IAB Discussion Paper
Beiträge zum wissenschaftlichen Dialog aus dem Institut für Arbeitsmarkt- und Berufsforschung

No. 2/2007

Regional Employment Forecasts with Spatial Interdependencies

Katharina Hampel, Marcus Kunz, Norbert Schanne, Rüdiger Wapler, Antje Weyh

Bundesagentur für Arbeit

Regional Employment Forecasts with Spatial Interdependencies

*Katharina Hampel, Marcus Kunz, Norbert Schanne,
Rüdiger Wapler, Antje Weyh (IAB)*

Contents

List of Figures

List of Tables

Abstract

The labour-market policy-mix in Germany is increasingly being decided on a regional level. This requires additional knowledge about the regional development which (disaggregated) national forecasts cannot provide. Therefore, we separately forecast employment for the 176 German labour-market districts on a monthly basis. We first compare the prediction accuracy of standard time-series methods: autoregressive integrated moving averages (ARIMA), exponentially weighted moving averages (EWMA) and the structural-components approach (SC) in these small spatial units. Second, we augment the SC model by including autoregressive elements (SCAR) in order to incorporate the influence of former periods of the dependent variable on its current value. Due to the importance of spatial interdependencies in small labour-market units, we further augment the basic SC model by lagged values of neighbouring districts in a spatial dynamic panel (SCSAR).

The prediction accuracies of the models are compared using the mean absolute percentage forecast error (MAPFE) for the simulated out-of-sample forecast for 2005. Our results show that the SCSAR is superior to the SCAR and basic SC model. ARIMA and EWMA models perform slightly better than SCSAR in many of the German labour-market districts. This reflects that these two moving-average models can better capture the trend reversal beginning in some regions at the end of 2004. All our models have a high forecast quality with an average MAPFE lower than 2.2 percent.

JEL-Classifications: C53, J21, O18

1 Introduction

Due to large differences in the regional labour-market performance in Germany, the labour-market policy-mix is increasingly being decided on a regional level. This implies that the local institutions, i.e. the districts of the Federal Employment Agency (*Agenturbezirke*), have an increased need for regional forecasts as a guideline for their decision process. In this paper, we focus on employment forecasts for these regional units.

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. For the latter, appropriate leading indicators on a small regional scale are hardly available. Moreover, it has often been shown (cf. for example the overview in Stock 2001) that simple methods perform nearly as well as more complex ones. Further, as we forecast employment 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 three standard univariate methods: autoregressive integrated moving average (ARIMA) models, exponentially weighted moving averages (EWMA) according to the seasonal Holt-Winters method and structural-component (SC) estimators. Then, we augment the basic SC model for autoregressive and spatial components. Using simulated out-of-sample forecasts we are then in a position to compare the results of the augmented models with the other models.

The paper is organised as follows: After describing the data and the regional variation in employment in Germany, we provide an overview of different approaches to regional forecasting. Section 4 describes the applied forecasting methods of our models. The presentation and discussion of our results follows, before a conclusion ends the paper.

2 Data and Regional Variation in Employment in Germany

Employment forecasts for the whole of Germany are relatively robust. However, such forecasts do not yield much information about the regional development within the country. Due to different industry structure, qualification, wage level, or other sources of local labour-market disparities, forecasts for a small spatial unit can differ from national forecasts and even predict opposite results. Considering regional distinctions, we forecast employment in the 176 German labour-market districts[1], which are, with the exception of Berlin and Hamburg, between NUTS 2 and NUTS 3 regions. First, we describe our data and the current labour-market situation in Germany particularly emphasising regional differences.

To analyse the current employment situation and to perform our forecasts, we use register data from the German Federal Employment Agency. This data covers all registered employees who are subject to obligatory social insurance in the German labour-market districts on a monthly basis. Our employment data at this level of aggregation starts in January 1996 and ends in December 2005. This relatively long time lag is caused by the time span necessary for deliverance and processing the data. Therefore, our employment forecasts for 2006 and 2007 are based on data which end in December 2005 but first become available in September 2006.

Figure 1 shows the average employment rate[2], the growth rate[3] and seasonal span[4] of employment. These represent the basic elements of a time series: level, trend and season.

---

[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 employment levels for 176 and not for 178 districts.

[2] The average employment rate is defined as $\bar{Y}_{emp} / \bar{Y}_{pop}$, where $\bar{Y}_{emp}$ is the average number of employees registered at their place of work and $\bar{Y}_{pop}$ the average population in the year. This is not identical to the labour-force participation rate where both the numerator and denominator are counted at the place of residence. This measurement is the only one which can be calculated for all labour-market districts as the population is only available at this regional level. A better reference parameter than the whole population would be the employable population. However, one problem persists for both measurements: Our data for the employees count them at their place of work, whereas the population is counted at their residency. This leads to an overestimation of the employment rate in districts where a relatively large number of employees commute in and to an underestimation in districts where the employees commute out.

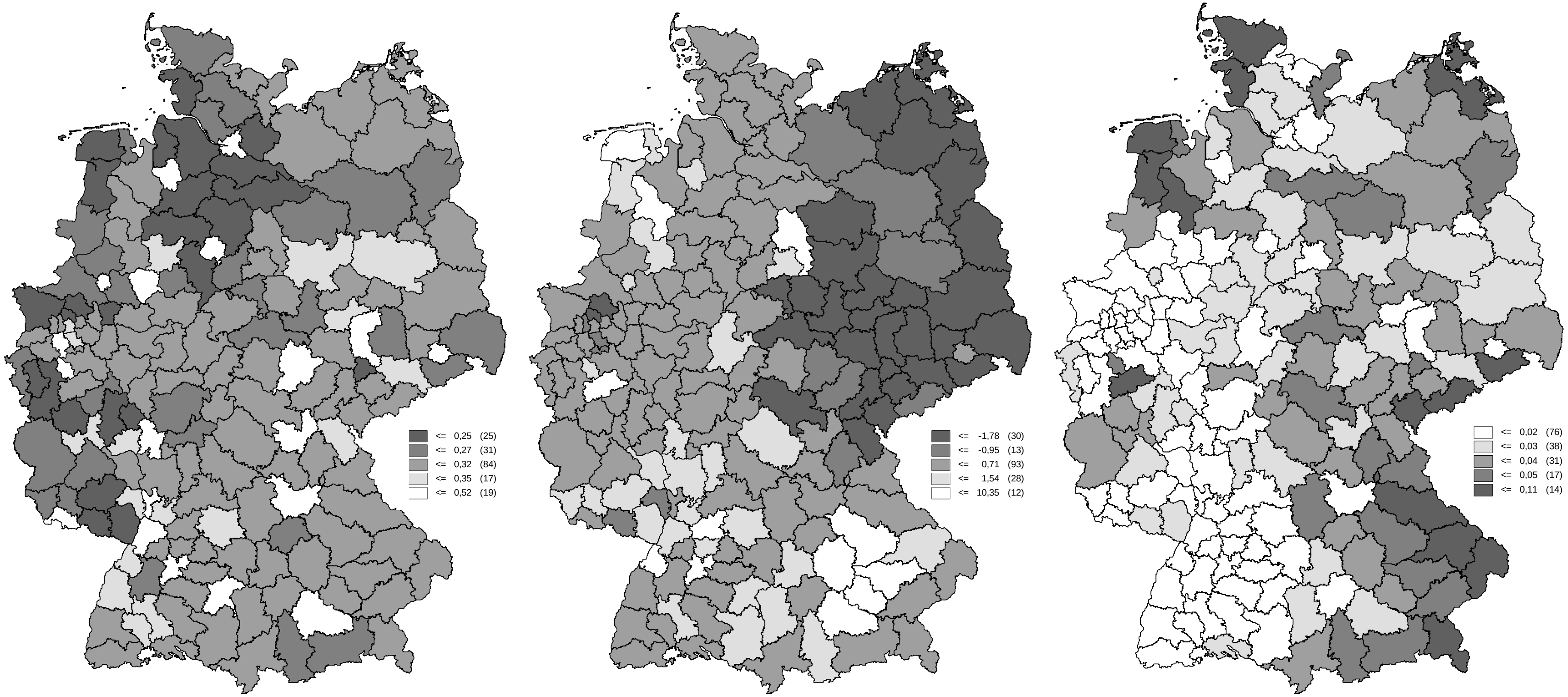
[3] This is defined as the average of $(Y_{Dec,t} - Y_{Dec,t-1}) / Y_{Dec,t-1}$ for every year, where $Y_{Dec,t}$ is the number of employed in December of year *t*.

[4] 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 employed in the respective year.

The often emphasised East-West perspective only holds for the growth rate of employment (and even here only partially) which is negative in nearly all eastern labour-market districts. High negative growth rates in western Germany exist in Recklinghausen and Gelsenkirchen (both situated in the Ruhr area). High positive growth rates can be observed especially in middle Bavaria.

No East-West differences can be seen for the employment rate and the seasonal span. High employment rates but low seasonal spans can generally be found in urbanised labour-market districts. Cities tend to have higher employment rates than their neighbourhood. This can be seen particularly well in the triangle between Bremen, Hamburg and Hanover. This may be due to the commuters who live in the regions of the triangle and work in the three cities. 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 eastern German low mountain ranges and in Bavaria. A dichotomy between eastern and western Germany can be seen in the right map of Figure 1. Interestingly, this dichotomy does not correspond to the former inner-German border.

Figure 1: Average employment rate, Growth rate and relative seasonal span of employment in Germany from 1996 to 2004



Average employment rate

Growth rate of employment

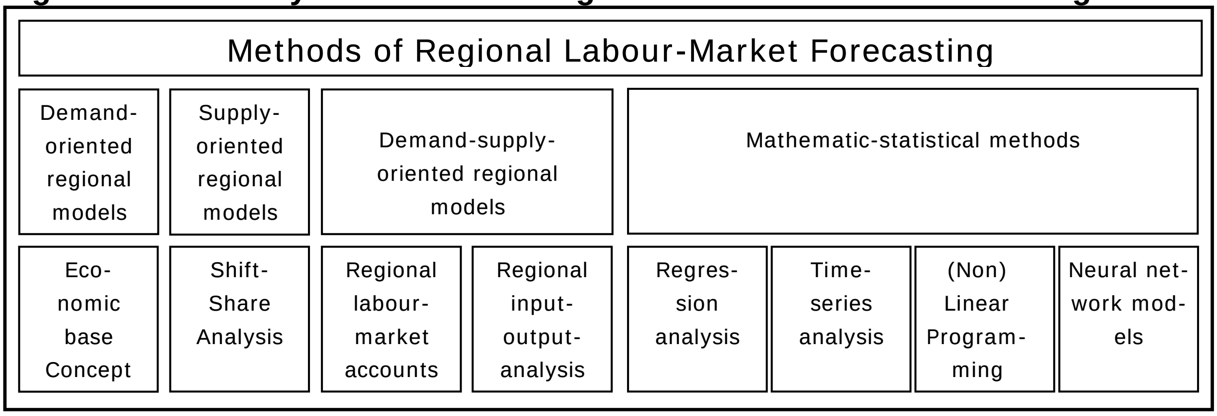
Seasonal span of employment

Source: Federal Employment Agency

3 A Review of the Literature

In this section we provide an overview of approaches of regional labour-market forecasts, and present – whenever they exist – examples of corresponding empirical specifications for Germany. However, the number of studies on regional forecasting is not as numerous as one would perhaps expect. Figure 2 shows a taxonomy of methods used for regional labour-market forecasts.

Figure 2: Taxonomy of Methods of Regional Labour-Market Forecasting



Methods of labour-market forecasting can roughly be divided into methods based mainly on labour-market theory, such as demand-oriented, supply-oriented and demand- and supply-oriented models and mathematical-statistical methods. A well-known demand-oriented regional model is the economic base concept which divides the regional economy into 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 is the demand for local products and services. For this reason, the economic base concept models the whole employment development as a function of employment in the regional export sector. Developed in the 1950s, the concept can in times of high import rates and complex regional economic relationships no longer be considered appropriate. The obvious shortcomings of this demand-based method have been described repeatedly (see e.g. Fritsch, 1991; Eckey, 1988; Wulf, 1970), the model is no longer used as a forecasting tool for local employment (Jaeger 1996, 5).

