Robert Lehmann; Klaus Wohlrabe:

Forecasting GDP at the regional level with many predictors

Munich Discussion Paper No. 2013-13

Department of Economics
University of Munich

Volkswirtschaftliche Fakultät
Ludwig-Maximilians-Universität München

Forecasting GDP at the regional level with many predictors

September 14, 2013

Abstract: In this paper, we assess the accuracy of macroeconomic forecasts at the regional level using a large data set at quarterly frequency. We forecast gross domestic product (GDP) for two German states (Free State of Saxony and Baden-Württemberg) and Eastern Germany. We overcome the problem of a 'data-poor environment' at the sub-national level by complementing various regional indicators with more than 200 national and international indicators. We calculate single–indicator, multi–indicator, pooled and factor forecasts in a pseudo real–time setting. Our results show that we can significantly increase forecast accuracy compared to an autoregressive benchmark model, both for short and long term predictions. Furthermore, regional indicators play a crucial role for forecasting regional GDP.

Keywords: regional forecasting, forecast combination, factor models model confidence set, data–rich environment

JEL Code: C32, C52, C53, E37, R11

Robert Lehmann*
Ifo Institute – Leibniz-Institute
for Economic Research
at the University of Munich e.V.
Branch Dresden
Einsteinstr. 3
01069 Dresden, Germany
Phone: +49(0)351/26476-21
lehmann@ifo.de

Klaus Wohlrabe
Ifo Institute – Leibniz-Institute
for Economic Research
at the University of Munich e.V.
Poschingerstr. 5
81679 Munich, Germany
Phone: +49(0)89/9224-1229
wohlrabe@ifo.de

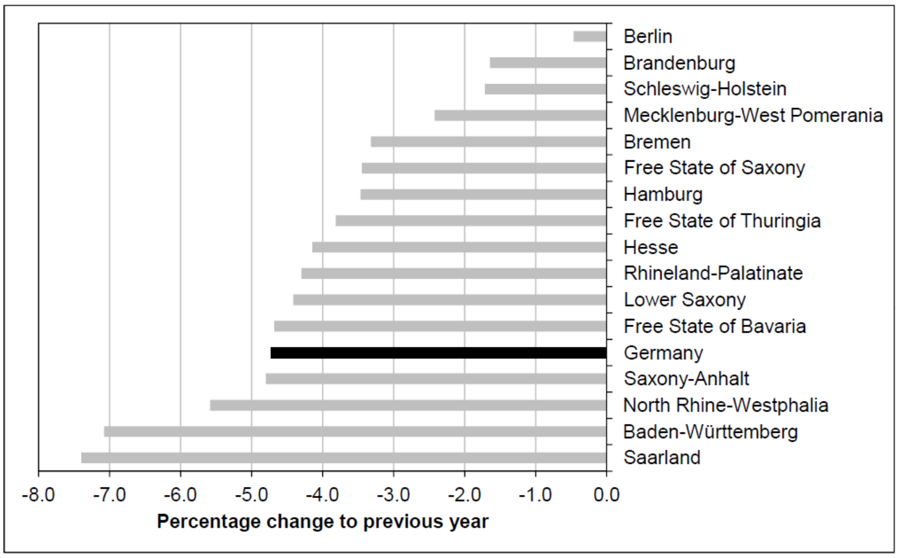
* Corresponding author.

1. Motivation

Regional policy makers are increasingly interested in reliable forecasts of macroeconomic variables (e.g., gross domestic product – GDP) at the regional level. Such forecasts are important to the decision-making process (e.g., for fiscal policy planning). Assuming identical business cycles at the regional and national level, decision makers can appraise future regional economic output with national forecasts. However, the use of national forecasts can lead to misestimates because of a high degree of regional heterogeneity (e.g., different economic structures).

A high heterogeneity among regional units is observable for Germany. The 16 German states are characterized by high disparity in their economic structures. This disparity is explicitly reflected in annual growth rates for real GDP. Figure 1 shows the annual growth rates of real GDP in 2009, the year after the economic meltdown. This shock clearly illustrates how (regional) economies with different economic structures are affected by national or supra-national business fluctuations. A more open economy with higher export quotas can grow or shrink faster than an economy that focuses on domestic or regional markets. Whereas the economic output of

Figure 1: **Percentage change of real GDP in 2009 for the German states**



Source: Working Group Regional Accounts VGRdL (2011), author´s illustration.

a highly industrialized and export-dependent German state such as North Rhine-Westphalia shrinks by 5.6% in 2009, the GDP growth rate of Berlin, which is characterized by a large number of different services, lies at -0.5% for the same year. The economic recession of 2009 affected the regional units with different intensities. Obviously, the growth rate of Germany (-4.7%) does not appear to be a good approximation for a decrease in GDP for all sub-national German regions.[1]

Regional macroeconomic aggregates are more difficult to forecast in comparison to national ones because of limited data availability and low publication frequency. In general, only annual

[1]Schirwitz *et al.* (2009) show that significant differences between regional business cycles in Germany exist.

information about regional GDP is provided by official statistics. For economic policy, it is crucial to know in what phase of the business cycle the whole economy actually is. The cyclical GDP movement, and therefore the knowledge of the current phase about the business cycle, can only be highlighted with quarterly data. More accurate predictions of regional GDP are only possible with such information. This information eventually reduces forecast errors and sends more accurate signals to regional policy makers.

The economic forecasting literature includes many studies on (supra-) national aggregates such as for the Euro Area (see, e.g., Bodo *et al.*, 2000; Forni *et al.*, 2003; Carstensen *et al.*, 2011) and Germany (see, e.g., Kholodilin and Siliverstovs, 2006; Breitung and Schumacher, 2008; Drechsel and Scheufele, 2012b); however, only a few attempts have been undertaken to predict economic output at the regional level.[2]

Bandholz and Funke (2003) construct a leading indicator for Hamburg, notably to predict turning points of economic output. Dreger and Kholodilin (2007) use regional indicators to forecast the GDP of Berlin. A study by Kholodilin *et al.* (2008) employs dynamic panel techniques to forecast GDP on an annual basis for all German states at the same time, accounting for spatial effects. The paper by Wenzel (2013) also studies the forecasting performance of business survey data for all German states within a panel framework. He found that business survey data are important for the prediction of regional economic growth. In addition, a few studies forecast regional labor market indicators for Germany. First, Longhi and Nijkamp (2007) predict employment figures for all West German regions and particularly address the problem of spatial correlation. Second, Schanne *et al.* (2010) forecast unemployment rates for German labor-market districts, using a global vector autoregression (GVAR) model with spatial interactions. All of these studies employ different data frequencies. Whereas Bandholz and Funke (2003) and Dreger and Kholodilin (2007) use annual GDP information disaggregated into quarterly data, Kholodilin *et al.* (2008), Longhi and Nijkamp (2007) and Wenzel (2013) have only annual information. Schanne *et al.* (2010) instead use data on a monthly basis. To the best of our knowledge, there is only one international study that examines the forecasting performance of regional economic output. Kopoin *et al.* (2013) evaluate whether national and international indicators have information to forecast real GDP at the level of Canadian provinces.

Our paper adds to these studies in several ways. First, we overcome the problem of data limitations at the regional level using a new data set with quarterly national accounts for Eastern Germany, the Free State of Saxony[3] and Baden-Württemberg. Altogether, we have 114 regional indicators, including the Ifo business climate for industry and trade in Saxony or new manufacturing orders for Baden-Württemberg. Second, we use regional, national and international indicators, and we assess their forecasting performance at the regional level. Most of the previously mentioned studies have only a few regional indicators and no national or international

[2]In his thesis, Vogt (2009) conducts a comprehensive survey of forecast activities for the German states.

[3]Vogt (2010) studies the properties of a few indicators to forecast Saxon GDP on a quarterly basis. He combines forecasts from different VAR models.

ones. Finally, our large data set enables us to study the forecasting accuracy of several pooling strategies and factor models. We are likely the first researchers to evaluate the properties of a large set of indicators and corresponding time series approaches at the regional level.

We combine different strands of the economic forecasting literature. In particular, we attempt to determine which indicators are important in forecasting regional GDP. Does early information come from international (World or European Union) or national (Germany) indicators? Alternatively, does sub-national or regional information increase forecasting performance? Trading partners such as the US and Europe (France, Poland, etc.), as well as the growing importance of Asian economies, create a stronger linkage between these countries and regional economies. These are two of several reasons why we include international indicators. Furthermore, shocks that hit the German economy are transmitted through different channels (e.g., the production of intermediate goods) to regional companies. Banerjee *et al.* (2005) construct a large data set containing leading indicators to forecast Euro-area inflation and GDP growth and add comprehensive information from the US economy, and they find that a set of these variables improves forecasting performance. Banerjee *et al.* (2006) analyze the importance of Euro-area indicators for the prediction of macroeconomic variables for five new Member States. Several studies analyze forecasting properties in a data–rich environment for different countries. Schumacher (2010) finds that international indicators do not deliver early information for forecasting German GDP if the data are not preselected. Otherwise, forecasting performance improves with international information. For the small and open economy of New Zealand, Eickmeier and Ng (2011) find that adding international data to nationwide information enhances the quality of economic forecasts. To improve forecasts of Canadian macroeconomic data (e.g., GDP and inflation), Brisson *et al.* (2003) use indicators from the US and other countries. In our study, we use international and German indicators, as well as several variables from the sub-national (Eastern Germany) and regional levels (Saxony, Baden-Württemberg). To the best of our knowledge, our study is the first to evaluate this question from a regional perspective.

Furthermore, we add to the existing literature on forecast combinations. Since the seminal work by Bates and Granger (1969), it is known that combining forecast outputs from different models can lead to improved forecast accuracy in comparison to univariate benchmarks or predictions from a single model.[4] Several empirical contributions exist for different single countries (see, e.g., Drechsel and Scheufele (2012a) and Drechsel and Scheufele (2012b) for Germany or Clements and Galvão (2009) for the US) or for several states simultaneously (see, e.g., Stock and Watson, 2004; Kuzin *et al.*, 2013). Studies at the regional level are absent. Given our large data set, we evaluate the forecast accuracy of different pooling strategies.

