.34	23.91	14.88	ARIMA
843 AA München	5.19	8.61	15.97	13.53	8.69	ARIMA
847 AA Passau	5.51	6.56	6.46	17.39	9.90	ARIMA
851 AA Pfarrkirchen	6.53	8.40	21.37	15.84	9.68	ARIMA
855 AA Rosenheim	6.63	5.97	64.94	21.78	9.69	Basic
859 AA Traunstein	7.84	5.98	8.89	12.32	9.17	Basic
863 AA Weilheim	6.86	5.92	41.88	15.08	9.31	Basic
900 Berlin	6.21	9.22	11.33	3.90	4.22	Panel
Mean	7.49	8.57	18.17	12.10	8.98	
Maximum	21.23	26.14	79.20	42.20	24.11	
Minimum	1.56	1.56	2.14	2.75	2.21	
Standard Deviation	3.98	4.52	14.84	6.68	4.13	