Great importance for the regional development is still being attributed to the determinants of production. In particular, the shift-share analysis (SSA) as a supply-oriented model is widely used to analyse regional employment (for a German example of regional labour-market forecasts with the SSA, see Tassinopoulos 1996). This approach interprets a variation in regional employment as a product of a structural (shift) and a local (share) component. The structural component focuses on the regional industrial structure and shows how a region would develop if the regional employment growth in an industry were analogous to the national development of the corresponding industry. The local component is defined as a residuum that remains once the structural influences have been removed from the observed variation. 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/Wolf 2002, 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 influences into supply-oriented projections. Nonetheless, the value of shift-share techniques as an analytical tool for regional analyses is generally considered as high.

There are two concepts of demand-supply-oriented regional models. The concept of labour-market accounts contrasts the development of labour supply and labour demand. Like in a balance sheet, labour-market data is either classified as asset (labour demand) or as liability (labour supply). The resulting negative gap to the totals (the working population in the region) is the number of unemployed on the liability side and the number of vacancies on the asset side of the balance sheet. Developments of the several balance sheet items are observed separately and assigned to business cycle or structural changes. This rather descriptive method of regional labour-market analysis can provide as a very good starting point for forecasting (as an example of a German labour-market account study, see Eltges/Maretzke/Peters 1993, Eltges/Wigger 1994, Klaus/Maußner 1988, Eckey/Stock 1996). However, as it implies no genuine forecasting device itself, the resulting predictions tend to be extremely conservative and need to be interpreted with extreme caution. The second concept is known as regional input-output analysis, an analytical tool to analyse inter-industry relationships in a region. They depict how the output of one industry serves as an input of another one, and thereby shows the interdependencies of different industries, as a customer on the one hand and as a supplier on the other. Input-output models are widely used in economic forecasting to predict flows between sectors (see e.g. Rickman/Miller 2003, Schindler/Israilevich/Hewings 1997). Problems with this concept can arise when the assumption of constant coefficients is violated and not incorporated by trend estimations (Jaeger 1996, 20).

Regressions, time-series analysis, the method of linear programming and the neural-network approach are considered as mathematic-statistical methods. The basic purpose of a regression analysis is the determination of the relationship between a dependent variable and an arbitrary number of exogenous variables, where the latter can for example consist of economic indicators or artificial structural components. In the former case, theoretically and empirically validated economic indicators which anticipate the labour-market development are needed to construct the regression model (see Oberhofer/Blien/Tassinopoulos 2000 for an example of a mixed approach of common extrapolation techniques and regression analysis). This often proves to be difficult even at a highly aggregated level and is nearly impossible at a regional level (see Hamm/Wienert 1989, 210). Further, in small spatial units, the risk of biased results caused by single events and influences which are not captured by the regressors, tends to be much higher than at an aggregate level. Thus, as a tool for regional forecasting, results of multivariate regression analysis are not fully satisfactory. Regression models do not necessarily require explanatory economic data. Instead, the dependent variable can be explained by structural components such as level, trend or seasonal patterns (see De Gooijer/Hyndman 2005). However, structural-component models have not been widely used as a forecasting tool for regional developments, mainly due to their limited explanatory power as deterministic models (cf. Ray 1989, Proietti 2000). As we show in our paper, these models can be augmented by non-deterministic components such as temporal or spatial lags to remove these limitations and to obtain both stability from the deterministic and flexibility from the stochastic models.

The most commonly used approach for (regional) forecasting is time-series analysis. A good overview is given by De Gooijer/Hyndman (2005). Unlike regressions, time-series analyses do not require any definitions of causalities. These methods assess regularities in the time series and try to describe the data-generating process either deterministically or stochastically. The simplest form of trend analysis and forecasting consists in smoothing techniques. Especially the method of exponentially weighted moving averages where the forecast values are calculated by averaging past data and more recent data is incorporated with an exponentially higher weight, performs surprisingly well (Satchell/Timmermann 1995, Chatfield et al. 2001).

An alternative approach to analysing and forecasting time series is based on autoregressive (AR) as well as on moving-average (MA) components (see Section 4.2). Forecasts can either only rely on past values of the dependent variable (univariate ARIMA models) or include exogenous economic information (multivariate extension of ARIMA). Dynamic regression models (also known as transfer functions, see e.g. Weller 1989, Weller 1990) and multivariate vector autoregressive (VARMA) models (see e.g. Patridge/Rickman 1998; Lutkepohl 2006) have been more commonly used in labour-market forecasts. However, parsimonious ARIMA models or transfer functions can still outperform VARMAs, as Edlund/Karlsson (1993) show for Swedish unemployment rates. A further extension of time-series models is to include spatial elements. It has been shown that neglecting spatial dependency can produce highly inaccurate forecasts (Giacomini/Granger 2004). Several recent studies have thus included spatial autocorrelation elements into VARMA models (cf. for example Arbia/Bee/Espa 2006, Beenstock/Felsenstein 2006). However, to the best of our knowledge, the only labour-market related study in this field is Hernandez-Murillo/Owyang (2006), but there are no German regional labour-market forecasts which include spatio-temporal elements. As the number of labour-market districts in Germany exceeds 64, the incorporation of spatial elements is not feasible with VARMA estimation techniques (see Arbia/Bee/Espa 2006).

The mathematical method of linear programming is used to maximise or minimise a function under constraints. The power of this method lies in considering forecast relevant information via restrictions, prediction floors and sensitivity analyses. However, a regional application for labour-market forecasts tends to be difficult as detailed regional data and functional relationships are required. For an empirical application of this approach to Germany we have to go back to the 1980s (see Thoss/Kleinschneider 1982, who use this approach for the district Borken/Westphalia). Instead, recent empirical work has been based on methods of non-linear programming. For example, Blien/Tassinopoulos (2001) produce regional employment forecasts for all western German districts based on a combination of top-down and bottom-up techniques.

Another recent approach in the set of mathematic-statistical methods for analysing and forecasting regional employment is to use artificial neural network (ANN) models (for an example of German labour-market forecasts see Patuelli et al., 2006). Longhi et al. 2005 use this approach and partially combine it with the SSA. In contrast to traditional statistical models, they neither require an identification process for the set of regressors they use, nor a linear specification of the relationships between the dependent 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 and substituted into one or more non-linear indicators. Whereas some authors report positive results from labour-market forecasts using ANNs (Swanson/White 1997 as well as Stock/Watson 1998, who state that ANNs perform at least slightly better than time-series techniques), others think that they are more powerful for financial variables than for labour-market forecasts (see amongst others Diebold 1998, 182).

Various authors have developed forecast models for single German labour-market regions (Bruch-Krumbein/Friese/Kollros 1994 for the South of Lower Saxony, Eltges/Wigger, 1994, for the district of Borken/Westphalia and Klaus/Maußner 1988, for 18 Bavarian regions). Others have applied one model to all German labour-market regions (Bade 1991, 1996, 1999, 2004, Blien/Tassinopoulos, 2001, Longhi et al. 2005, and Patuelli et al. 2006). However, to our knowledge, there have so far not been any attempts to systematically perform German labour-market forecasts with individually specified regional models for all labour-market districts. Moreover, the benefit of spatial lag components for regional forecasting has so far been neglected in German regional forecast studies. These gaps are filled by our paper.

4 Applied Forecast Methodology

Despite the common critique that pure time-series decompositions neglect economic theory, we focus on them for three reasons. First, many variables which would be necessary to model economic relations are not available at the required regional level. Second, as the relevant future values of the economic covariates are not known at the time the forecasts are performed, they have to be approximated by their past. Third, if the same variables which currently influence the employment level also influenced it in the past, then this information is automatically included when using past values of the series of interest in order to forecast its future development. Moreover, focusing on lagged values of the series has the advantage that it uses past information efficiently in the statistical sense.

Therefore, we apply two univariate time-series models, exponentially weighted moving averages and ARIMA. These simple models often perform nearly as well as more complex methods. Here they are used as reference models against which more complicated models can later be tested. In a second step, we present a deterministic structural-components model and extend this basic model by including either autoregressive elements or spatial dependencies. 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 order to evaluate the models, we perform simulated out-of-sample forecasts for the last year where data is available.

To a large extent, the variable-selection procedure is automised. 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 specification for violations of the underlying assumptions of the respective models as described below in more detail.

4.1 Exponentially Weighted Moving Averages

As stated in the name, exponentially weighted moving average (EWMA) models base their predictions on a large number of previous observations of the endogenous variable where the weights of the previous values decline exponentially the further they are in the past. Hence, the basic structure of the model is given by:

$$E(y_{t+1} \mid I_t) = ay_t + a(1-a)y_{t-1} + a(1-a)^2 y_{t-2} + \cdots + a(1-a)^t y_0 \tag{1}$$

where I_t is the information available at time *t* and *a* is the weight. The focus of these models is on the autoregressive structure and on an underlying stochastic process. As well, they can be split into a level, trend and seasonal component. As employment follows a regular cyclical pattern, the seasonal Holt-Winters method is applied. Here it is assumed that the amplitude of the seasonal variance remains constant over time, hence the additive method is used.[5] The equation to be estimated is given by:

$$y_{t+\tau} = a_t + b_t \cdot \tau + s_{t+\tau-L} + \varepsilon_t \tag{2}$$

where a_t denotes the level, b_t the trend and s_t the seasonal figure at time t. The level, trend and seasonal component are modelled stochastically. They are determined by the parameters α, β and γ which are simultaneously estimated using maximum likelihood. These parameters define the update equations for the components as:

$$a_t = \alpha\left[y_t - s_{(t-L)}\right] + (1-\alpha)(a_{t-1} + b_{t-1}) \tag{3}$$

$$b_t = \beta\left[a_t - a_{t-1}\right] + (1-\beta)b_{t-1} \tag{4}$$

$$s_t = \gamma(y_t - a_t) + (1-\gamma)s_{(t-L)} \tag{5}$$

where *L* denotes the number of lags in months. Hence, with monthly data, *L=12* shows seasonal patterns.

4.2 Autoregressive Integrated Moving Averages

Autoregressive integrated moving average (ARIMA) models are a standard procedure when forecasting time series. Usually, these models are implemented according to the Box-Jenkins forecast method (cf. Box/Jenkins 1970 and Greene 2003) which proceeds 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) It is tested which previous periods are necessary to best explain 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, stepwise tests are performed to test whether inclusion of these lags or errors

5 If the multiplicative method had been used, then (2) would have been estimated as:

$$y_{t+\tau} = (a_t + b_t \cdot \tau)s_{t+\tau-L} + \varepsilon_t$$

However, this model is only justified if it is assumed that the seasonal variance increases with time. The model was tested here and it indeed turned out that the additive method delivered better results than the multiplicative approach.

into the regression improves the model fit. Typically, for selection either measures of simulated forecast errors such as the mean squared error (MSE) or information criteria such as those of Akaike (AIC) or Schwartz (BIC) are used.

(4) When no additional lag diminishes the selection criterion, the residuals are tested for white noise (Portmanteau test), i.e., if the estimation has minimum variance. If the test is not rejected, the efficient estimate is used for the forecast.

To remove seasonal effects, we first use yearly differences of regional employment. The resulting data is tested for unit roots using the augmented Dickey-Fuller test (cf. Bierens 2001). If the test indicates the presence of unit roots with and without a trend, we first compute (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 the following ARMA equation:

$$y_t = \mu_t + \sum_{k=1}^{p} y_{t-k}\alpha_k + u_t \qquad \text{with } u_t = \sum_{k=1}^{q} u_{t-k}\rho_k + \varepsilon_t \tag{6}$$

In most applications, all lags up to lag *p* (*q*) are included into the regression, where *p* (the highest autoregressive lag) and *q* (the correlated error furthest in the past) are determined by an analysis of the correlogram. However, some lags might not provide relevant information about the development of the time series: One looses degrees of freedom without improving the estimation, and particularly small samples perform better if these coefficients are set to zero. Therefore, we rank the lags according to their absolute PAC and AC values respectively, and, starting with the highest, add them stepwise to the equation. This procedure is known as “simple-to-general”.