Finally, our paper studies the forecasting performance of several factor models. This class of models proved to enhance forecast accuracy at the national level (see, e.g., Schumacher (2007), Breitung and Schumacher (2008) and Schumacher (2010) for Germany or Stock and Watson (2002) for the US). To the best of our knowledge, regional studies are missing.

[4]For recent surveys, see Timmermann (2006) and Stock and Watson (2006).

The paper is organized as follows. In section 2, we describe our data and empirical setup. The results are discussed in Section 3. Section 4 offers a conclusion.

2. Data and Empirical Setup

2.1. Data

2.1.1. Gross domestic product at the regional level

The official statistics in Germany do not provide temporal disaggregated macroeconomic data (e.g., quarterly GDP) for regional units. Only annual information is available. Therefore, it is either problematic to find a suitable target variable to forecast or the number of observations is insufficient. In our paper, we use a new data set that solves these two problems of availability and length of the time series.

To the best of our knowledge, three different sources currently exist that provide publicly available quarterly national accounts at the German regional or sub-national level. First, Nierhaus (2007) computes quarterly GDP for the German state Free State of Saxony. He applies the temporal disaggregation method of Chow and Lin (1971), which is also used for official statistics of the European Union. The method is based on a stable regression relationship between annual aggregates and indicators with a higher frequency (e.g., monthly). This relationship makes it possible to transform annual into quarterly data. For this transformation, Nierhaus (2007) uses official German statistics: regional turnovers for Saxony or quarterly data from national accounts for Germany (e.g., gross value added). Second, Vullhorst (2008) uses – like Nierhaus (2007) – the temporal disaggregation method of Chow and Lin (1971) to calculate quarterly national accounts for the state of Baden-Württemberg. For the temporal disaggregation of annual GDP for Baden-Württemberg, nearly the same indicators are used as for Saxony (e.g., regional turnovers for the manufacturing sector in Baden-Württemberg or quarterly gross value added from national accounts for Germany). Third, the Halle Institute for Economic Research (IWH) provides quarterly data on GDP for Eastern Germany (excluding Berlin). The quarterly data for Eastern Germany are not calculated with the method of Chow and Lin (1971) but with a so-called extrapolation method (see Brautzsch and Ludwig, 2002). Instead of using a stable regression relationship between the annual aggregate and an indicator, the extrapolation method applies quarterly shares in the annual aggregate.[5] The two methods (Chow-Lin and extrapolation) have in common that they use high-frequency indicators. If no regional indicators are available, the IWH also applies quarterly data from national accounts for Germany.

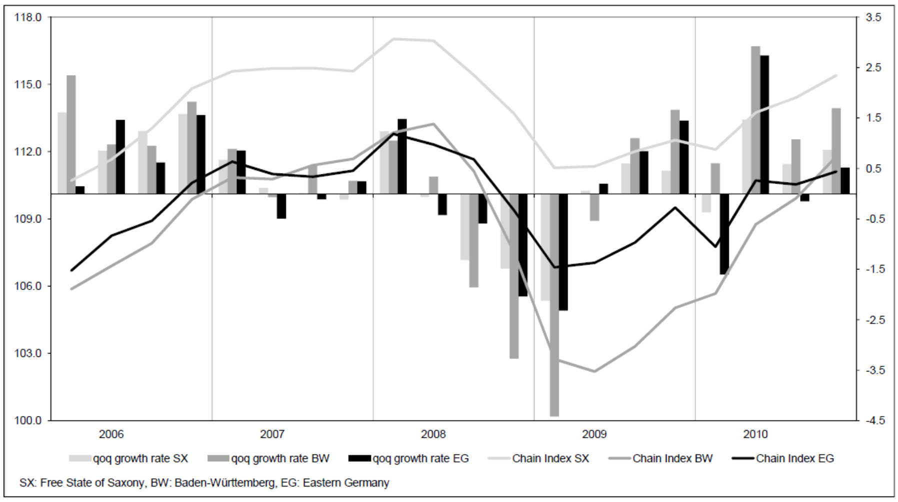
As one would suggest, regional indicators that are used for temporal disaggregation must per-

[5] The extrapolation method becomes clearer using the example of manufacturing. Given that x% of all turnovers in the Eastern German manufacturing sector, which is the indicator used by the IWH for manufacturing, are gained in the first quarter of a given year, it is assumed that also x% of total gross value added in the manufacturing sector in that year is produced in the first quarter. Thus, the development of total gross value added in the manufacturing sector is identical to the development of total turnovers.

form well for forecasting regional GDP. To avoid such a bias, we do not consider such indicators for our analysis. These indicators are the following: turnovers in the manufacturing sector (Saxony and Eastern Germany), working hours (Eastern Germany) and turnovers in the construction sector (Saxony and Baden-Württemberg), as well as for the Saxon retail sale and wholesale trade.

For all three GDP target variables, the time series are available for the period 1996:01 to 2010:04.[6] The data are provided in real terms, and we make a seasonal adjustment to calculate quarter-on-quarter (qoq) growth rates. Figure 2 shows the Chain Index, as well as qoq growth rates for the Saxon, Baden-Württemberg and Eastern German GDP from 2006:01 to 2010:04.

Figure 2: **Real GDP for Saxony, Baden-Württemberg and Eastern Germany**



Note: Chain Index 2000 = 100 (left scale), quarter-on-quarter growth rate (right scale, in %), seasonally adjusted with Census X-12-ARIMA.
Source: Ifo Institute, Statistical Office of Baden-Württemberg and IWH, author´s calculations and illustration.

During that period, the movements of the two curves for the chain indices for Saxony and Eastern Germany are predominantly identical. Only the levels of quarter-on-quarter growth rates differ slightly for different points in time. The movement of the GDP for Baden-Württemberg is similar but much more volatile than the output for Saxony and Eastern Germany.

2.1.2. Set of indicators

Our data set contains 361 indicators that can be used to assess their forecasting performance for our target variables. All indicators are from different sources and are grouped into seven different categories: macroeconomic variables (94), finance (31), prices (12), wages (4), surveys (74), international (32) and regional (114).[7] Macroeconomic variables contain industrial pro-

[6] The data are updated intermittently by the institutions. Quarterly national accounts for Saxony are available under *dresden@ifo.de*. The data are not available on the homepage of the Ifo Institute because they will be revised due to a change in the classification of economic activities in Germany. The data for Baden-Württemberg are available upon request from the regional Statistical Office of Baden-Württemberg under *vgr@stala.bwl.de*. For Eastern Germany, quarterly data can be downloaded from the homepage of the IWH (http://www.iwh-halle.de/c/start/prognose/baro.asp).

[7] For a complete description of our data, see Table 4 in the Appendix.

duction measures, turnovers, new orders and employment figures, as well as data on foreign trade and government tax revenues. All of these macroeconomic indicators are measured at the national level (here: Germany). The category of financial variables includes data on interest rates, government bond yields, exchange rates and stock indices. Furthermore, we have data on consumer and producer prices, as well as price indices for exports and imports. In addition to these quantitative data, we use qualitative information. Indicators from the category surveys are obtained from consumer, business and expert surveys (Ifo, ZEW, GfK and the European Commission). In addition, composite leading indicators for Germany (e.g., from the OECD) and the Early Bird index of the Commerzbank are grouped in this category. International data cover a set of indicators for the European Union and the US from the previously mentioned categories, e.g., the Economic Sentiment Indicator for France and US industrial production. Finally, we add different regional indicators for Eastern Germany, the Free State of Saxony and Baden-Württemberg. The regional category covers quantitative (turnovers, prices and data on foreign trade) and qualitative information (Ifo and the business survey of the IWH). To avoid biased forecasts, we excluded potential regional indicators from our analysis that are used for temporal GDP disaggregation. Additionally, we do not consider sectoral quarterly gross value added for Germany because this indicator, as mentioned in the previous section, is also used for temporal disaggregation.

The data set is predominantly the same one used by Drechsel and Scheufele (2012a), and we add regional indicators for Eastern Germany, the Free State of Saxony and Baden-Württemberg (38 indicators for every single region). Most of these indicators are available on a monthly basis. Hence, a transformation into quarterly data is necessary. First, we seasonally adjust the monthly indicators.[8] Second, we calculate a three-month average for each quarter. If necessary, we transform our data to obtain stationary time series. Table 4 in the Appendix also contains information about the transformation of all indicators.

2.1.3. Publication lags and real–time aspect

Because official statistics have a substantial publication delay, we must account for this fact in our forecasting exercise. Hard indicators such as turnovers normally have a publication lag of several months. The same holds for regional GDP, which is also calculated with a substantial time lag. In contrast, soft indicators (e.g., survey results) are available immediately. Table 4 in the Appendix contains information about the publication lag (months) of each indicator and target variable.[9] Whereas real GDP for Saxony and Eastern Germany is available almost three months after the last month of the elapsed quarter, GDP for Baden-Württemberg has a publication lag of two months. The reason for this discrepancy is the fact that the data are available earlier for the Statistical Offices and need not be requested by the two research

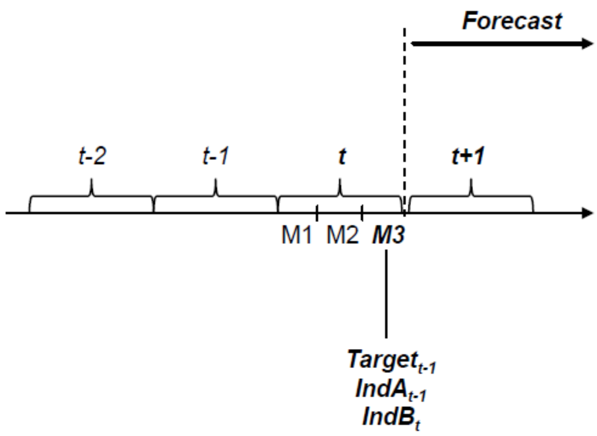
[8] We apply the Census X-12-ARIMA seasonal adjustment approach.