Many studies conclude that lag selection based on information criteria performs better than other methods, see e.g. Inoue/Kilian (2006) or Stock (2001). Here, the decision whether a lag is maintained in the further estimations is based on the corrected Akaike information criterion (AICC):

$$AICC = \ln\sigma^2 + \frac{(T+k)}{T-k-2} \tag{7}$$

where T is the number of observations, k the number of estimated parameters and σ the estimated standard deviation. This information criterion often yields a more appropriate parameter selection than those of Akaike or Schwartz: Typically the AIC leads to more variables than necessary while the BIC leads to an underfit (cf. Hurvich/Tsai 1989).

4.3 Basic Structural-Components Model

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

$$Y_t = \mu_t + \gamma_t + \psi_t + \varepsilon_t \tag{8}$$

with

Y_t	the dependent variable (employment) in monthly differences
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 exogenous variables, nor, in contrast to the ARIMA and EWMA 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:

$$\mu_t = \mu_0 + \beta_0 t + \upsilon_t \text{ with } \upsilon_t \sim i.i.d.\left(0, \sigma_\upsilon(t)^2\right) \tag{9}$$

where μ_0 is the initial level, β_0 the slope parameter and υ_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 modelled 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):

$$\gamma_t = \sum_{j=1}^{[s/2]} \left(\alpha_j \cos \lambda_j t + \delta_j \sin \lambda_j t\right) \text{ with } \lambda_j = 2\pi j / s \tag{10}$$

Once the level, trend and seasonal components have been included, a first regression is run. All subsequent regressions use the linear trend in addition to those variables which are significant at the 10 percent-level. However, if multicollinearity between the quadratic and cubic trend components arises either the quadratic or cubic term is kept depending on which is more significant.

Economic theory differentiates between short-, medium- and long-term business cycles. As the data for our simulated out-of-sample forecasts only covers eight years, we can at best capture short-term cycles.[6] Just like the seasonal component, business cycles are modelled by cosine and sine functions. 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 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. If it turns out that both cycle components are insignificant, we test for joint significance and if the test is not rejected include the one with the (in absolute terms) higher t-statistics. Once all (significant) components have been established, the full model can be regressed using standard OLS-regression techniques.

4.4 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 stable time series, the structural-components method is appropriate when the aim is 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

---

6 As we require roughly at least half the sample length to perform reliable estimations, the maximum cycle length is limited to 40 months.

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. We denote this augmented model by SCAR. It can be written as:

$$Y_t = \mu_t + \gamma_t + \psi_t + \theta_t + \varepsilon_t\,, \tag{11}$$

where μ_t, γ_t, ψ_t and ε_t are defined as in Section 4.3 and θ_t represents the autoregressive component modelled as:

$$\theta_t = \sum_{s=1}^{S=26} \vartheta_s Y_{t-s}\ . \tag{12}$$

where ϑ_s are the parameters to be estimated.

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 *S* is set to a maximum of 26. Obviously not all lags should be added in the final model. To guarantee parsimonious parameter usage, we apply the same lag selection procedure as in the ARIMA model. We sort the lagged values according to their absolute partial autocorrelation function (PAC) values, include them stepwise while maintaining the components of the basic SC model as well as all previously tested lags which have improved the AICC (cf. Section 4.2).

4.5 Structural Components with Spatial Interdependencies

Particularly when forecasting on a small regional scale, it seems plausible that the development of the dependent variable in neighbouring regions has an impact on the region being analysed (cf. Section 2). This relationship between neighbours can be described as a spatial autoregressive process. To model the spatial relationship 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/Granger 2004).

Due to the reciprocal connections between regions, it is necessary to regress and forecast with panel techniques. To keep up the basic idea of the structural-components model, i.e. to account for the regional heterogeneity, the data is written in block diagonal form. This “seemingly unrelated regression estimation” (SURE) form allows for specific coefficients for each labour-market district and the spatial process parameters.

Hence, the structural-component model with spatial autoregressive elements (which we abbreviate by SCSAR) can be written as:

$$\vec{Y}_t = \vec{\mu}_t + \vec{\gamma}_t + \vec{\psi}_t + \vec{\xi}_t + \vec{\varepsilon}_t \,, \qquad (13)$$

where $\vec{Y}_t = (Y'_{1,t}, \ldots, Y'_{N,t})'$ denotes the vector of employment at time *t* over all regions, and the components are defined analogously to Section 4.3. The spatial component in region *i*, ξ_{it}, is defined as:

$$\xi_{it} = \sum_{\tau} \sum_{j=1}^{N} w_{ij} Y_{j,(t-\tau)} \kappa_{i\tau} \,, \quad \tau \in \{1, \ldots, 13\}, \qquad (14)$$

where w_{ij} is the spatial weight defined by contiguity, i.e. $w_{ij} = 1$ if a region *j* shares a border with region *i* and 0 otherwise. $\kappa_{i\tau}$ are the parameters to be estimated. We maintain all components that were significant in the basic structural-components model. In addition, we include up to thirteen months lagged values of the neighbours’ average. Note that in contrast to most estimations of spatial autoregressive processes, we allow for individually specified parameters of spatial dependence for each region.

We rank the thirteen lagged vectors of the spatial elements according to their correlation to the residual measured by a partial spatial autocorrelation function, PSAC, similar to the PAC function in time-series analysis. Then, we apply a sequential two-step selection procedure. In the first step we add all elements of the vector of τ month lagged spatial lags to the estimation, in order to receive their t-statistics. In the second step, we test whether the inclusion of the significant elements of this vector improves the AICC as compared to the previous estimation.

To sum up, for each labour-market district we estimate five different models: EWMA, ARIMA, SC, SCAR and SCSAR. In order to evaluate the model performance, we check the quality of the forecast results by running simulated out-of-sample forecasts using the last twelve months in which data is available (01/2004-12/2004). By doing this, we are able to calculate several error measures, on which the discussion of the results in the following section is based.

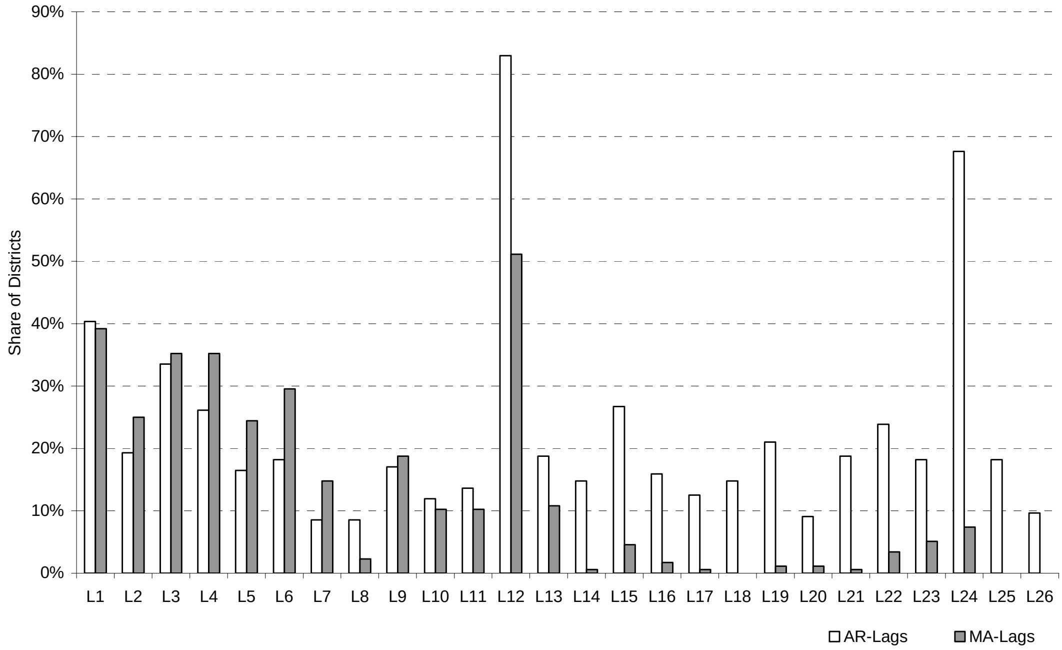
5 Results and Discussion

Whilst the mean square forecast error (MSFE) is a suitable accuracy measure to compare the forecast performance of the models for the same region, we are also interested in comparing the quality of the forecasts of the individual models amongst the different labour-market districts. When doing this, it is important to explicitly account for the size of the districts. Therefore, we need a relative accuracy measure. To this end, the focus here is on the mean absolute percentage forecast error (MAPFE). This measure is calculated as the difference of the forecasts with the observed values relative to the observed value for each month and labour-market district and then averaging over the twelve months of the simulated forecast period. Finally, we compare the model forecasts using this accuracy measure as well as a discussion of the models' strengths and weaknesses.

5.1 Results of the Models

In our standardised ARIMA model selection, the time series are first differenced annually. This new time series is tested for stationarity. If it is not stationary, we further difference on a monthly basis and again test for stationarity. In nearly all labour-market districts (173) both differences are needed and only in three labour-market districts is the seasonal difference sufficient. The stepwise lag selection first of autoregressive and subsequently of moving-average terms follows. On average, nearly six (5.86) AR lags and slightly more than three (3.36) MA lags are included to obtain the final estimation model. Despite the differentiation, the most frequently used autoregressive lags are the typically seasonal lags of 12 and 24 months (see Figure 3). The one-year lag is selected in 83 percent and the two-year lag in 68 percent of all cases. The next most common lags of 1 and 3 months have frequencies of 40 percent and 34 percent, respectively. With the exception of four lags, all other autoregressive elements are selected in more than 10 percent but less than 30 percent 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 twelve period lagged error dominates the other lags and is chosen in nearly half of all cases. The lags which capture the one-month till the six-month errors, still occur in more than 20 percent of the districts.

Figure 3: Frequencies of the Selected AR and MA-Lags in the ARIMA Estimates



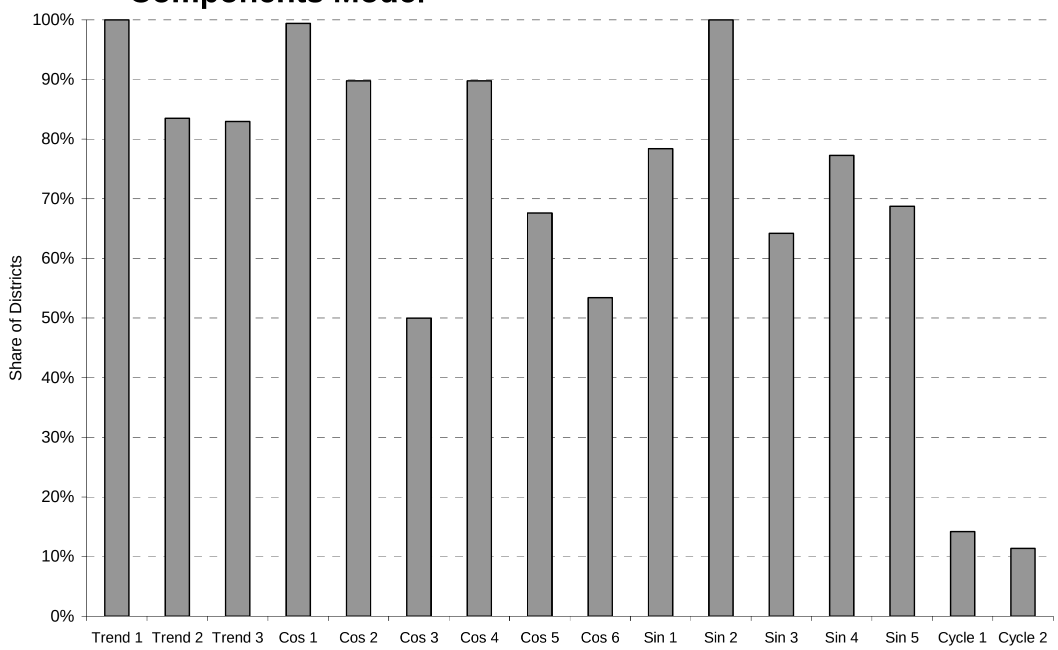
Lt: t month lagged values of the dependent variable

As shown in Table 1 on page 29, our ARIMA-models have an average MAPFE of 0.90 percent across the 176 labour-market districts in the simulated out-of-sample forecasts. The best result is achieved for the labour-market district of Bremen which has a MAPFE of only 0.09 percent. By contrast, the prediction for Zwickau deviates from the actual figures by 5.66 percent. The standard deviation as a measure for the variation is 0.75 percentage points and can be used as a further indicator when comparing the accuracy of the predictions. Interesting is also the spatial distribution of the forecast errors. Geographically concentrated patterns of lower (higher) MAPFEs indicate that the model fits better (worse) for these regions. The ARIMA predictions have relatively low MAPFEs e.g. in central

Bavaria. High prediction errors mainly occur in Rhineland-Palatinate and Mecklenburg-Western Pomerania.

The EWMA model forms its predictions by estimating three labour-market district specific parameters for the level, trend and seasonal influences. As described above in Section 4.1, the values for the smoothing parameters have to be between 0 and 1. High smoothing parameters attach a high value to current observations of a time series and lead to a fast adaptation, whereas low values consider past observations as important and signify a slower adjustment. The level parameter α shows an average value of 0.90 and ranges between 0.63 and 1.00. For the trend, the smoothing parameter β takes on values between 0.00 and 0.23 with an average of 0.07, and the seasonal smoother γ covers the complete interval from 0.00 to 1.00 with a mean value of 0.51. The EWMA model shows a mean MAPFE of only 0.66 percent. The minimum MAPFE was calculated for Goeppingen with 0.08 percent, the maximum value of 3.52 percent resulted in Helmstedt. The standard deviation is 0.55 percentage points. In general, the EWMA method produces good forecast results especially for many labour-market districts in the North-East and the South of Germany. Some labour-market districts in Mecklenburg-Western Pomerania, Saxony and Saxony-Anhalt have relatively high MAPFEs.

Figure 4: Frequencies of the 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: cosine business cycle; Cycle 2: sine business cycle

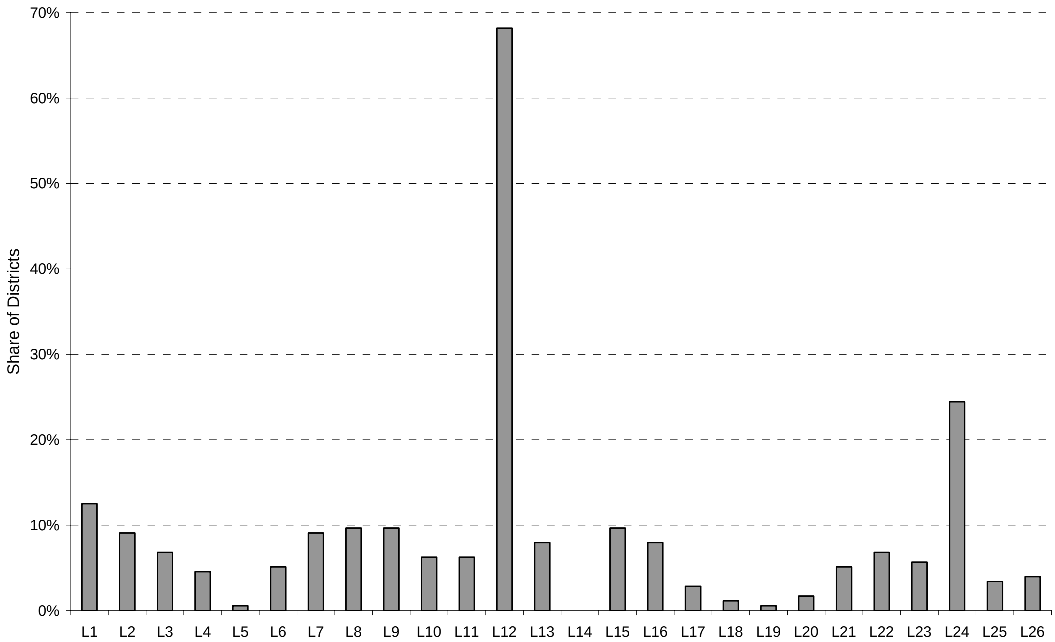
The basic SC model contains trend, season and business-cycle components. Due to the unique behaviour of the time series in each labour-market district and our automised selection of only significant components, the composition of the selected components differs between the labour-market districts. However, some components are more frequently used than others (see Figure 4).

The most important component is the linear time trend, which is kept by definition in every labour-market district. Also the quadratic and cubic trends are kept in more than 82 percent of the final estimations. Every sine and cosines function is included at least in half of all cases. The most commonly used seasonal components are the full year cosines and the half year sine function, which are kept in nearly all districts. 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 only 16 districts is the cycle length affected by the censoring (see Section 4.3) and is hence limited to 40 months. In 53 of 176 regions the cycle length is 23 or 35 months. The average length is 27 months. Two different types of business cycles are used: one is modelled as a sine and the other one as a cosines function. Hence, they are shifted in time but do not differ in length and amplitude. The sine cycle is included in nearly 14 percent and the cosines cycle in about 11 percent of the 176 simulated out-of-sample estimations.

The evaluation of the basic SC model for the simulated out-of-sample forecasts shows a mean MAPFE of 1.73 percent. The results also show a wide range in the calculated MAPFEs. The best fit was achieved in Celle with a MAPFE of 0.12 percent, the highest value was observed in Gotha with 8.81 percent. The standard deviation over the 176 labour-market districts is 1.09 percentage points. There are also differences in the spatial distribution of the MAPFEs. Basic SC models perform better in most parts of North Rhine-Westphalia and Saxony-Anhalt, whereas in Thuringia the predictions are fairly poor.

As described in Section 4.4, we augment the basic SC model for autoregressive elements to improve the short-term adjustment of the time series. Starting point is the full set of significant components used in the basic model. The results of the sequentially added autoregressive elements clearly show the importance of the one-year lag which is used in 120 labour-market districts, and the two-year lag, added in about 24 percent of all agencies (see Figure 5). On average, 2.29 AR lags are included in addition to the basic components.

Figure 5: Frequencies of the Selected AR-Lags in the Structural-Components Model

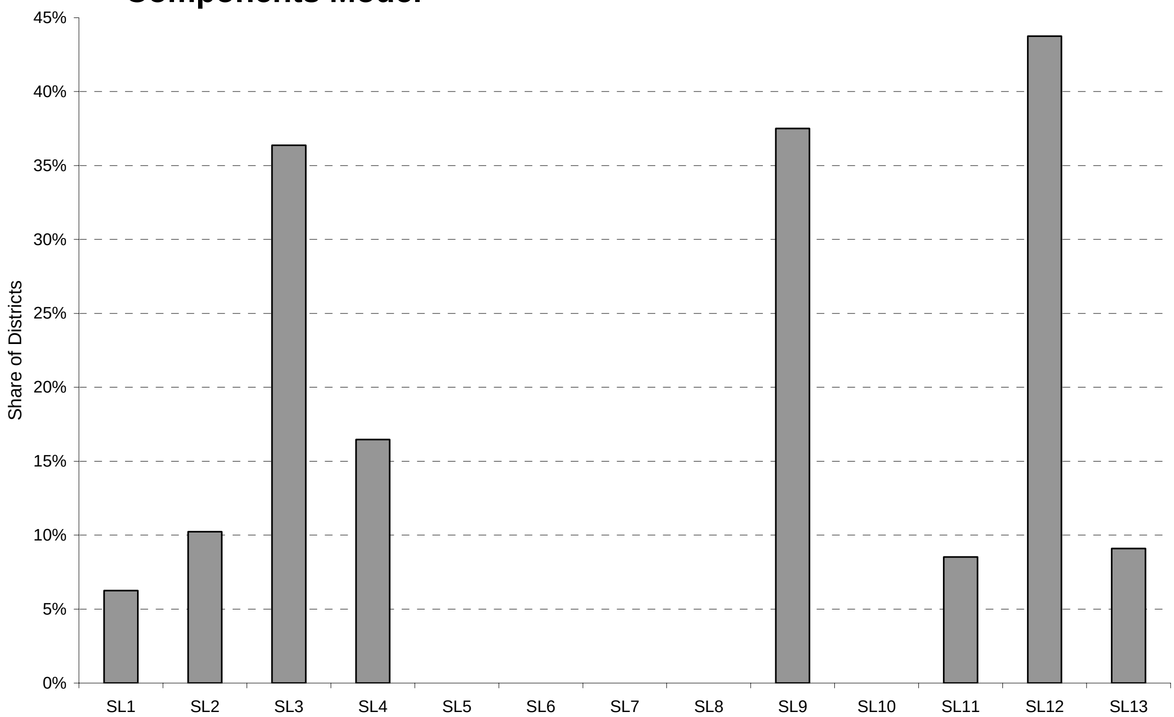


Lt: t month lagged values of the dependent variable

Surprisingly, the inclusion of the autoregressive elements leads to an increase in the mean MAPFE of 0.40 percentage points in comparison to the basic model and results in a MAPFE of 2.13 percent. The fits range from 0.31 percent in Freising up to 5.50 percent in Gotha. In the forecast for Freising, the commonly used structural components as mentioned above and additionally the lag 6 are used, whereas for Gotha only the twelve-month lag and the 25-month lag are included. The standard deviation over the 176 labour-market districts is with 1.01 percentage points a little lower than in the basic model. Geographically, the SC model with autoregressive components seems to fit better for most of the eastern federal states of Germany, but worse for most regions in Mecklenburg-Western Pomerania and Lower Saxony. Compared with the results of the basic estimations, the MAPFE of the autoregressive approach is lower in only 25 (14 percent) labour-market districts and higher in 151 (86 percent) cases. For those districts where the SCAR-model is better, the MAPFE improves by 0.92 percentage points. If the results are poorer, the MAPFE increases by 0.62 percentage points on average.

As described in Section 4.5, we also 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 the addition of the spatial lags. To calculate the effect of the change in the estimation procedure, we also estimate a panel model with only the significant components used in the basic model. The results for the panel approach show a mean MAPFE of 1.02 percent, implying that the change of the estimation technique causes an average reduction of the forecast error of 0.71 percentage points. Compared to the forecast estimated with the panel approach, the average MAPFE of the SC model with spatial interdependencies is again 0.03 percentage points lower and amounts to only 0.99 percent. The most commonly selected spatial lags are the twelve-month, the nine-month and the three-month lag, which are included in nearly 44, 38 and 36 percent of the labour-market districts, respectively (see Figure 6).

Figure 6: Frequencies of the Selected Spatial Lags in the Structural-Components Model



SLt: t month lagged values of the spatially lagged dependent variable

By including a geographical component in which employment 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 by the results where the standard deviation of the MAPFE decreases from 1.09 percentage points in the basic model to 0.68. The results in the spatial model range from 0.12 percent deviation in Freiburg to 3.48 percent in Riesa. Districts with high MAPFEs are dispersed over the whole of Germany. Low MAPFEs are found in the city states Hamburg, Berlin and Bremen as well as in Brandenburg. In comparison to the basic model, the results are better in 142 (80.7 percent) labour-market districts. A worsening of the MAPFE can be found in 34 (19.3 percent) cases. The mean improvement of 0.45 percentage points is nearly as high as the worsening of 0.46 percentage points.

5.2 Comparison of the Models

According to the accuracy measures of the prediction, at least within the SC models a ranking seems obvious, with SCSAR as best and SCAR as worst: In contrast to the inclusion of autoregressive elements, the introduction of spatial elements leads to an improvement of the prediction measure in form of a lower average, minimum, quantiles and maximum MAPFE as well as a lower standard deviation of the prediction measure compared to the basic model. A comparison of SCSAR with the ARIMA and EWMA models shows that their prediction accuracies do not deviate by much. EWMA has the lowest average, minimum and quantiles MAPFE, as well as the lowest standard deviation. However, the lowest maximum MAPFE is obtained in the SCSAR model which again demonstrates the compensatory effect of the spatial component.