[9] The time lag varies between 0 and 2.5 months. For each indicator with a publication lag, we assume a time lag of one quarter.

institutes. We presume that these lags are constant over time and have not changed since the first time the data were released.

Most of the macroeconomic indicators for Germany are available one and a half months later. The majority of financial variables are published with no lag. Nearly all survey-based or soft indicators have no publication lag and can be downloaded immediately at the end of each month. Regional indicators have some special characteristics in comparison to national or international data. Whereas the indicators from survey results have no publication delay, macroeconomic indicators are not available until two and a half months after the end of the quarter of interest. In particular, this circumstance must be considered when forecasting regional GDP. The timeline in Figure 3 shows exemplarily our forecasting approach for short-term forecasts (one-quarter-ahead). In this figure, t stands for the current quarter. *M1, M2* and *M3* denote

Figure 3: **Timeline for short-term forecasts**



the respective months of that quarter. We hold ***M3*** in bold characters to symbolize that every forecast round is made at the last month of each quarter; e.g., the forecast for the first quarter 2010 is calculated at the end of December 2009. With this assumption, we only have to distinguish between three publication lags. First, for our three GDP variables ($Target_{t-1}$), information is only available until the last quarter; thus, *Target* is indexed by *t-1*. Second, the set of indicators that have a publication lag is labeled by $IndA_{t-1}$; we use only the information with a time lag of one quarter. Finally, all remaining indicators with no publication delay are denoted by $IndB_t$. Therefore, our forecasting approach uses only information that is available at the point when a forecast is made.

When dealing with publication lags, we have to mention the real–time aspect of this analysis. Concerning our target variables, we are only able to model publication lags but no continuous data revisions. The reason is straightforward. Quarterly national accounts for Saxony were not available before 2007. Nierhaus (2007) first calculated quarterly real GDP for Saxony at the end of 2007 and provided the whole series from 1996 onwards. Thus, we are not able to observe substantial revisions of previous years. The same holds for Baden-Württemberg and Eastern Germany. Finally, for a consistent real–time analysis, the real–time data flow for all indicators would be necessary and preferable. Unfortunately, for such a large data set, such a data flow is currently unavailable. Thus, we refer to our analysis pseudo real–time. How we implement the previously mentioned publication lags is described in the next section together with our empirical model.

2.2. Indicator forecasts

To generate multiple step-ahead forecasts, we use the following autoregressive distributed lag (ADL) model,

$$y_{t+h}^k = \alpha + \sum_{i=1}^{p} \beta_i y_{t-i} + \sum_{j=m}^{q} \gamma_j x_{t+1-j}^k + \varepsilon_t^k \ , \qquad (1)$$

where y_{t+h}^k stands for the h-step-ahead model k of the quarter-on-quarter growth rate of the Saxon, Baden-Württemberg or Eastern German real GDP and x_t^k denotes the exogenous indicator from the regional, national or international level. Because we use quarterly data, a maximum of 4 lags is allowed for both the lagged dependent and independent variables. The optimal lengths for p and q are determined by the Bayesian Information Criterion (BIC). To consider the availability of our indicators, m is introduced. The variable m takes a value of one, whenever no publication delay exists. If a variable is not available immediately, m takes a value of two.

We apply a recursive forecasting approach with a rolling estimation window. The initial estimation period ranging from 1996:01 to 2002:4 ($T = 28$) is moved forward successively by one quarter. In every step, the forecasting model of Equation (1) is newly specified. For each forecast horizon, the first forecast is calculated for 2003:1 and the last for 2010:4. Our forecast horizon h has four dimensions: $h \in \{1, 2, 3, 4\}$. Because we implement the ADL model as a direct-step forecast, we always produce $N = 32$ forecasts for $h = 1$ (short term) or $h = 4$ (long term) and every model k. As the benchmark, we choose the standard AR(p) process.[10]

There may be an information gain from applying a multi–indicator forecast model. Hence, combining regional with national indicators may reduce forecast errors due to a combination of different information sets; thus, we modify the model in Equation (1) by adding another indicator,

$$y_{t+h}^k = \alpha + \sum_{i=1}^{p} \beta_i y_{t-i} + \sum_{j=m}^{q} \gamma_j r_{t+1-j}^k + \sum_{l=m}^{q} \gamma_j z_{t+1-j}^k + \varepsilon_t^k \ . \qquad (2)$$

We only estimate models for every regional indicator (r_t^k) in combination with an indicator from the national level (z_t^k).[11] Therefore, we have $\mathbf{38 \cdot 118 = 4,484}$ extra models for all three

[10] We also tested the AR(1) process, the Random-Walk and an in-sample-mean forecast and found similar results.

[11] Because of computational reasons, we restrict the multi–indicator forecast approach to 118 national indicators, which include industrial production, new orders, new registrations of vehicles, exports, imports and surveys.

regional units.

2.3. Combination strategies

It is well known that an appropriate in-sample fitted model could have a bad out-of-sample performance, thus producing high forecast errors. Stock and Watson (2006) and Timmermann (2006) have shown the advantage of combining forecasting output from different models. This advantage has been confirmed in numerous empirical studies for different countries (see, e.g., Drechsel and Maurin, 2011; Eickmeier and Ziegler, 2008). Evidence for the advantage of pooling at the regional level is absent. With our paper, we fill this gap.
A forecast obtained by pooling $\widehat{y}_{t+h}^{Pool}$ is based on the individual indicator forecasts $\widehat{y}_{t+h}^{k}$ and a weighting scheme w_{t+h}^{k}:

$$\widehat{y}_{t+h}^{Pool} = \sum_{k=1}^{K} w_{t+h}^{k} \widehat{y}_{t+h}^{k} \quad \text{with} \sum_{k=1}^{K} w_{t+h}^{k} = 1\,. \tag{3}$$

Because the weights are indexed by time, they are varying with every re-estimation of our ADL model and every forecasting horizon h. K represents the number of models we consider for pooling.
A very simple but empirically well-working scheme (see, e.g., Timmermann, 2006) is (i) equal weights: $w^k = 1/K$. The weights are not time varying and depend only on the number of included individual forecasting models K. In addition to a simple mean, we consider (ii) a median approach. This weighting scheme is time varying and more robust against outliers.
In addition to these simple approaches, we can calculate different weights from two categories: in-sample and out-of-sample. We follow the studies by Drechsel and Scheufele (2012a) and Drechsel and Scheufele (2012b) and apply in-sample and out-of-sample weighting schemes.
We use two **in-sample** measures for the calculation of our weights: (iii) BIC and (iv) R^2. The two schemes differ only slightly. Whereas the model with the lowest BIC gets the highest weight, the weight of a single model increases with higher R^2. The weights from these two schemes are time varying and have the following form:

$$w_{t+h}^{k,BIC} = \frac{\exp\left(-0.5 \cdot \Delta_k^{BIC}\right)}{\sum_{k=1}^{K} \exp\left(-0.5 \cdot \Delta_k^{BIC}\right)} \tag{4}$$

$$w_{t+h}^{k,R^2} = \frac{\exp\left(-0.5 \cdot \Delta_k^{R^2}\right)}{\sum_{k=1}^{K} \exp\left(-0.5 \cdot \Delta_k^{R^2}\right)}\,, \tag{5}$$

with $\Delta_k^{BIC} = BIC_{t+h}^{k} - BIC_{t+h,min}$ and $\Delta_k^{R^2} = R^2_{t+h,max} - R^2_{t+h,k}$.
When applying **out-of-sample** weights, it is appropriate to use the forecast errors of different

All these indicators are labeled with an **X** in Table 4 in the appendix (column *Multi*).

models. First, we apply a (v) trimmed mean.[12] This weighting scheme filters indicators with bad performance and does not consider the forecasts of those models. Consistent with the literature, we use three different thresholds: 25%, 50% and 75% of all indicators in ranked order. If an indicator's performance lies within the worst (25%, 50% or 75%) performers, the outcome of that specific forecasting model is not considered for pooling. All other forecasts are combined with equal weights. Second, discounted mean squared forecast errors are used as weights (vi) to combine several model outcomes. This approach is based on Diebold and Pauly (1987) and is applied, e.g., by Costantini and Pappalardo (2010) and Stock and Watson (2004). The weights from this approach have the following form:

$$w_{t+h}^{k} = \frac{\lambda_{t+h,k}^{-1}}{\sum_{k=1}^{K} \lambda_{t+h,k}^{-1}} \,. \tag{6}$$

$\lambda_{t+h,k} = \sum_{n=1}^{N} \delta^{t-h-n} \left(FE_{t+h,n}^{k} \right)^2$ represents the sum of discounted (δ) forecast errors of the single–indicator model k. The literature finds no consensus on how the discount rate δ should be chosen. We experimented with different values for δ, which show similar performances. In our setup, we use $\delta = 0.1$.

In this study, we will only combine forecasts that are calculated from regional indicators (either for Saxony, Baden-Württemberg or Eastern Germany) or the full sample excluding the other two regional units.[13]

2.4. Factor models

When dealing with large data sets – where the cross-section dimension is large – standard econometric methodologies are not able to handle all available information. Next to the combination of forecast results (pooling), static and dynamic factor models yield good forecasting results (see Stock and Watson, 2002; Marcellino *et al.*, 2003; Forni *et al.*, 2005). The idea behind these models is to extract or summarize the inherent information of a large set of time series within some common factors. This approach allows us to specify a parsimonious model and thereby alleviate the uncertainty about parameter estimates (see Giannone *et al.*, 2008), which would be the case when estimating a model with nearly all available indicators.

In this paper, we apply three different approaches for estimating the common factors of the underlying series. To save space, we refer to the cited literature for further details on each approach. First, we use the standard principal components (PC) method to estimate the factors. Following Giannone *et al.* (2008), we apply the two-step estimator proposed by Doz *et al.* (2011). This two-step estimation procedure, which uses principal components and Kalman filtering (PCKF), has proven to provide some efficiency improvements in comparison to standard

[12] For the effectiveness of this approach, see, e.g., Drechsel and Scheufele (2012b) or Timmermann (2006).