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. In total, the EWMA model fits best in 85 labour-market districts, i.e. in nearly half of all cases. ARIMA performs best in 45 cases (25 percent), followed by SCSAR in 36 labour-market districts (20 percent). The SCAR model is best in only four districts and the basic SC model in six cases. Hence, the SC model in its different variations has the lowest MAPFE in 46 labour-market districts (26 percent). The labour-market districts where the spatially augmented model is the best are primarily situated in central Bavaria, in Mecklenburg-Western Pomerania and Brandenburg on the border to Poland and in Lower Saxony on the border to Saxony-Anhalt. In Baden-Wuertemberg, Rhineland Palatinate and Saarland, SCSAR is rarely the best model.

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

Statistics of MAPFE		ARIMA	EWMA	Basic SC	SCAR	SCSAR
Mean		0.90	0.66	1.73	2.13	0.99
Standard deviation		0.75	0.55	1.09	1.01	0.68
Minimum		0.09	0.08	0.12	0.31	0.12
50 %-Quantile		0.71	0.49	1.50	2.15	0.81
75 %-Quantile		1.21	0.82	2.22	2.79	1.31
95 %-Quantile		2.06	1.77	3.49	3.83	2.31
Maximum		5.66	3.52	8.81	5.50	3.48
Comparison with ARIMA	Better than ARIMA		121 (68.75 %)	28 (15.91 %)	17 (9.66 %)	77 (43.75 %)
	Worse than ARIMA		55 (31.25 %)	148 (84.09 %)	159 (90.34 %)	99 (56.25 %)
Comparison with EWMA	Better than EWMA			21 (11.93 %)	17 (9.66 %)	56 (31.82 %)
	Worse than EWMA			155 (88.07 %)	159 (90.34 %)	120 (68.18 %)
Comparison with basic SC	Better than basic SC				25 (14.20 %)	142 (80.68 %)
	Worse than basic SC				151 (85.80 %)	34 (19.32 %)
Comparison with SCAR	Better than basic SC					153 (86.93 %)
	Worse than basic SC					23 (13.07 %)

Figure 7: Spatial Distribution of the Best Models

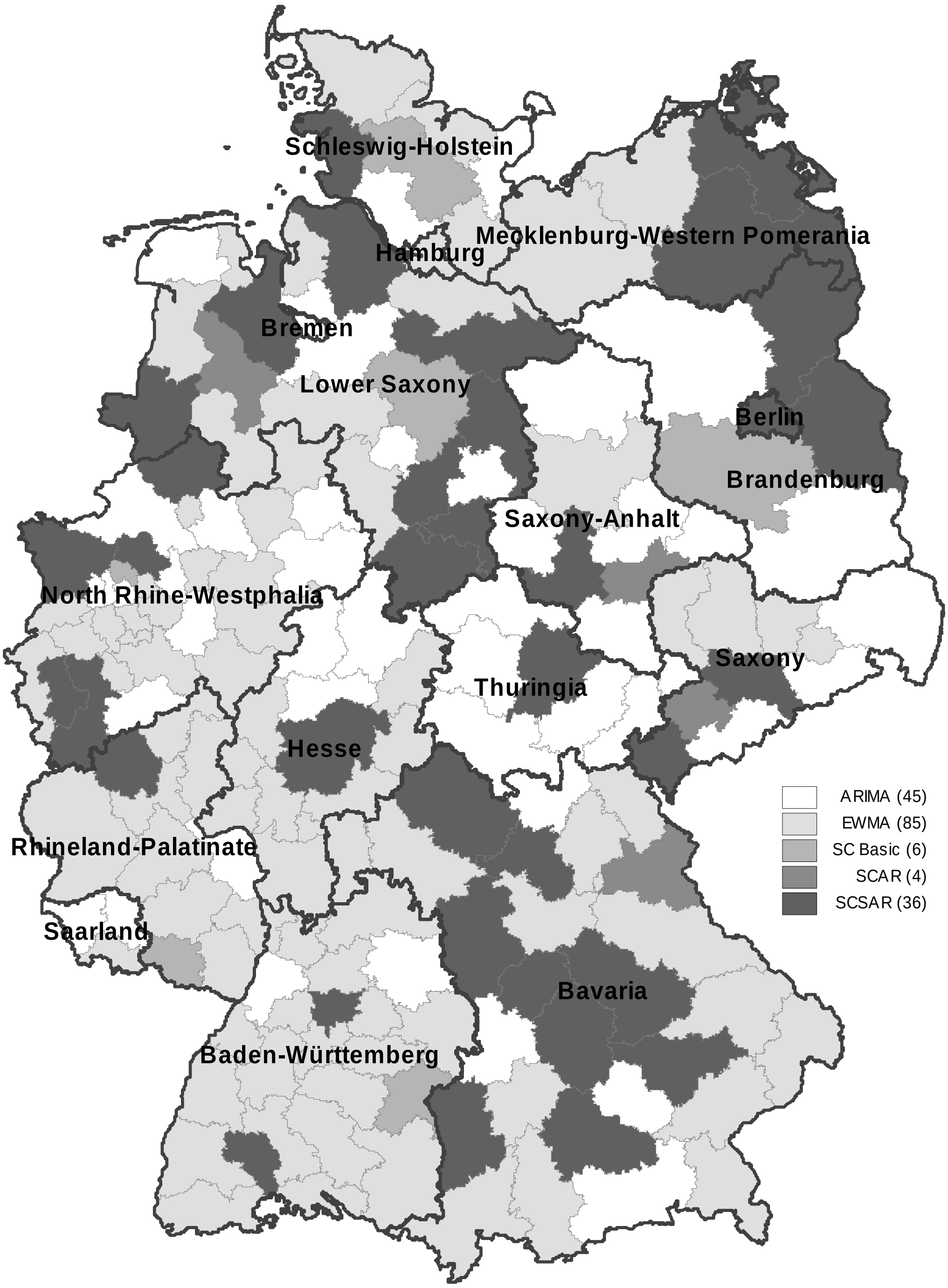


Figure 7 only shows the geographical distribution of the "best" model, no matter how small the gap between the "best" and the "second best" model is. However, we want to systematically analyse the quality of all models to be sure not to loose any information. Therefore, tests on the structures of the calculated MAPFEs of all models need to be applied.

5.3 Statistical Analysis of the Forecast Performance

To confirm our findings, we perform further statistical tests on the forecast errors (MAPFEs). First, we check the similarity of the forecast performance yielded by the various models in the same region. A second test analyses the independence between the MAPFEs and the basic time-series elements which are discussed in Section 2.

All models applied in this paper are pure time-series estimations, i.e. they only include the past values to gain information. Hence, patterns found in the past should be reproduced well and can be extrapolated into the future. On the other hand, structural breaks and turning points due to economic trend reversals can hardly be captured. If these presumptions are correct, the forecast performance of the models in a region should be positively correlated. The pairwise correlation of the MAPFEs is shown in Table 2.

Table 2: Correlation of the MAPFE between the Models

	MAPFE ARIMA	MAPFE EWMA	MAPFE SC	MAPFE SCAR
MAPFE EWMA	0.4384***			
MAPFE SC	0.2119***	0.3413***		
MAPFE SCAR	0.2729***	0.1926**	0.6995***	
MAPFE SCSAR	0.1347*	0.2931***	0.0538	-0.0512

**** Significant at the 1 %-level, ** significant at the 5 %-level,* significant at the 10 %-level*

As the significantly positive correlation indicates, the models perform poorly in the same regions, or work well, respectively. Noticeable is the high correlation between the basic SC and the SCAR model, as well as the one between EWMA and ARIMA. These pairs of models tend to cover the same structures and consecutively produce similarly precise forecasts. However, the correlation coefficients are clearly smaller than one, i.e. the models are not close substitutes to each other. In contrast to the correlation between SCSAR and the two moving-average models, the MAPFE of SCSAR is not significantly correlated with the other SC models, although they partly incorporate the same components. This difference reflects the additional information that is provided by the recent development of the neighbouring labour-market districts.

The test on independence of the forecast performance is carried out by regressing the MAPFE of each model on variables representing the basic time-series elements. The forecast error does not depend on these elements, if the coefficients are insignificant. However, if they have a significant impact, the information provided by the time series is not exploited completely. Hence, in this case there is potential to improve the forecast performance. The hypothesis that the model error (MAPFE) does not depend on a time-series component is only rejected in two cases. First, the seasonal component shows a significant positive sign for the EWMA, i.e. the EWMA model performs less well the higher the seasonal span which implies that the seasonal figure could be captured better. Second, the growth rate of employment has a negative influence on the MAPFE in the basic SC model. The higher the employment losses are, the higher the MAPFE. The losses tend to be extrapolated further on, even if the trends reverse (as happened in several parts of Germany at the end of 2004). The gap between the real value and the forecast can be reduced by including temporally lagged elements, if the turning point is observable at the end of the data.

Table 3: Regression of the MAPFE and Possible Determining Factors for Each Model

	MAPFE ARIMA	MAPFE EWMA	MAPFE SC	MAPFE SCAR	MAPFE SCSAR
Growth rate of employment	0.0028 (0.04)	-0.0386 (0.51)	-0.1189* (1.95)	0.0141 (0.28)	-0.0355 (0.89)
Seasonal span of employment	4.2530 (1.38)	13.3695*** (4.52)	8.3382 (1.58)	4.7221 (0.77)	1.2518 (0.48)
Average employment rate	0.3585 (0.29)	-0.3260 (0.51)	-0.7443 (0.53)	0.2400 (0.16)	0.7141 (0.65)
observations	176	176	176	176	176
F-Value	0.64	9.06***	2.61*	0.22	0.37
r-squared	0.0077	0.1678	0.0532	0.0057	0.0095

**** Significant at the 1%-level, ** significant at the 5%-level,* significant at the 10%-level*

Summing up, the tests indicate that the time-series structures, i.e. level, trend, and season, are modelled properly. We exploit the provided information to a large extent, and develop improvements such as the augmentation of the basic SC model by autoregressive and spatial autoregressive elements. Only in the EWMA model there seems to be some potential to improve the seasonal adjustment. Nonetheless, it turns out to be the best model with respect to the number of regions where it performs best as well as the distribution of the MAPFEs. Even the other models applied in our paper perform well, as can be seen by the average MAPFE which is smaller than 2.2 percent for all, and smaller than 1 percent in three models.

6 Conclusion

In this paper we estimate employment with different time-series models for all (176) labour-market districts in Germany. As the conditions in these districts are very heterogeneous, we employ individually specified 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 labour-market district. Only these variables are included in the final regressions. Although we specify the models parsimoniously, it turns out that the selection of components greatly varies between the labour-market districts. This confirms the importance of modelling each labour-market district individually.

We evaluate the models using simulated out-of-sample forecasts for 2005 and calculating different accuracy measures for this time period. Overall, we find that the forecast quality of all our models is very high. Three of our models have a mean average percentage forecast error of less than one percent and the other models of around two percent. Additionally, we find a great variation in the best model across the regions. Therefore, it is not sufficient to run a forecast with only one model for all labour-market districts. Instead, better results can be achieved by forecasting with a number of models and subsequently seeing which performs best in which region.

Our results clearly show that the inclusion of spatial information improves the forecast quality in the structural-components model by estimating a spatial dynamic panel. Ideally, the information on spatial co-development should be included in all models. Theoretically, the inclusion of spatial lags in the autoregressive models has been developed; unfortunately this is not technically possible in the ARIMA model with 176 labour-market districts at present. For the EWMA model the theoretical and practical integration of spatial elements remains work for future research.

Although all our models have a high forecast quality, we still see potential for improvements by individually combining the different model results for each region using appropriate pooling techniques. First results indicate that this is indeed the case. However, we leave this work for a planned subsequent paper.

Literature

Arbia, G./Bee, M./Espa, G. (2006): Aggregation of regional economic time series with different correlation structures, paper presented at the International Workshop on Spatial Econometrics and Statistics, 25-27 May 2006, Rome.

Bade, F.-J. (1991): Regionale Beschäftigungsprognose 1995, in: Mitteilungen aus der Arbeitsmarkt- und Berufsforschung, 1, S. 25-44.

Bade, F.-J. (1996): Regionale Beschäftigungsprognose 2002. Fortschreibung und Ex-Post-Kontrolle der Prognose 2000, in: Informationen zur Raumentwicklung, 9, S. 571-596.

Bade, F.-J. (1999): Regionale Entwicklung der Erwerbstätigkeit 1997-2004, in: Mitteilungen aus der Arbeitsmarkt- und Berufsforschung, 32, S. 603-617.

Bade, F.-J. (2004): Die Regionale Entwicklung der Erwerbstätigkeit bis 2010, in: Informationen zur Raumentwicklung, 3/4, S. 169-186.

Beenstock, M./Felsenstein, D. (2006): Spatial Vector Autoregressions, paper presented at the International Workshop on Spatial Econometrics and Statistics, 25-27 May 2006, Rome.

Bierens, H.-J. (2001): Unit Roots. In: Baltagi, B. (Ed.): A Companion to Theoretical Econometrics, Malden (MA) chap. 29, S. 610-633.

Blien, U./Tassinopoulos, A. (2001): Forecasting Regional Employment with the ENTROP Method, in: Regional Studies, 35, S. 113-124.

Blien, U./Wolf, K. (2002): Regional Development of Employment and Deconcentration Processes in Eastern Germany. An Analysis with an Econometric Analogue to Shift-Share Techniques, in: Johansson, I and R. Dahlberg (Eds.), Uddevalla Symposium 2001: Regional Economies in Transition. Papers presented at the Uddevalla Symposium 2001, 14-16 June, Vänersborg, Sweden, Trollhättan University, S. 179-197.

Box, G./Jenkins, G. (1970): Time Series Analysis: Forecasting and Control, San Francisco.

Bruch-Krumbein, W./Friese, C./Kollros, H. (1994): Bevölkerung und Arbeitsmarkt 1982 bis 1992 und Prognose bis zum Jahr 2000. Regionalprozessanalyse für Südniedersachsen, Institut für Regionalforschung, Göttingen.

Chatfield, C./Koehler, A. B./Ord, J. K./Snyder, R. D. (2001): A New Look at Models for Exponential Smoothing, in: The Statistician, 50, S. 147-159.

De Gooijer J. G./Hyndman, R. J. (2005): 25 Years of IIF Time Series Forecasting: A Selective Review. Tinbergen Institute Discussion Paper TI 2005-068/4, Tinbergen.

Diebold, F. X (1998): The Past, Present and Future of Macroeconomic Forecasting, in: Journal of Economic Perspectives, 12, S. 175-192.

Eckey, H.-F./Stock, W. (1996): Arbeitsmarktbilanz für Nordrhein-Westfalen. Analyse und Prognose. Ruhr-Forschungsinstitut für Innovations- und Strukturpolitik, Nr. 2/1996, Bochum.

Eckey, H. F. (1988): Methoden zur Prognose von Arbeitsplätzen in Regionen, in: Akademie für Raumforschung und Landesplanung (Ed.): Regionalprognosen, Hannover, 205-234.

Edlund, P.-O./Karlsson, S. (1993): Forecasting the Swedish Unemployment rate. VAR Vs Transfer Function Modelling, in: International Journal of Forecasting, 9, S. 61-76.

Eltges, M./Maretzke, S./Peters, A. (1993): Zur Entwicklung von Arbeitskräfteangebot und -nachfrage auf den regionalen Arbeitsmärkten Deutschlands, in: Informationen zur Raumentwicklung, 12, S. 831-852.

Eltges, M./Wigger, R. (1994): Regionale Arbeitsmarktprognose: Methodik und Anwendung, Arbeitspapier 4/1994 der Bundesforschungsanstalt für Landeskunde und Raumordnung.

Fritsch, M. (1991): Exportbasistheorie, in: Wirtschaftswissenschaftliches Studium, 10, S. 527-529.

Giacomini, R./Granger, C. W. J. (2004): Aggregation of Space-time processes, in: Journal of Econometrics, 118, S. 7-26.

Greene, W. H. (2003): Econometric Analysis, 5th edition, New Jersey.

Hamm, R./Wienert, H. (1989): Ein Verfahren zur Regionalisierung gesamträumlicher Wirtschaftsentwicklungen – dargestellt am Beispiel der Produktion in den Regionen des Ruhrgebiets, in: RWI-Mitteilungen, 40, S. 203-219.

Harvey, A. C. (2004): Forecasting with Unobserved Components Time Series Models. , in: Elliott, G.; C. W.J. Granger and A. Timmermann (eds.): Handbook of Economic Forecasting, Chap. 7, Amsterdam et al.: Elsevier.

Hassler, U. (2000): Leitfaden zum Schätzen und Testen von Kointegration, in: Gaab, W.; Heilemann, U.; Wolters, J. (Eds.): Arbeiten mit ökonometrischen Modellen, Heidelberg, S. 85-115.

Hernandez-Murillo, R./Owyang, M. T. (2006): The information content of regional employment data for forecasting aggregate conditions, in: Economic Letters, 90, S. 335-339.

Hurvich, C. M./Tsai, C. L. (1989): Regression and Time Series Model Selection in Small Samples, in: Biometrika, 76, S. 297-307.

Inoue A./Kilian, L. (2006): On the Selection of Forecasting Models, in: Journal of Econometrics, 127, S. 273-306.

Jaeger, U. (1996): Regionale Beschäftigungsprognose: Eine empirische Anwendung von Transferfunktionen zur Prognose der kurzfristigen Beschäftigungsentwicklung in Nordrhein-Westfalen auf Kreisebene, Köln.

Klaus, J./Maußner, A. (1988): Regionale Arbeitsmarktanalysen mittels vergleichender Arbeitsmarktbilanzen, in: Mitteilungen aus der Arbeitsmarkt- und Berufsforschung, 21, S. 74-82.

Longhi, S./Nijkamp, P./Reggiani, A./Blien, U. (2005): Developments in Regional Labour Markets in Germany. A Comparative Analysis of the Forecasting Performance of Competing Statistical Models. In: Australasian Journal of Regional Studies, 11, S. 175-196.

Lutkepohl, H. (2006): Forecasting with VARMA models, in: Elliott, G.; C. W.J. Granger and A. Timmermann (eds.): Handbook of Economic Forecasting, Chap. 6, Amsterdam et.al.: Elsevier.

Oberhofer, W./Blien, U./Tassinopoulos, A. (2000): Forecasting regional employment with a generalized extrapolation method, Paper prepared for presentation at the 40th European Congress ‘European Monetary Union and Regional Policy’ in Barcelona 2000.

Patridge, M. D./Rickman, D. S. (1998): Generalizing the Bayesian Vector Autoregression Approach for Regional Interindustry Employment Forecasting, in: Journal of Economics and Statistics, 16, S. 461-465.

Patuelli, R./Reggiani, A./Nijkamp, P./Blien, U. (2006): New Neural Network Methods for Forecasting Regional Employment. An Analysis of German Labour Markets. Amsterdam: Tinbergen Institute. Discussion paper 2006-020/3.

Proietti, T. (2000): Comparing Seasonal Components for Structural Time-Series Models, in: International Journal of Forecasting, 16, S. 247-260.

Ray, W. D. (1989): Rates of Convergence to Steady State for a Linear Growth Version of a Dynamic Linear Model (DLM), in: International Journal of Forecasting, 5, S. 537-545.

Rickman, D. S./Miller, S. R. (2003): An Evaluation of Alternative Strategies for Integrating Input-Output Information into Industry Employment Forecasting Equations, in: Review of Regional Studies, 32, S. 133-147.

Satchell, S./Timmermann, A. (1995): On the Optimality of Adaptive Expectations: Muth revisited, in: International Journal of Forecasting, 11, S. 407-416.

Schindler, G. R./Israilevich, P. R./Hewings, G. J. D. (1997): Regional Economic Performance: An Integrated Approach, in: Regional Studies, 31, S. 131-137.

Stock, J. H. (2001): Forecasting Economic Time Series. In: Baltagi, B.: A Companion to Theoretical Econometrics, Blackwell, Malden (MA).

Stock, J. H./Watson, M. W. (1998): A Comparison of Linear and Nonlinear Univariate Models for Forecasting Macroeconomic Time Series, NBER Working Paper 6607.

Swanson, N. R./White, H. (1997): Forecasting Economic Time Series Using Flexible versus Fixed Specification and Linear Versus Nonlinear Econometric Models, in: International Journal of Forecasting, 13, S. 439-461.

Sweeney, S. H. (2004): Regional Occupational Employment Projections. Modelling Supply Constraints in the Direct-Requirements Approach, in: Journal of Regional Science, 44, S. 263-288.

Tassinopoulos, A. (1996): Eine regionale Beschäftigungsprognose: Ergebnisse für Arbeitsmarktregionen auf dem Gebiet der alten Bundesländer, in: Mitteilungen aus der Arbeitsmarkt- und Berufsforschung, 29, S. 363-377.

Thoss, R./Kleinschneider, H. (1982): Arbeitsmarktanalyse und -prognose für den Kreis Borken/Westfalen, Beiträge zum Siedlungs- und Wohnungswesen und zur Raumplanung, 81, Münster.

Weller, B. R. (1989): National Indicator Series as Quantitative Predictors of Small Regions Monthly Employment Levels, in: International Journal of Forecasting, 5, S. 241-247.

Weller, B. R. (1990): Predicting Small Region Sectoral Responses to Charges in Aggregate Economic Activity: A Time Series Approach, in Journal of Forecasting, 9, S. 273-281.

Wulf, J. (1970): Über einige Probleme arbeitsmarktbezogener Regionalprognosen, in: Mitteilungen aus der Arbeitsmarkt- und Berufsforschung, 3, S. 6-16.

Appendix

Table A. 1: Accuracy Measures

Agency	Mean Average Percentage Forecast Error (MAPFE)					
	ARIMA	EWMA	SC	SCAR	SCSAR	Best model
031 AA Neubrandenburg	3.98	3.48	2.86	4.63	2.06	SCSAR
032 AA Rostock	1.81	1.80	2.62	3.43	1.96	EWMA
033 AA Schwerin	1.74	1.01	1.15	1.94	1.02	EWMA
034 AA Stralsund	1.54	2.58	2.50	2.59	1.09	SCSAR
035 AA Cottbus	0.27	1.65	0.38	0.51	0.87	ARIMA
036 AA Eberswalde	0.78	1.09	3.56	0.96	0.56	SCSAR
037 AA Frankfurt (Oder)	0.78	0.80	3.36	2.75	0.31	SCSAR
038 AA Neuruppin	0.35	0.83	2.89	1.55	1.07	ARIMA
039 AA Potsdam	0.31	0.40	0.20	0.63	0.32	SC
042 AA Dessau	0.49	1.60	1.69	2.69	1.55	ARIMA
043 AA Halberstadt	0.39	0.83	0.46	0.72	0.42	ARIMA
044 AA Halle	1.24	0.82	0.94	0.68	0.80	SCAR
045 AA Magdeburg	1.20	0.66	1.16	1.66	1.22	EWMA
046 AA Merseburg	0.63	1.57	1.02	0.64	0.75	ARIMA
047 AA Sangerhausen	1.95	1.00	1.20	1.51	1.00	SCSAR
048 AA Stendal	0.40	0.51	0.84	1.13	0.52	ARIMA
049 AA Wittenberg	0.77	1.76	1.29	1.36	1.57	ARIMA
070 AA Altenburg	0.53	0.64	3.38	3.43	0.56	ARIMA
071 AA Annaberg-Buchholz	0.65	1.53	1.53	1.62	1.59	ARIMA
072 AA Bautzen	0.44	0.71	0.97	0.85	0.66	ARIMA
073 AA Chemnitz	0.51	0.77	0.65	0.46	0.44	SCSAR
074 AA Dresden	0.41	0.27	1.22	1.74	0.29	EWMA
075 AA Leipzig	0.94	0.36	2.75	0.49	1.02	EWMA
076 AA Oschatz	0.93	0.67	0.85	1.20	1.00	EWMA
077 AA Pirna	1.33	1.57	2.07	2.14	1.58	ARIMA
078 AA Plauen	2.31	1.97	4.76	2.24	1.50	SCSAR
079 AA Riesa	1.17	1.04	5.44	4.84	3.48	EWMA
092 AA Zwickau	5.66	1.48	0.85	0.85	1.79	SCAR
093 AA Erfurt	0.77	0.69	3.31	0.77	0.64	SCSAR
094 AA Gera	0.31	0.74	3.64	4.17	0.53	ARIMA
095 AA Gotha	0.35	1.78	8.81	5.50	2.66	ARIMA
096 AA Jena	1.60	1.95	4.42	3.81	2.80	ARIMA
097 AA Nordhausen	0.42	0.57	3.97	3.05	1.42	ARIMA
098 AA Suhl	0.59	0.76	3.45	1.91	2.01	ARIMA
111 AA Bad Oldesloe	0.65	0.30	1.56	2.15	0.74	EWMA
115 AA Elmshorn	0.37	0.46	1.83	2.20	0.81	ARIMA
119 AA Flensburg	0.63	0.29	1.66	2.10	0.46	EWMA
123 AA Hamburg	1.00	0.13	1.51	2.24	0.91	EWMA
127 AA Heide	0.78	1.31	2.73	4.27	0.62	SCSAR
131 AA Kiel	0.24	0.21	0.90	2.81	1.02	EWMA
135 AA Lübeck	0.27	0.28	1.04	1.62	0.50	ARIMA
139 AA Neumünster	0.71	0.59	0.47	0.59	0.77	SC