[13] E.g., for the Free State of Saxony, we use only the indicators for Saxony or all indicators excluding those from Eastern Germany and Baden-Württemberg.

principal component methods. As a third approach, we estimate the common factors via quasi maximum likelihood (QML) (see Doz *et al.*, 2012).[14]

In the next step, we must decide how many common factors shall be extracted from the data. We choose between one and three common factors. Additionally, a decision must be regarding which data source (cross-section and time dimension) should be used to estimate the factors. We have the choice of using either the full sample of indicators (FS) or only the information from regional ones (S, BW or EG). Furthermore, we can extract the factors from (i) monthly data and then aggregate these factors to quarterly information (M), or we aggregate the monthly indicators and then extract the factors from (ii) quarterly data (Q). In the end, we can use the extracted factors in two ways to generate forecasts for real GDP. First, we put the factors directly into the ADL model from Equation (1), such that lagged values from the dependent variable and the common factors are used to forecast real GDP. Second, we apply a standard OLS estimate, where GDP is explained via a constant and the common factors available at time t (see Giannone *et al.*, 2008). The second method considers neither lagged values nor the dependent variable. To sum up, we test three different approaches with up to three common factors. We have two underlying databases from which the factors are extracted, as well as two frequencies and forecasting approaches, which results in 72 factor models for each regional unit.

2.5. Forecast evaluation

To analyze the forecast accuracy of different strategies (indicator models, factor models or pooling techniques), we first calculate forecast errors from our forecasting exercise. Let $\widehat{y}^k_{t+h}$ denote the h-step-ahead forecast of model k; then, the resulting forecast error is: $FE^k_{t+h} = y^k_{t+h} - \widehat{y}^k_{t+h}$. The forecast error for the AR(p)-benchmark is FE^{AR}_{t+h}. In a second step, we use the root mean squared forecast error (RMSFE) as a loss function to assess the overall performance of a model. The RMSFE for the h-step-ahead forecast is defined as:

$$RMSFE^k_h = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(FE^k_{t+h,n}\right)^2}\,. \tag{7}$$

The respective RMSFE for the autoregressive benchmark is $RMSFE^{AR}_h$. Finally, we construct a relative RMSFE (rRMSFE),

$$rRMSFE^k_h = \frac{RMSFE^k_h}{RMSFE^{AR}_h}\,, \tag{8}$$

to decide whether a model k is performing better or worse in comparison to the AR benchmark model. If this ratio is less than one, the indicator model leads to smaller forecast errors for the

[14] We abstract from the ragged edge data problem (see Wallis, 1986) by extracting factors using only information up to $t-1$.

respective horizon h. Otherwise, the simple autoregressive model is preferable.
Because we have a large set of competing models, pairwise testing would result in the problem of data snooping. This problem means that pairwise tests signal a higher accuracy of one model just by chance.[15] To overcome this problem, we apply the superior predictive ability (SPA) test proposed by Hansen (2005). This test is based on the seminal paper by White (2000). The idea of the SPA test is to examine whether a benchmark model performs better in comparison to a whole set of competitors. Under the null hypothesis, no competing model should beat the benchmark model. Because teh SPA test is a multiple test, the null hypothesis is formulated as follows,

$$H_0 : E\left(d_{k,t+h}\right) \leq 0 \quad k = 1, ..., K\,. \tag{9}$$

The difference $d_{k,t+h}$ is defined as $d_{k,t+h} = \left(FE^0_{t+h}\right)^2 - \left(FE^k_{t+h}\right)^2$, whereas FE^0_{t+h} is the forecast error of the benchmark. Whenever the null is rejected, at least one competitor performs better than the chosen benchmark model. Every single–indicator, forecast combination approach and factor model serves as the benchmark. Thus, the corresponding benchmark errors ($\left(FE^0_{t+h}\right)^2$) are used. However, because the expectations under the null are unknown, they can be estimated consistently by the sample mean $\overline{d}_{k,t+h}\ \forall i \in \{1, \ldots, k\}$. The original reality check test statistic was proposed by White (2000) but suffers from the inclusion of poor or irrelevant models. Thus, we use the modification proposed by Hansen (2005), which is stable against irrelevant or poor competitors. The corresponding p-values are calculated via bootstrap because the distribution under the null is not identified. The test by Hansen (2005) requires a rolling window approach. With the SPA test, we can decide whether at least one model outperforms the benchmark. However, we are not able to say that these models are the best ones (with some specific confidence). To find the best models, we apply the model confidence set (MCS) procedure proposed by Hansen *et al.* (2011). This procedure is closely related to the SPA test; however, we do not have to specify a benchmark model. The MCS procedure is a model selection algorithm, which filters a set of models from a given entirety of models. The resulting set contains the best models with a given confidence level (see Hansen *et al.*, 2011). Because we have a large set of indicators and therefore a large set of models, we can apply this procedure to find a set of superior models. The null hypothesis is defined as,

$$H^h_{0,M} : \mu^h_{ij} = 0 \quad \forall i, j \in M^h\,, \tag{10}$$

whereas $\mu^h_{ij} \equiv E(d^h_{ij,t}) \equiv E(RMSFE^h_{i,t} - RMSFE^h_{j,t})$ denotes the expected difference in the root mean squared forecast errors of model i and j ($i, j \subset k$) for a given forecast horizon. The procedure tries to find the best set $M^{*,h}$ ($M^{*,h} \equiv \{i \in M^{0,h} : \mu^h_{ij} \leq 0\, \forall j \in M^{0,h}\}$), containing all models that are significantly superior to other models from a starting set $M^{0,h}$ (see Hansen *et al.*, 2011). Because our data set allows us to evaluate a large number of competing models

[15]Imagine a set of repeated draws from a normal distribution. In some cases, this fact would result in values that lie near the critical values, whereby the null is rejected.

with the MCS procedure, we must restrict the algorithm to a limited starting set.[16] The reason is that this procedure is computational very demanding.[17] Thus, our starting set $M^{0,h}$ always contains the best 250 models (from every category) in terms of RMSFE.

3. Results

This section presents the results for our three target variables. First, we discuss the general results of our forecasting exercise. Second, we present detailed and selected results that are consistent with the specific economic structures of our regional units.

3.1. General Results

The summary tables are divided into four quadrants, each representing one single forecast horizon (h). In the upper (lower) left, $h = 1$ ($h = 3$) is shown, and the upper (lower) right presents $h = 2$ ($h = 4$). To obtain an impression about how well the several models are performing, we add the RMSFE of the autoregressive benchmark model (in %) for each forecast horizon and region. Every quadrant shows the top 20 models from our forecasting exercise due to the rRMSFE of Equation (8). These rRMSFE are presented in the column *Ratio*. The column *SPA p-value* shows the p-values from the test proposed by Hansen (2005). An **X** in column *MCS* indicates whether a model is included in the set of best models, based on the test by Hansen *et al.* (2011). To increase readability, we add one column with acronyms for the different forecast models. National indicators are denoted with (N), while (I) represents international and (R) regional indicators. Combination strategies are denoted with (C). (M) stands for multi–indicator and (F) for factor models. Tables 1, 2 and 3 present the estimation results for our three regional units.

[16] If we would not restrict our starting set, then the MCS procedure must consider 4862 different models. Among them, we have 4 benchmarks, 16 combination and 72 factor models, 286 single–indicator and 4484 multi–indicator models.

[17] For both tests (Hansen, 2005; Hansen *et al.*, 2011), we employ a block bootstrap approach with a block size of 12 and 2500 replications.