Agency	Mean Average Percentage Forecast Error (MAPFE)					
	ARIMA	EWMA	SC	SCAR	SCSAR	Best model
211 AA Braunschweig	0.27	1.12	0.54	0.54	0.80	ARIMA
214 AA Bremen	0.09	1.03	1.90	3.50	0.72	ARIMA
217 AA Bremerhaven	1.51	0.20	2.16	2.68	1.14	EWMA
221 AA Celle	0.22	0.20	0.12	0.57	1.85	SC
224 AA Emden	0.42	2.30	0.58	0.58	0.53	ARIMA
227 AA Goslar	1.01	0.51	1.23	2.37	0.26	SCSAR
231 AA Göttingen	1.57	1.09	2.56	3.33	0.36	SCSAR
234 AA Hameln	0.90	0.46	2.62	3.71	1.49	EWMA
237 AA Hannover	0.29	0.54	3.48	3.48	2.85	ARIMA
241 AA Helmstedt	3.56	3.52	2.39	2.86	1.96	SCSAR
244 AA Hildesheim	0.57	0.95	2.45	2.41	0.55	SCSAR
247 AA Leer	0.97	0.42	0.91	1.94	0.67	EWMA
251 AA Lüneburg	0.52	0.49	1.72	2.82	1.47	EWMA
254 AA Nienburg	1.90	0.60	2.58	4.04	0.82	EWMA
257 AA Nordhorn	1.09	0.52	0.86	0.73	0.35	SCSAR
261 AA Oldenburg	0.62	0.44	0.91	1.94	0.22	SCSAR
264 AA Osnabrück	1.06	0.16	1.25	2.12	0.30	EWMA
267 AA Stade	0.47	0.55	1.15	1.95	0.15	SCSAR
271 AA Uelzen	0.96	0.97	2.57	3.64	0.36	SCSAR
274 AA Vechta	2.01	1.41	0.81	0.47	1.16	SCAR
277 AA Verden	0.19	0.30	0.96	1.52	1.09	ARIMA
281 AA Wilhelmshaven	1.58	0.29	1.75	3.19	1.51	EWMA
311 AA Aachen	1.10	0.75	1.73	3.11	1.40	EWMA
313 AA Ahlen	0.42	0.65	2.34	2.29	0.70	ARIMA
315 AA Bergisch Gladbach	0.75	0.17	1.44	2.94	0.99	EWMA
317 AA Bielefeld	0.35	0.28	1.77	2.54	1.37	EWMA
321 AA Bochum	1.84	1.07	1.09	1.09	2.76	EWMA
323 AA Bonn	0.32	0.47	1.64	1.64	1.65	ARIMA
325 AA Brühl	1.28	0.31	0.81	2.30	0.30	SCSAR
327 AA Coesfeld	0.13	0.33	1.97	2.44	0.63	ARIMA
331 AA Detmold	0.34	0.46	2.30	2.64	1.80	ARIMA
333 AA Dortmund	0.31	0.53	1.06	1.06	0.51	ARIMA
335 AA Düren	0.37	0.77	1.03	1.03	0.26	SCSAR
337 AA Düsseldorf	0.92	0.34	1.24	1.24	2.01	EWMA
341 AA Duisburg	0.33	0.39	1.10	1.10	0.76	ARIMA
343 AA Essen	0.27	0.33	1.15	2.48	0.64	ARIMA
345 AA Gelsenkirchen	0.54	1.33	0.24	0.43	0.65	SC
347 AA Hagen	0.24	0.20	1.34	1.34	0.72	EWMA
351 AA Hamm	1.50	0.16	1.96	1.96	0.45	EWMA
353 AA Herford	1.55	0.72	1.92	2.97	1.10	EWMA
355 AA Iserlohn	0.27	0.49	0.92	1.41	0.62	ARIMA
357 AA Köln	0.50	0.35	0.87	2.98	1.23	EWMA
361 AA Krefeld	1.62	0.37	1.88	2.77	0.88	EWMA
363 AA Meschede	0.30	0.30	1.70	2.15	1.15	EWMA
365 AA Mönchengladbach	1.34	0.36	1.84	1.84	2.12	EWMA
367 AA Münster	0.15	0.15	0.92	1.07	0.20	EWMA

Agency	Mean Average Percentage Forecast Error (MAPFE)					
	ARIMA	EWMA	SC	SCAR	SCSAR	Best model
371 AA Oberhausen	0.13	0.49	0.48	0.86	0.37	ARIMA
373 AA Paderborn	0.29	0.60	0.90	0.95	1.92	ARIMA
375 AA Recklinghausen	0.72	1.16	4.60	3.28	0.71	SCSAR
377 AA Rheine	0.76	0.29	0.92	2.02	0.25	SCSAR
381 AA Siegen	0.55	0.26	1.79	1.79	0.45	EWMA
383 AA Soest	0.66	0.40	0.52	0.73	0.56	EWMA
385 AA Solingen	1.49	0.52	2.33	2.33	2.55	EWMA
387 AA Wesel	1.09	0.82	2.51	2.51	0.27	SCSAR
391 AA Wuppertal	0.44	0.42	2.09	2.34	2.14	EWMA
411 AA Bad Hersfeld	0.57	0.47	0.93	1.07	0.87	EWMA
415 AA Darmstadt	0.83	0.60	1.91	2.57	1.22	EWMA
419 AA Frankfurt	2.57	0.27	1.12	3.10	1.34	EWMA
423 AA Fulda	0.77	0.32	2.20	2.51	0.46	EWMA
427 AA Gießen	0.71	0.37	1.28	1.83	0.23	SCSAR
431 AA Hanau	1.66	1.26	2.57	2.57	2.48	EWMA
435 AA Kassel	0.31	0.92	0.69	0.69	0.66	ARIMA
439 AA Korbach	0.47	0.60	0.77	1.28	1.07	ARIMA
443 AA Limburg	1.51	0.54	2.86	2.97	2.22	EWMA
447 AA Marburg	0.45	0.61	1.33	1.45	0.90	ARIMA
451 AA Offenbach	0.42	0.15	1.50	1.50	0.92	EWMA
455 AA Wetzlar	0.80	0.38	1.21	1.94	1.78	EWMA
459 AA Wiesbaden	0.88	0.28	1.49	2.77	1.11	EWMA
511 AA Bad Kreuznach	2.37	0.99	2.75	3.29	2.06	EWMA
515 AA Kaiserslautern	1.68	1.24	2.41	2.80	1.63	EWMA
519 AA Koblenz	0.37	0.24	0.79	1.86	0.37	EWMA
523 AA Ludwigshafen	0.51	0.18	1.62	2.02	0.78	EWMA
527 AA Mainz	0.21	0.29	1.15	1.15	0.25	ARIMA
531 AA Mayen	1.85	1.42	2.76	3.39	0.50	SCSAR
535 AA Montabaur	0.56	0.24	1.71	2.68	0.93	EWMA
539 AA Neunkirchen	0.19	0.37	2.08	2.34	1.25	ARIMA
543 AA Landau	0.24	0.16	2.50	2.87	0.46	EWMA
547 AA Neuwied	0.81	0.28	2.21	2.26	0.92	EWMA
551 AA Pirmasens	0.72	0.43	0.28	0.41	1.95	SC
555 AA Saarbrücken	1.98	1.80	3.33	4.15	2.19	EWMA
559 AA Saarlouis	0.34	1.00	1.92	2.06	1.21	ARIMA
563 AA Trier	1.61	0.68	1.88	2.21	0.80	EWMA
611 AA Aalen	2.78	0.15	1.50	1.41	0.26	EWMA
614 AA Balingen	0.21	0.17	1.87	2.96	1.56	EWMA
617 AA Freiburg	0.79	0.11	1.23	1.92	0.12	EWMA
621 AA Göppingen	0.24	0.08	1.19	1.19	0.87	EWMA
624 AA Heidelberg	0.60	0.58	1.37	2.55	1.04	EWMA
627 AA Heilbronn	0.34	0.24	1.32	2.18	0.66	EWMA
631 AA Karlsruhe	0.20	0.26	1.16	1.97	0.80	ARIMA
634 AA Konstanz	2.19	0.13	2.32	3.01	0.61	EWMA
637 AA Lörrach	1.68	0.20	1.22	2.15	0.49	EWMA
641 AA Ludwigsburg	0.54	0.36	1.01	2.17	0.31	SCSAR

Agency	Mean Average Percentage Forecast Error (MAPFE)					
	ARIMA	EWMA	SC	SCAR	SCSAR	Best model
644 AA Mannheim	1.16	0.32	1.30	2.42	0.97	EWMA
647 AA Nagold	0.66	0.54	1.51	1.91	2.33	EWMA
651 AA Offenburg	0.95	0.43	0.93	1.48	1.30	EWMA
654 AA Pforzheim	0.80	0.41	2.11	2.24	0.52	EWMA
657 AA Rastatt	2.48	0.29	3.44	3.44	2.94	EWMA
661 AA Ravensburg	0.96	0.09	0.78	2.06	0.54	EWMA
664 AA Reutlingen	0.62	0.51	1.14	1.06	0.87	EWMA
667 AA Rottweil	0.27	0.19	0.88	1.05	0.26	EWMA
671 AA Waiblingen	0.93	0.40	1.82	2.81	0.61	EWMA
674 AA Schwäbisch Hall	0.14	0.28	1.86	1.86	0.84	ARIMA
677 AA Stuttgart	0.42	0.22	0.63	1.41	0.24	EWMA
681 AA Tauberbischofsheim	1.51	0.27	1.74	2.78	1.18	EWMA
684 AA Ulm	0.27	0.65	0.14	1.60	0.90	SC
687 AA Villingen-Schwenningen	1.17	0.77	1.39	2.85	0.20	SCSAR
711 AA Ansbach	0.53	0.35	1.29	1.62	0.22	SCSAR
715 AA Aschaffenburg	1.66	1.09	3.47	3.47	2.30	EWMA
719 AA Bamberg	0.26	0.37	1.52	1.87	0.23	SCSAR
723 AA Bayreuth	0.51	0.42	2.26	2.63	1.06	EWMA
727 AA Coburg	0.49	0.98	2.34	2.93	0.62	ARIMA
731 AA Hof	1.98	0.89	3.53	3.71	1.76	EWMA
735 AA Nürnberg	1.60	0.26	1.30	2.72	0.57	EWMA
739 AA Regensburg	0.99	0.94	1.61	2.48	0.29	SCSAR
743 AA Schwandorf	0.77	0.39	1.81	3.87	1.06	EWMA
747 AA Schweinfurt	0.57	0.82	1.41	1.90	0.25	SCSAR
751 AA Weiden	0.76	0.47	0.46	0.46	0.94	SCAR
755 AA Weißenburg	0.94	0.39	1.46	1.55	0.34	SCSAR
759 AA Würzburg	0.71	0.17	0.87	1.56	0.19	EWMA
811 AA Augsburg	1.13	0.33	1.47	2.49	0.71	EWMA
815 AA Deggendorf	0.76	0.57	0.82	0.61	0.95	EWMA
819 AA Donauwörth	0.28	0.39	1.30	1.70	0.75	ARIMA
823 AA Freising	0.22	0.42	1.14	0.31	1.15	ARIMA
827 AA Ingolstadt	0.49	0.57	1.22	2.63	0.36	SCSAR
831 AA Kempten	0.65	0.40	1.08	2.84	1.69	EWMA
835 AA Landshut	0.22	0.49	0.84	1.24	0.22	SCSAR
839 AA Memmingen	1.31	0.31	1.11	1.11	0.25	SCSAR
843 AA München	1.52	0.56	1.57	2.76	0.46	SCSAR
847 AA Passau	1.30	0.72	2.66	4.02	0.94	EWMA
851 AA Pfarrkirchen	0.74	0.25	1.49	2.17	0.59	EWMA
855 AA Rosenheim	0.24	0.38	1.34	2.63	0.69	ARIMA
859 AA Traunstein	1.39	0.94	2.48	2.79	1.63	EWMA
863 AA Weilheim	1.30	0.65	2.10	3.13	1.18	EWMA
900 Berlin	0.65	0.51	1.96	2.95	0.36	SCSAR
Mean	0.90	0.66	1.73	2.13	0.99	
Maximum	5.66	3.52	8.81	5.50	3.48	
Minimum	0.09	0.08	0.12	0.31	0.12	
Standard deviation	0.75	0.55	1.09	1.01	0.68	