Table 1: **Results for the Free State of Saxony**

Target variable: quarter-on-quarter growth rate GDP Free State of Saxony									
h=1		RMSFE AR(p): 0.993%			**h=2**		RMSFE AR(p): 0.992%		
Model	Acronym	Ratio	SPA p-value	MCS	Model	Acronym	Ratio	SPA p-value	MCS
MSFE weighted (FS)	(C)	0.582	1.000	X	MSFE weighted (FS)	(C)	0.620	1.000	X
IFOOOHCONSAX – GFKESE	(M)	0.730	0.439	X	MSFE weighted (S)	(C)	0.740	0.156	X
IFOOOHCONSAX – GFKCCC	(M)	0.737	0.448	X	PCWHSAX – GFKUE	(M)	0.773	0.002	
Trimmed 25 (FS)	(C)	0.740	0.000		PCWHSAX – EUCSUE	(M)	0.773	0.001	X
IFOOOHCONSAX – IFOEXEMAN	(M)	0.745	0.178	X	PCWHSAX – IFOBSCONNDUR	(M)	0.798	0.059	X
MSFE weighted (S)	(C)	0.754	0.018		PCWHSAX – GFKESE	(M)	0.800	0.025	
IFOOOHCONSAX – GFKCCIN	(M)	0.758	0.330		PCWHSAX – IFOBECONNDUR	(M)	0.803	0.008	
IFOOOHCONSAX – EUCSCCI	(M)	0.758	0.317	X	PCWHSAX – IFOBCCONNDUR	(M)	0.808	0.082	X
IFOBEMAN	(N)	0.763	0.002		PCWHSAX – GFKBCE	(M)	0.809	0.017	
IFOOOHCONSAX – IFOUNFWCON	(M)	0.764	0.348	X	Trimmed 25 (FS)	(C)	0.817	0.002	
IFOOOHCONSAX – GFKUE	(M)	0.766	0.304		PCWHSAX – GFKCCC	(M)	0.818	0.019	
IFOOOHCONSAX – EUCSUE	(M)	0.766	0.327		PCWHSAX – EUBSSPEIND	(M)	0.820	0.001	
IFOBECAP	(N)	0.766	0.092		PCWHSAX – EUBSRTCI	(M)	0.825	0.024	
IFOOOHCONSAX – EUBSPEIND	(M)	0.780	0.221		PCWHSAX – EUBSEMPEIND	(M)	0.825	0.004	
IFOBCMAN	(N)	0.785	0.038		PCWHSAX – IFOBEINT	(M)	0.830	0.022	
IFOOOHCONSAX – IFOBECONNDUR	(M)	0.792	0.043		HCNOSAX – IFOBEINT	(M)	0.832	0.090	
IFOOOHCONSAX – GFKIE	(M)	0.793	0.077		PCWHSAX – GFKCCIN	(M)	0.834	0.014	
IFOBCIT	(N)	0.793	0.022		PCWHSAX – EUCSCCI	(M)	0.834	0.013	
IFOOOHCONSAX – IFOBCCAP	(M)	0.794	0.121		CONFIRMSAX – EUBSSPEIND	(M)	0.834	0.000	
Trimmed 25 (S)	(C)	0.797	0.007		CONFIRMSAX – IFOBEINT	(M)	0.835	0.000	
h=3		RMSFE AR(p): 0.946%			**h=4**		RMSFE AR(p): 1.021%		
Model	Acronym	Ratio	SPA p-value	MCS	Model	Acronym	Ratio	SPA p-value	MCS
MSFE weighted (FS)	(C)	0.724	1.000	X	MSFE weighted (FS)	(C)	0.507	1.000	X
MSFE weighted (S)	(C)	0.816	0.123	X	MSFE weighted (S)	(C)	0.713	0.026	
PCWHSAX – IFOBCCONNDUR	(M)	0.850	0.636	X	Trimmed 25 (S)	(C)	0.805	0.000	
Trimmed 25 (FS)	(C)	0.852	0.000		Trimmed 25 (FS)	(C)	0.821	0.002	
PCWHSAX – EUBSPTIND	(M)	0.857	0.522	X	IFOBSITSAX – IFOEXEMAN	(M)	0.844	0.001	
PCWHSAX – IFOBCINT	(M)	0.863	0.572		ICWHSAX	(R)	0.844	0.000	
PCWHSAX – IFOBSCONDUR	(M)	0.899	0.328		IFOBCITSAX – IFOAOIWT	(M)	0.854	0.000	
Trimmed 25 (S)	(C)	0.907	0.000		IFOBEMANSAX – IFOEXEMAN	(M)	0.883	0.000	
HCNOSAX – EUBSOBLIND	(M)	0.908	0.424		IFOBEITSAX – IFOEXEMAN	(M)	0.895	0.001	
PCWHSAX – IFOBCCONDUR	(M)	0.910	0.158		HCWHSAX – IFOEXEMAN	(M)	0.900	0.000	
PCWHSAX – IFOBSCONNDUR	(M)	0.928	0.016		IFOBEITSAX – EUBSRTCI	(M)	0.900	0.003	
HCNOSAX – IFOBSINT	(M)	0.928	0.314		IFOBEMANSAX – EUBSRTCI	(M)	0.908	0.000	
HCNOSAX – IFOBEINT	(M)	0.929	0.293		HCTOSAX – GFKPL	(M)	0.908	0.000	
PCWHSAX – EUBSPEIND	(M)	0.930	0.321		QML1QOLS (S)	(F)	0.909	0.000	
CONEMPSAX – IFOBCINT	(M)	0.930	0.165		IFOBSMANSAX – IFOEXEMAN	(M)	0.914	0.002	
Trimmed 50 (FS)	(C)	0.933	0.000		Trimmed 50 (FS)	(C)	0.916	0.002	
CONWHSAX – EUBSPTIND	(M)	0.933	0.379		IFOCUCONSAX – IFOEXEMAN	(M)	0.919	0.000	
IFOBSMANSAX – GFKFSE	(M)	0.935	0.001		Trimmed 50 (S)	(C)	0.922	0.001	
HCNOSAX – ZEWES	(M)	0.935	0.166		EXVALUESAX – IFOBECAP	(M)	0.924	0.000	
Trimmed 50 (S)	(C)	0.936	0.000		CONFIRMSAX – IFOEXEMAN	(M)	0.925	0.000	

Note: The table reports the best 20 models with the smallest rRMSFE (column *Ratio*). The column *SPA p-value* presents the outcome of the SPA test by Hansen (2005).
An **X** in column *MCS* denotes that this model is among the best ones, decided by the test of Hansen *et al.* (2011). Table 4 in the appendix shows the acronyms used for the different indicators.
Acronyms: (FS) Full Sample, (S) Saxony, (I) international, (N) national, (R) regional indicators, (C) combinations, (M) multi–indicator and (F) factor models.
Source: author´s calculations.

Table 2: **Results for Baden-Württemberg**

Target variable: quarter-on-quarter growth rate GDP Baden-Württemberg									
h=1		RMSFE AR(p): 1.708%			**h=2**		RMSFE AR(p): 1.740%		
Model	Acronym	Ratio	SPA p-value	MCS	Model	Acronym	Ratio	SPA p-value	MCS
MSFE weighted (BW)	(C)	0.589	1.000	X	MSFE weighted (FS)	(C)	0.731	1.000	X
MSFE weighted (FS)	(C)	0.624	0.281	X	MSFE weighted (BW)	(C)	0.759	0.226	X
Trimmed 25 (BW)	(C)	0.681	0.062	X	IFOBSITBW – EUBSRTCI	(M)	0.781	0.198	X
Trimmed 25 (FS)	(C)	0.710	0.066	X	Trimmed 25 (FS)	(C)	0.787	0.053	
IFOBCITBW	(R)	0.725	0.000		IFOBCMANBW – EUBSRTCI	(M)	0.792	0.196	
IFOBCMANBW	(R)	0.747	0.006		IFOCUCONBW – GFKPL	(M)	0.799	0.002	
EUBSPEIND	(N)	0.755	0.028		IFOBCITBW – EUBSRTCI	(M)	0.808	0.030	
IFOIOFGMAN	(N)	0.758	0.000		IFOBEITBW – EUCSFSP	(M)	0.810	0.026	
Trimmed 50 (BW)	(C)	0.773	0.098		Trimmed 25 (BW)	(C)	0.815	0.024	
IFOBCCAP	(N)	0.774	0.078		IFOCUCONBW – GFKFSE	(M)	0.818	0.466	
IFOBSCAP	(N)	0.778	0.140		IFOBCWTBW – EUBSRTCI	(M)	0.822	0.010	
EUBSINDCI	(N)	0.779	0.002		IFOBSMANBW – EUBSRTCI	(M)	0.825	0.452	
EUBSSFGIND	(N)	0.781	0.000		KIBW – GFKWTB	(M)	0.825	0.026	
IFOBCMAN	(N)	0.784	0.003		IFOBCMANBW – GFKFSE	(M)	0.828	0.004	
Trimmed 50 (FS)	(C)	0.791	0.104		IFOBCMANBW – GFKCCC	(M)	0.830	0.076	
IFOBEINT	(N)	0.791	0.007		IFOBSMANBW – EUBSEMPEIND	(M)	0.830	0.419	
EUCSESI	(N)	0.793	0.000		IFOEMPECONBW – EUBSRTCI	(M)	0.830	0.024	
KIBW – COMBAEB	(M)	0.795	0.060		PCWHBW – EUBSRTCI	(M)	0.830	0.000	
KIBW – GFKCCC	(M)	0.800	0.125		IFOBSMANBW – GFKESE	(M)	0.831	0.008	
KIBW – GFKCCIN	(M)	0.800	0.154		IFOBCMANBW – GFKCCIN	(M)	0.831	0.067	
h=3		RMSFE AR(p): 1.645%			**h=4**		RMSFE AR(p): 1.664%		
Model	Acronym	Ratio	SPA p-value	MCS	Model	Acronym	Ratio	SPA p-value	MCS
MSFE weighted (FS)	(C)	0.714	1.000	X	MSFE weighted (FS)	(C)	0.649	1.000	X
ICNOBW – NRHT	(M)	0.802	0.182	X	MSFE weighted (BW)	(C)	0.705	0.243	X
CONNOBW – GFKBCE	(M)	0.828	0.297	X	PCNOBW – IFOBECONNDUR	(M)	0.816	0.000	
PCNOBW – IFOBCCONNDUR	(M)	0.832	0.068	X	Trimmed 25 (FS)	(C)	0.849	0.001	
PCNOBW – IFOOOHMAN	(M)	0.840	0.009		PCNOBW – GFKWTB	(M)	0.874	0.000	
IFOBEITBW – IFOEXEMAN	(M)	0.842	0.000		PCNOBW – GFKFSE	(M)	0.884	0.001	
Trimmed 25 (FS)	(C)	0.847	0.000		PCNOBW – GFKMPP	(M)	0.891	0.001	
PCNOBW – GFKUE	(M)	0.848	0.011		ICTOBW – EUBSSPEIND	(M)	0.891	0.013	
PCNOBW – EUCSUE	(M)	0.848	0.013		Trimmed 25 (BW)	(C)	0.894	0.006	
PCNOBW – IFOBSCONDUR	(M)	0.853	0.109		HCWHBW – GFKPL	(M)	0.899	0.000	
PCNOBW – IFOBSINT	(M)	0.853	0.023		PCNOBW – GFKFSL	(M)	0.904	0.000	
CONNOBW – GFKUE	(M)	0.858	0.104		ICWHBW – EUBSSPEIND	(M)	0.905	0.031	
CONNOBW – EUCSUE	(M)	0.858	0.106		PCNOBW – EUBSSPEIND	(M)	0.906	0.001	
HCWHBW – EUBSSSCI	(M)	0.858	0.244		IFOCUCONBW – GFKFSE	(M)	0.908	0.024	
PCNOBW – EUBSOBLIND	(M)	0.870	0.006		IFOBSMANBW – EUBSSFGIND	(M)	0.910	0.033	
PCNOBW – IFOBCCONDUR	(M)	0.873	0.020		IPMET	(N)	0.913	0.000	
PCNOBW – EUBSSPEIND	(M)	0.874	0.017		HCWHBW – GFKWTB	(M)	0.915	0.003	
KIBW – GFKWTB	(M)	0.876	0.079		ICNOBW – IFOAOIWT	(M)	0.922	0.008	
HCNOBW – EUBSSSCI	(M)	0.876	0.207		ICTOBW – IFOBCINT	(M)	0.927	0.029	
CONNOBW – IFOBSCONDUR	(M)	0.880	0.105		KIBW – GFKWTB	(M)	0.930	0.052	

Note: The table reports the best 20 models with the smallest rRMSFE (column *Ratio*). The column *SPA p-value* presents the outcome of the SPA test by Hansen (2005).
An **X** in column *MCS* denotes that this model is among the best ones, decided by the test of Hansen *et al.* (2011). Table 4 in the appendix shows the acronyms used for the different indicators.
Acronyms: (FS) Full Sample, (BW) Baden-Württemberg, (I) international, (N) national, (R) regional indicators, (C) combinations, (M) multi–indicator and (F) factor models.
Source: author´s calculations.

Table 3: **Results for Eastern Germany**

Target variable: quarter-on-quarter growth rate GDP Eastern Germany									
h=1		RMSFE AR(p): 1.226%			**h=2**		RMSFE AR(p): 1.274%		
Model	Acronym	Ratio	SPA p-value	MCS	Model	Acronym	Ratio	SPA p-value	MCS
MSFE weighted (FS)	(C)	0.815	1.000	X	MSFE weighted (FS)	(C)	0.782	1.000	X
MSFE weighted (EG)	(C)	0.829	0.577	X	MSFE weighted (EG)	(C)	0.815	0.507	X
Trimmed 25 (EG)	(C)	0.864	0.285	X	IFOBSITEG – EUBSEMPEIND	(M)	0.876	0.414	X
Trimmed 25 (FS)	(C)	0.877	0.170	X	Trimmed 25 (FS)	(C)	0.879	0.032	X
EUCSITESI	(I)	0.907	0.002		IWHOLKMANEG – EUBSSSCI	(M)	0.882	0.518	X
IFOBSMANEG – ZEWES	(M)	0.916	0.324	X	IFOBCITEG – IFOAOIRS	(M)	0.882	0.148	X
IFOBSITEG – IFOIOFGMAN	(M)	0.917	0.007		IFOBSMANEG – GFKCCIN	(M)	0.887	0.430	
Trimmed 50 (EG)	(C)	0.925	0.008		IFOBSMANEG – EUCSCCI	(M)	0.887	0.433	X
Trimmed 50 (FS)	(C)	0.927	0.013		IWHOLKMANEG – GFKFSE	(M)	0.887	0.452	X
IWHOLKCONEG – IFOIOFGMAN	(M)	0.931	0.083		IFOBSMANEG – GFKCCC	(M)	0.889	0.416	
IFOBCITEG – IFOIOFGMAN	(M)	0.932	0.000		HCWHEG – IFOUNFWCON	(M)	0.890	0.239	
IFOBSMANEG	(R)	0.933	0.005		HCNOEG – IFOAOIRS	(M)	0.890	0.369	X
IFOBSITEG – IFOEOARS	(M)	0.933	0.002		IFOBSITEG – EUBSSFGIND	(M)	0.890	0.307	
IFOBSITEG – EUBSOBLIND	(M)	0.935	0.020		HCWHEG – EUBSINDCI	(M)	0.890	0.296	
IFOBSITEG – IFOOOHMAN	(M)	0.937	0.006		IFOBCITEG – EUBSSFGIND	(M)	0.891	0.175	
IFOBCMANEG – GFKESL	(M)	0.937	0.005		CONFIRMEG – IFOUNFWCON	(M)	0.891	0.188	
DREUROREPO	(N)	0.938	0.097		IFOBCWTEG – EUBSSFGIND	(M)	0.891	0.352	
IFOBCMANEG – IFOBEINT	(M)	0.938	0.005		IFOBCWTEG – IFOIOFGMAN	(M)	0.891	0.312	
IFOBSMANEG – GFKCCC	(M)	0.942	0.002		IFOBSMANEG – IFOBSINT	(M)	0.892	0.294	
IFOBCITEG – EUBSEMPEIND	(M)	0.942	0.014		IFOBSMANEG – IFOBCINT	(M)	0.893	0.293	
h=3		RMSFE AR(p): 1.319%			**h=4**		RMSFE AR(p): 1.223%		
Model	Acronym	Ratio	SPA p-value	MCS	Model	Acronym	Ratio	SPA p-value	MCS
MSFE weighted (FS)	(C)	0.742	1.000	X	MSFE weighted (FS)	(C)	0.654	1.000	X
IFOBSMANEG – ZEWPS	(M)	0.856	0.454	X	Trimmed 25 (FS)	(C)	0.836	0.010	X
Trimmed 25 (FS)	(C)	0.872	0.027	X	MSFE weighted (EG)	(C)	0.872	0.165	X
IFOBERSEG – IFOBECONNDUR	(M)	0.891	0.379	X	Trimmed 25 (EG)	(C)	0.888	0.126	X
IFOBCWTEG – IFOBECONNDUR	(M)	0.892	0.360	X	Trimmed 50 (FS)	(C)	0.901	0.000	
MSFE weighted (EG)	(C)	0.895	0.061	X	IFOBECONEG	(R)	0.921	0.017	
HCWHEG – IFOBECONNDUR	(M)	0.899	0.577		ZEWES	(N)	0.923	0.000	
HCNOEG – GFKUE	(M)	0.900	0.460		Trimmed 50 (EG)	(C)	0.929	0.003	
HCNOEG – EUCSUE	(M)	0.900	0.442		CONHW	(N)	0.934	0.002	
IFOBCRSEG – IFOBECONNDUR	(M)	0.900	0.482	X	CONTOEG – GFKPL	(M)	0.943	0.125	X
HCWHEG – IFOBCCONNDUR	(M)	0.901	0.556		DAXSPI	(N)	0.955	0.200	X
HCWHEG – GFKUE	(M)	0.901	0.585		Trimmed 75 (FS)	(C)	0.956	0.002	
HCWHEG – EUCSUE	(M)	0.901	0.590	X	TOVEMD	(N)	0.957	0.063	
IFOBSMANEG – GFKCCIN	(M)	0.902	0.413		NOCEOD	(N)	0.961	0.002	
IFOBSMANEG – EUCSCCI	(M)	0.902	0.412		CONNREPE	(N)	0.970	0.057	
IWHSITCONEG – IFOBCCONDUR	(M)	0.902	0.574		NOMECHD	(N)	0.972	0.043	
HCWHEG – GFKCCIN	(M)	0.904	0.601		GFKIE	(N)	0.976	0.000	
HCWHEG – EUCSCCI	(M)	0.904	0.592		PCWHEG	(R)	0.988	0.007	
HCWHEG – EUBSPTIND	(M)	0.905	0.489		Trimmed 75 (EG)	(C)	0.989	0.002	
HCWHEG – COMBAEB	(M)	0.906	0.568		HCTOEG	(R)	0.992	0.000	

Note: The table reports the best 20 models with the smallest rRMSFE (column *Ratio*). The column *SPA p-value* presents the outcome of the SPA test by Hansen (2005).
An **X** in column *MCS* denotes that this model is among the best ones, decided by the test of Hansen *et al.* (2011). Table 4 in the appendix shows the acronyms used for the different indicators.
Acronyms: (FS) Full Sample, (EG) Eastern Germany, (I) international, (N) national, (R) regional indicators, (C) combinations, (M) multi–indicator and (F) factor models.
Source: author´s calculations.

For all three GDP target variables, the AR(p) benchmark model is significantly outperformed. This result holds true for all considered forecasting horizons. However, we must consider that forecast improvements in comparison to the autoregressive benchmark decrease with longer forecast horizons. It becomes even more difficult to predict regional GDP in the long term. This fact is also indicated by the MCS test. With the exception of Eastern Germany, only few models are included in the set of best models in the long term.

Differences across the regions exist in the overall forecasting performance and the composition of indicators. The most accurate forecasts are observable for the Free State of Saxony and Baden-Württemberg. For Eastern Germany, the RMSFE is slightly higher in comparison to the other two regions. What we can see from the three tables is that pooling performs best for all three regional target variables. Next to MSFE weighted combination strategies, trimmed means in particular produce lower forecast errors than the benchmark models. As indicated by the tests, no competitor has a higher accuracy than pooling models. Additionally, combination strategies are part of the set of best models.

Another interesting result is that in most cases multi–indicator models outperform single-indicator models. Adding another national indicator to a regional one clearly enhances the forecast accuracy of regional GDP. Single–indicator models perform well for Baden-Württemberg in the short term ($h = 1$) and for Eastern Germany in the long term ($h = 4$). We have to state that the most important forecasting signals come from regional and national indicators. International indicators do not play an important role in predicting regional GDP.

Because we use a large data set, it is interesting to examine the differences between pooling and factor models. Whereas the combination of forecasts from different models performs quite well, the forecast improvement by factor models is not very impressive. We find rRMSFEs that are smaller than one; however, these models are not very competitive in comparison to pooling or multi–indicator forecasts in our case. With the exception of Saxony, no factor model is among the top 20.