Recently published

No.	Author(s)	Title	Date
1/2004	Bauer, T. K. Bender, S. Bonin, H.	Dismissal protection and worker flows in small establishments	7/04
2/2004	Achatz, J. Gartner, H. Glück, T.	Bonus oder Bias? : Mechanismen geschlechtsspezifischer Entlohnung published in: Kölner Zeitschrift für Soziologie und Sozialpsychologie 57 (2005), S. 466-493 (revised)	7/04
3/2004	Andrews, M. Schank, T. Upward, R.	Practical estimation methods for linked employer-employee data	8/04
4/2004	Brixy, U. Kohaut, S. Schnabel, C.	Do newly founded firms pay lower wages? First evidence from Germany	9/04
5/2004	Kölling, A. Rässler, S.	Editing and multiply imputing German establishment panel data to estimate stochastic production frontier models published in: Zeitschrift für ArbeitsmarktForschung 37 (2004), S. 306-318	10/04
6/2004	Stephan, G. Gerlach, K.	Collective contracts, wages and wage dispersion in a multi-level model	10/04
7/2004	Gartner, H. Stephan, G.	How collective contracts and works councils reduce the gender wage gap	12/04
1/2005	Blien, U. Suedekum, J.	Local economic structure and industry development in Germany, 1993-2001	1/05
2/2005	Brixy, U. Kohaut, S. Schnabel, C.	How fast do newly founded firms mature? : empirical analyses on job quality in start-ups published in: Michael Fritsch, Jürgen Schmude (Ed.): Entrepreneurship in the region, New York et al., 2006, S. 95-112	1/05
3/2005	Lechner, M. Miquel, R. Wunsch, C.	Long-run effects of public sector sponsored training in West Germany	1/05
4/2005	Hinz, T. Gartner, H.	Lohnunterschiede zwischen Frauen und Männern in Branchen, Berufen und Betrieben published in: Zeitschrift für Soziologie 34 (2005), S. 22-39, as: Geschlechtsspezifische Lohnunterschiede in Branchen, Berufen und Betrieben	2/05
5/2005	Gartner, H. Rässler, S.	Analyzing the changing gender wage gap based on multiply imputed right censored wages	2/05
6/2005	Alda, H. Bender, S. Gartner, H.	The linked employer-employee dataset of the IAB (LIAB) published in: Schmollers Jahrbuch. Zeitschrift für Wirtschafts- und Sozialwissenschaften 125 (2005), S. 327-336, (shortened) as: The linked employer-employee dataset created from the IAB establishment panel and the process-produced data of the IAB (LIAB)	3/05
7/2005	Haas, A. Rothe, T.	Labour market dynamics from a regional perspective : the multi-account system	4/05
8/2005	Caliendo, M. Hujer, R. Thomsen, S. L.	Identifying effect heterogeneity to improve the efficiency of job creation schemes in Germany	4/05
9/2005	Gerlach, K. Stephan, G.	Wage distributions by wage-setting regime	4/05

10/2005	Gerlach, K. Stephan, G.	Individual tenure and collective contracts	4/05
11/2005	Blien, U. Hirschenauer, F.	Formula allocation : the regional allocation of budgetary funds for measures of active labour market policy in Germany	4/05
12/2005	Alda, H. Allaart, P. Bellmann, L.	Churning and institutions : Dutch and German establishments compared with micro-level data	5/05
13/2005	Caliendo, M. Hujer, R. Thomsen, S. L.	Individual employment effects of job creation schemes in Germany with respect to sectoral heterogeneity	5/05
14/2005	Lechner, M. Miquel, R. Wunsch, C.	The curse and blessing of training the unemployed in a changing economy : the case of East Germany after unification	6/05
15/2005	Jensen, U. Rässler, S.	Where have all the data gone? : stochastic production frontiers with multiply imputed German establishment data published in: Zeitschrift für ArbeitsmarktForschung, Jg. 39, H. 2, 2006, S. 277-295	7/05
16/2005	Schnabel, C. Zagelmeyer, S. Kohaut, S.	Collective bargaining structure and its determinants : an empirical analysis with British and German establishment data published in: European Journal of Industrial Relations, Vol. 12, No. 2. S. 165-188	8/05
17/2005	Koch, S. Stephan, G. Walwei, U.	Workfare: Möglichkeiten und Grenzen published in: Zeitschrift für ArbeitsmarktForschung 38 (2005), S. 419-440	8/05
18/2005	Alda, H. Bellmann, L. Gartner, H.	Wage structure and labour mobility in the West German private sector 1993-2000	8/05
19/2005	Eichhorst, W. Konle-Seidl, R.	The interaction of labor market regulation and labor market policies in welfare state reform	9/05
20/2005	Gerlach, K. Stephan, G.	Tarifverträge und betriebliche Entlohnungsstrukturen published in: C. Clemens, M. Heinemann & S. Soretz (Hg.): Auf allen Märkten zu Hause, Marburg 2006	11/05
21/2005	Fitzenberger, B. Speckesser, S.	Employment effects of the provision of specific professional skills and techniques in Germany	11/05
22/2005	Ludsteck, J. Jacobebbinghaus, P.	Strike activity and centralisation in wage setting	12/05
1/2006	Gerlach, K. Levine, D. Stephan, G. Struck, O.	The acceptability of layoffs and pay cuts : comparing North America with Germany	1/06
2/2006	Ludsteck, J.	Employment effects of centralization in wage setting in a median voter model	2/06
3/2006	Gaggermeier, C.	Pension and children : Pareto improvement with heterogeneous preferences	2/06
4/2006	Binder, J. Schwengler, B.	Korrekturverfahren zur Berechnung der Einkommen über der Beitragsbemessungsgrenze	3/06
5/2006	Brixy, U. Grotz, R.	Regional patterns and determinants of new firm formation and survival in western Germany	4/06
6/2006	Blien, U. Sanner, H.	Structural change and regional employment dynamics	4/06
7/2006	Stephan, G. Rässler, S. Schewe, T.	Wirkungsanalyse in der Bundesagentur für Arbeit : Konzeption, Datenbasis und ausgewählte Befunde	4/06

8/2006	Gash, V. Mertens, A. Romeu Gordo, L.	Are fixed-term jobs bad for your health? : a comparison of West-Germany and Spain	5/06
9/2006	Romeu Gordo, L.	Compression of morbidity and the labor supply of older people	5/06
10/2006	Jahn, E. J. Wagner, T.	Base period, qualifying period and the equilibrium rate of unemployment	6/06
11/2006	Jensen, U. Gartner, H. Rässler, S.	Measuring overeducation with earnings frontiers and multiply imputed censored income data	6/06
12/2006	Meyer, B. Lutz, C. Schnur, P. Zika, G.	National economic policy simulations with global interdependencies : a sensitivity analysis for Germany	7/06
13/2006	Beblo, M. Bender, S. Wolf, E.	The wage effects of entering motherhood : a within-firm matching approach	8/06
14/2006	Niebuhr, A.	Migration and innovation : does cultural diversity matter for regional R&D activity?	8/06
15/2006	Kiesl, H. Rässler, S.	How valid can data fusion be?	8/06
16/2006	Hujer, R. Zeiss, C.	The effects of job creation schemes on the unemployment duration in East Germany	8/06
17/2006	Fitzenberger, B. Osikominu, A. Völter, R.	Get training or wait? : long-run employment effects of training programs for the unemployed in West Germany	9/06
18/2006	Antoni, M. Jahn, E. J.	Do changes in regulation affect employment duration in temporary work agencies?	9/06
19/2006	Fuchs, J. Söhnlein, D.	Effekte alternativer Annahmen auf die prognostizierte Erwerbsbevölkerung	10/06
20/2006	Lechner, M. Wunsch, C.	Active labour market policy in East Germany : waiting for the economy to take off	11/06
21/2006	Kruppe, T.	Die Förderung beruflicher Weiterbildung : eine mikroökonometrische Evaluation der Ergänzung durch das ESF-BA-Programm	11/06
22/2006	Feil, M. Klinger, S. Zika, G.	Sozialabgaben und Beschäftigung : Simulationen mit drei makroökonomischen Modellen	11/06
23/2006	Blien, U. Phan, t. H. V.	A pilot study on the Vietnamese labour market and its social and economic context	11/06
24/2006	Lutz, R.	Was spricht eigentlich gegen eine private Arbeitslosenversicherung?	11/06
25/2006	Jirjahn, U. Pfeifer, C. Tsertsvadze, G.	Mikroökonomische Beschäftigungseffekte des Hamburger Modells zur Beschäftigungsförderung	11/06
26/2006	Rudolph, H.	Indikator gesteuerte Verteilung von Eingliederungsmitteln im SGB II : Erfolgs- und Effizienzkriterien als Leistungsanreiz?	12/06
27/2006	Wolff, J.	How does experience and job mobility determine wage gain in a transition and a non-transition economy? : the case of east and west Germany	12/06
28/2006	Blien, U. Kirchhof, K. Ludewig, O.	Agglomeration effects on labour demand	12/06

29/2006	Blien, U. Hirschenauer, F. Phan, t. H. V.	Model-based classification of regional labour markets : for purposes of labour market policy	12/06
30/2006	Krug, G.	Kombilohn und Reziprozität in Beschäftigungsverhältnissen : eine Analyse im Rahmen des Matching-Ansatzes	12/06
1/2007	Moritz, M. Gröger, M.	The German-Czech border region after the fall of the Iron Curtain : Effects on the labour market : an empirical study using the IAB Employment Sample (IABS)	1/07

Stand: 9.1.2007

Imprint

IABDiscussionPaper
No. 2 / 2007

Editorial address
Institut für Arbeitsmarkt- und Berufsforschung
der Bundesagentur für Arbeit
Weddigenstr. 20-22
D-90478 Nürnberg

Editorial staff
Regina Stoll, Jutta Palm-Nowak

Technical completion
Jutta Sebald

Download of this DiscussionPaper:
http://doku.iab.de/discussionpapers/2007/dp0207.pdf

Website
http://www.iab.de

For further inquiries contact the corresponding author:
Norbert Schanne, Tel. 0911/179-5904,
or e-mail: norbert.schanne@iab.de