3.2. Detailed regional results

3.2.1. Free State of Saxony

Pooling (MSFE weighted (FS), $rRMSFE = 0.582$) and multi–indicator models yield the best results for the Saxon GDP in our pseudo real–time setting (see Table 1). The multi–indicator models are dominated by two regional indicators in the short and mid–term: orders on hand in the Saxon construction sector (IFOOOHCONSAX) and working hours in the sector of public construction (PCWHSAX). These results are not surprising because construction traditionally plays an important role in Eastern German states. The MCS test also indicates that multi–indicator models are part of the best set of models in the short and mid–term. In the long term ($h = 4$), only the MSFE weighted model is within the set of the best models. A closer look at the multi–indicator models reveals that surveys, in particular, (consumer or business) produce lower forecast errors than our benchmark model and that regional indicators are essential when forecasting GDP. The Ifo business climate for industry and trade in Germany (IFOBCIT, $rRMSFE = 0.793$) in the short term or in Saxony (IFOBCITSAX) in the long term has a higher forecast accuracy than the autoregressive process. These results are consistent with forecasting literature for Germany. One of the most important leading indicators for German GDP is the Ifo business climate for industry and trade.[18] This phenomenon also applies to Saxony (Lehmann *et al.*, 2010). Turning to consumer surveys, Table 1 reveals that these indicators are very helpful in predicting Saxon GDP in the short and mid–term. Particularly the consumer confidence climate (GFKCCC) significantly reduces forecast errors and, in combination with IFOOOHCONSAX, is part of the best set of models. This result is straightforward because Eastern German manufacturing firms mainly interact on domestic markets (see Ragnitz, 2009). Furthermore, exports (EXVALUE, $h = 4$) and export expectations in the manufacturing sector (IFOEXEMAN, short and long term) improve forecast accuracy. The latter indicator is also part of the set of best models in the short term. Within the Eastern German states, the Saxon economy has the highest degree of openness (approximately 40% of all turnovers in the manufacturing sector come from abroad). Another highlight is the importance of business expectations from capital (IFOBECAP, $rRMSFE = 0.766$) and intermediate goods producers (IFOBEINT) in the medium and long term. This result is straightforward because the Saxon industry is predominantly described by these two sectors. Approximately 80% of all turnovers in 2011 come from intermediate and capital goods (e.g., vehicle manufacturing, which is the dominant sector in the Saxon industry) producers. Saxon firms are strongly linked to the Western German economy; therefore, national indicators are useful for predicting Saxon GDP. In comparison to the other regions, factor models belong to the top 20 only in Saxony (QML1QOLS, $rRMSFE = 0.909$, $h = 4$).

3.2.2. Baden-Württemberg

As we have seen from the results for Saxony, pooling of forecast outcomes also produces the lowest forecast errors in Baden-Württemberg. For all forecast horizons, pooling models dominate all other competitors and are always part of the best set of models. The best combination strategy predicts GDP one quarter ahead almost 40% more accurately then the AR benchmark (see MSFE weighted in Table 2). In contrast to Saxony, single–indicator models perform better than multi–indicator models in the short term ($h = 1$). In particular, regional survey results such as the Ifo business climate for industry and trade in Baden-Württemberg (IFOBCITBW, $rRMSFE = 0.725$) and a regional business cycle indicator (KIBW) outperform the autoregressive benchmark. Additionally, survey results from the manufacturing sector (IFOBCMANBW, $rRMSFE = 0.747$) and from capital goods producers (IFOBCCAP, $rRMSFE = 0.774$) provide important forecasting signals in our pseudo real–time setting. These results can be ex-

[18] For a recent survey, see Abberger and Wohlrabe (2006).

plained by the economic structure of Baden-Württemberg. Baden-Württemberg has the highest share of manufacturing among the German states; approximately 30% of nominal gross value added is generated in this sector. Manufacturing of motor vehicles (e.g., Daimler AG, which explains the performance of NRHT for $h = 3$), machinery and equipment, the fabrication of metal products and highly innovative capital goods producers such as the Bosch Group predominantly describe the industrial structure in manufacturing. As in Saxony, the multi–indicator models are dominated in the medium and long terms by two indicators: the Ifo business climate in manufacturing (IFOBCMANBW) and new orders in the public construction sector (PCNOBW). The latter indicator is indeed part of the best model set. Another interesting result is the importance of export expectations in the manufacturing sector (IFOEXEMAN) in the mid term. Baden-Württemberg has one of the highest export quotas of the German states; more than 50% of all industrial turnovers are generated in foreign countries. The most important trading partners come from the Euro Area, followed by the US. For companies such as Daimler AG and the Bosch Group, the US is one of the most relevant markets.

3.2.3. Eastern Germany

Regional business surveys provided by the Ifo Institute (IFOBSMANEG, $rRMSFE = 0.933$) and the IWH (IWHOLKMANEG) are able to predict Eastern German GDP more accurately than the autoregressive benchmark in the short and mid term. Considering national variables, we also find results that are consistent with the Eastern German economic structure. The Ifo business climate for intermediate goods producers (IFOBCINT, $h = 2$), macroeconomic variables for Germany (e.g., NOMECHD, $h = 4$) and the consumer sentiment indicator (GFKCCIN, mid term) help for the prediction of Eastern German GDP. First, Eastern German firms interact mostly on domestic markets and have a lower export quota in comparison to their Western German counterparts (see Ragnitz, 2009). Second, the Eastern German industrial sector is mainly characterized by intermediate goods producers. Nearly 40% of all turnovers in 2011 were achieved in this industrial main group. Ragnitz (2009, p. 55) states that most Eastern German firms are still so-called “extended workbenches” (*verlängerte Werkbänke*) of Western German companies. Overall, Western German economic development is a crucial factor for quarter-on-quarter GDP growth in Eastern Germany. Another interesting result is that single–indicator models perform better in the long term than multi–indicator models (see $h = 4$ in Table 3). Additionally, the multi–indicator models are not dominated by a small number of indicators to the same extent as in the other two regions. Only the business situation for industry and trade in Eastern Germany (IFOBSITEG) in the short term or the working hours for the Eastern German housing construction sector (HCWHEG) in the mid term stand out from this overall picture. In line with the results for Saxony and Baden-Württemberg, pooling has the highest forecast accuracy in terms of RMSFE. This class of models dominate all competitors in the short and long term and are part of the model confidence set. In contrast to Saxony and Baden-Württemberg, a larger number of models are included in the set of best models in

Eastern Germany.

4. Conclusion

This paper analyzes the forecasting performance of single–indicator, multi–indicator, factor models and pooling techniques in a pseudo real–time setting at the regional level. We use a large data set with international, national and regional variables. As target variables, we use unique quarterly data for GDP that are provided by different sources for the period 1996:01 to 2010:04. Our paper is the first to systematically use time series techniques to forecast regional GDP. Altogether, it is possible to predict GDP at the regional level at a quarterly frequency. A large number of indicators produce lower forecast errors than the benchmark model. The different results for our three target variables show that high heterogeneity exists between regional units. An important reason for this heterogeneity is the regional economic structure, as the highlighted section shows. Furthermore, we can conclude that regional indicators have a high forecasting power. Whenever regional variables are available, these indicators are worth considering for forecasting. As our results show, regional variables deliver good forecasting signals or information. Because we use a large data set, pooling strategies can improve forecasting accuracy. For all three regional units, MSFE weights outperform all other weighting schemes, as well as single–indicator and multi–indicator forecasts. Hence, pooling in a regional context is just as important as on the national level. Another way to handle large data sets is to apply factor models. Despite the fact that this class of models improves forecast accuracy, which is in line with the existing literature, factor models are not that competitive compared to pooling or multi–indicator models in our case. Finally, we have shown, that in most cases, multi–indicator models significantly improve forecast accuracy in comparison to single–indicator models. By adding national variables to regional indicators, forecasts become even better at the regional level. Regional policy makers have to rely on accurate macroeconomic forecasts. With our exercise, we are able to reduce forecast errors significantly and therefore reduce uncertainty about future macroeconomic development at the regional level. This approach renders regional economic policy more assessable. Further research is necessary for different countries (e.g., the US or EU) and aggregation levels. It would be interesting to know whether it is better to predict regional GDP directly or through its different components. This issue was analyzed for Germany as a whole by Drechsel and Scheufele (2012a); however, to date, no regional study exists.

Acknowledgements: We thank two anonymous referees for detailed comments and suggestions that substantially improved the paper. Furthermore, we are grateful to Marcel Thum, Michael Kloß, Alexander Eck and seminar participants at the Dresden University of Technology and the Business School of Economics and Law Berlin for their helpful comments and suggestions. Comments from the participants at the 13th IWH/CIREQ Macroeconometric Workshop, the 33rd International Symposium on Forecasting and the 53rd Congress of the European Regional Science Association are also gratefully acknowledged. We thank Katja Drechsel and Rolf Scheufele for providing their data set on leading indicators.

References

Abberger, K. and Wohlrabe, K. (2006). Einige Prognoseeigenschaften des ifo Geschäftsklimas – Ein Überblick über die neuere wissenschaftliche Literatur. *ifo Schnelldienst*, **59** (22), 19–26.

Bandholz, H. and Funke, M. (2003). Die Konstruktion und Schätzung eines Konjunkturfrühindikators für Hamburg. *Wirtschaftsdienst*, **83** (8), 540–548.

Banerjee, A., Marcellino, M. and Masten, I. (2005). Leading Indicators for Euro-area Inflation and GDP Growth. *Oxford Bulletin of Economics and Statistics*, **67** (Supplement s1), 785–813.

—, — and — (2006). Forecasting macroeconomic variables for the new member states. In M. J. Artis, A. Banerjee and M. Marcellino (eds.), *The central and eastern European countries and the European Union*, Cambridge: Cambridge University Press, pp. 108–134.

Bates, J. M. and Granger, C. W. J. (1969). The Combination of Forecasts. *Operational Research Quarterly*, **20** (4), 451–468.

Bodo, G., Golinelli, G. and Parigi, G. (2000). Forecasting industrial production in the Euro area. *Empirical Economics*, **25** (4), 541–561.

Brautzsch, H. U. and Ludwig, U. (2002). *Vierteljährliche Entstehungsrechnung des Bruttoinlandsprodukts für Ostdeutschland: Sektorale Bruttowertschöpfung*. IWH Discussion Papers No. 164.

Breitung, J. and Schumacher, C. (2008). Real-time forecasting of German GDP based on a large factor model with monthly and quarterly data. *International Journal of Forecasting*, **24** (3), 386–398.

Brisson, M., Campbell, B. and Galbraith, J. W. (2003). Forecasting some low-predictability time series using diffusion indices. *Journal of Forecasting*, **22** (6-7), 515–531.

Carstensen, K., Wohlrabe, K. and Ziegler, C. (2011). Predictive Ability of Business Cycle Indicators under Test: A Case Study for the Euro Area Industrial Production. *Journal of Economics and Statistics*, **231** (1), 82–106.

Chow, G. C. and Lin, A. (1971). Best linear unbiased interpolation, distribution and exploration of time series by related series. *The Review of Economics and Statistics*, **53** (4), 372–375.

Clements, M. P. and Galvão, A. B. (2009). Forecasting US output growth using Leading Indicators: An appraisal using MIDAS models. *Journal of Applied Econometrics*, **24** (7), 1187–1206.

Costantini, M. and Pappalardo, C. (2010). A hierarchical procedure for the combination of forecasts. *International Journal of Forecasting*, **26** (4), 725–743.

Diebold, F. X. and Pauly, P. (1987). Structural change and the combination of forecasts. *Journal of Forecasting*, **6** (1), 21–40.

Doz, C., Giannone, D. and Reichlin, L. (2011). A two-step estimator for large approximate dynamic factor models based on Kalman filtering. *Journal of Econometrics*, **164** (1), 188–205.

—, — and — (2012). A Quasi–Maximum Likelihood Approach for Large, Approximate Dynamic Factor Models. *The Review of Economics and Statistics*, **94** (4), 1014–1024.

Drechsel, K. and Maurin, L. (2011). Flow of Conjunctural Information and Forecast of Euro Area Economic Activity. *Journal of Forecasting*, **30** (3), 336–354.

— and Scheufele, R. (2012a). *Bottom-up or Direct? Forecasting German GDP in a Data-rich Environment*. Swiss National Bank Working Papers 2012-16.

— and — (2012b). The performance of short-term forecasts of the german economy before and during the 2008/2009 recession. *International Journal of Forecasting*, **28** (2), 428–445.

Dreger, C. and Kholodilin, K. A. (2007). Prognosen der regionalen Konjunkturentwicklung. *Quarterly Journal of Economic Research*, **76** (4), 47–55.

Eickmeier, S. and Ng, T. (2011). Forecasting national activity using lots of international predictors: An application to New Zealand. *International Journal of Forecasting*, **27** (2), 496–511.

— and Ziegler, C. (2008). How Successful are Dynamic Factor Models at Forecasting Output and Inflation? A Meta-Analytic Approach. *Journal of Forecasting*, **27** (3), 237–265.

Forni, M., Hallin, M., Lippi, M. and Reichlin, L. (2003). Do financial variables help forecasting inflation and real activity in the euro area? *Journal of Monetary Economics*, **50** (6), 1243–1255.

—, —, — and — (2005). The Generalized Dynamic Factor Model: One-Sided Estimation and Forecasting. *Journal of the American Statistical Association*, **100** (471), 830–840.

Giannone, D., Reichlin, L. and Small, D. (2008). Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics*, **55** (4), 665–676.

Hansen, P. R. (2005). A Test for Superior Predictive Ability. *Journal of Business and Economic Statistics*, **23** (4), 365–380.

—, Lunde, A. and Nason, J. M. (2011). The Model Confidence Set. *Econometrica*, **79** (2), 453–497.

Kholodilin, K. A., Kooths, S. and Siliverstovs, B. (2008). A Dynamic Panel Data Approach to the Forecasting of the GDP of German Länder. *Spatial Economic Analysis*, **3** (2), 195–207.

— and Siliverstovs, B. (2006). On the forecasting properties of the alternative leading indicators for the German GDP: recent evidence. *Journal of Economics and Statistics*, **226** (3), 234–259.

Kopoin, A., Moran, K. and Paré, J.-P. (2013). Forecasting regional GDP with many factor models: How useful are national and international data? *Economics Letters*, **forthcoming**.

Kuzin, V., Marcellino, M. and Schumacher, C. (2013). Pooling versus Model Selection for Nowcasting GDP with Many Predictors: Empirical Evidence for Six Industrialized Countries. *Journal of Applied Econometrics*, **28** (3), 392–411.

Lehmann, R., Speich, W. D., Straube, R. and Vogt, G. (2010). Funktioniert der ifo Konjunkturtest auch wirtschaftlichen Krisenzeiten? Eine Analyse der Zusammenhänge zwischen ifo Geschäftsklima und amtlichen Konjunkturdaten für Sachsen. *ifo Dresden berichtet*, **17** (3), 8–14.

Longhi, S. and Nijkamp, P. (2007). Forecasting Regional Labor Market Developments under Spatial Autocorrelation. *International Regional Science Review*, **30** (2), 100–119.

Marcellino, M., Stock, J. H. and Watson, M. W. (2003). Macroeconomic forecasting in the Euro area: Country specific versus area-wide information. *European Economic Review*, **47** (1), 1–18.

Nierhaus, W. (2007). Vierteljährliche Volkswirtschaftliche Gesamtrechnungen für Sachsen mit Hilfe temporaler Disaggregation. *ifo Dresden berichtet*, **14** (4), 24–36.

Ragnitz, J. (2009). East Germany Today: Successes and Failures. *CESifo Dice Report*, **7** (4), 51–58.

Schanne, N., Wapler, R. and Weyh, A. (2010). Regional unemployment forecasts with spatial interdependencies. *International Journal of Forecasting*, **26** (4), 908–926.

Schirwitz, B., Seiler, C. and Wohlrabe, K. (2009). Regionale Konjunkturzyklen in Deutschland – Teil II: Die Zyklendatierung. *ifo Schnelldienst*, **62** (14), 24–31.

Schumacher, C. (2007). Forecasting German GDP Using Alternative Factor Models Based on Large Datasets. *Journal of Forecasting*, **26** (4), 271–302.

— (2010). Factor forecasting using international targeted predictors: The case of German GDP. *Economics Letters*, **107** (2), 95–98.

Stock, J. H. and Watson, M. W. (2002). Macroeconomic Forecasting Using Diffusion Indexes. *Journal of Business & Economic Statistics*, **20** (2), 147–162.

— and — (2004). Combination forecasts of output growth in a seven-country data set. *Journal of Forecasting*, **23** (6), 405–430.

— and — (2006). Forecasting with many Predictors. In G. Elliott, C. W. J. Granger and A. Timmermann (eds.), *Handbook of Economic Forecasting*, vol. 1, *10*, Elsevier, pp. 515–554.

Timmermann, A. (2006). Forecast Combinations. In G. Elliott, C. W. J. Granger and A. Timmermann (eds.), *Handbook of Economic Forecasting*, vol. 1, *4*, Elsevier, pp. 135–196.

Vogt, G. (2009). *Konjunkturprognose in Deutschland – Ein Beitrag zur Prognose der gesamtwirtschaftlichen Entwicklung auf Bundes- und Länderebene*. ifo Beiträge zur Wirtschaftsforschung Nr. 36, Ifo Institute – Leibniz-Institute for Economic Research at the University of Munich.

— (2010). VAR-Prognose-Pooling: Ein Ansatz zur Verbesserung der Informationsgrundlage der ifo Dresden Konjunkturprognosen. *ifo Dresden berichtet*, **17** (2), 32–40.

Vullhorst, U. (2008). Zur indikatorgestützten Berechnung des vierteljährlichen Bruttoinlandsprodukts für Baden-Württemberg. *Statistisches Monatsheft Baden-Württemberg*, **6** (9), 32–35.

Wallis, K. F. (1986). Forecasting with an econometric model: The 'ragged edge' problem. *Journal of Forecasting*, **5** (1), 1–13.

Wenzel, L. (2013). *Forecasting Regional Growth in Germany: A panel approach using Business Survey Data*. HWWI Research Paper 133.

White, H. (2000). A Reality Check for Data Snooping. *Econometrica*, **68** (5), 1097–1126.

Working Group Regional Accounts VGRdL (2011). *Gross domestic product, gross value added in Germany by Bundesland and East-West-Regions*. Working Group Regional Accounts VGRdL, Series 1, State results Volume 1, Date of calculation: August 2010 / February 2011, Stuttgart 2011.

A. Indicators

Table 4: **Indicators, Acronyms and Transformations**

Acronym	Indicator	Multi	Lag	Transformation
Target Variables				
GDPBW	GDP - Baden-Württemberg		2	1
GDPSAX	GDP - Free State of Saxony		3	1
GDPEG	GDP - Eastern Germany		3	1
Macroeconomic Variables				
IPTOT	industrial production (IP): total (incl. construction)	**X**	1.5	1
IPCON	IP construction: total	**X**	1.5	1
IPENY	IP energy supply: total	**X**	1.5	1
IPMQU	IP manufacturing: mining and quarrying	**X**	1.5	1
IPMAN	IP manufacturing: total	**X**	1.5	1
IPCAP	IP manufacturing: capital goods	**X**	1.5	1
IPCONDUR	IP manufacturing: consumer durables	**X**	1.5	1
IPCONNDUR	IP manufacturing: consumer non-durables	**X**	1.5	1
IPINT	IP manufacturing: intermediate goods	**X**	1.5	1
IPCONG	IP manufacturing: consumer goods	**X**	1.5	1
IPCHEM	IP manufacturing: chemicals	**X**	1.5	1
IPMET	IP manufacturing: basic metals	**X**	1.5	1
IPMECH	IP manufacturing: mechanical engineering	**X**	1.5	1
IPMOT	IP manufacturing: motor vehicles, trailers	**X**	1.5	1
IPEGS	IP manufacturing: energy, gas etc. supply	**X**	1.5	1
IPVEM	IP manufacturing: motor vehicles, trailers etc.	**X**	1.5	1
TOCON	turnover (TO): construction	**X**	1.5	1
TOMQD	TO: mining and quarrying, domestic		1.5	1
TOMQF	TO: mining and quarrying, foreign		1.5	1
TOMAND	TO: manufacturing total, domestic		1.5	1
TOMANF	TO: manufacturing total, foreign		1.5	1
TOCAPD	TO: capital goods, domestic		1.5	1
TOCAPF	TO: capital goods, foreign		1.5	1
TOCONDURD	TO: consumer durables, domestic		1.5	1
TOCONDURF	TO: consumer durables, foreign		1.5	1
TOCONNDURD	TO: consumer non-durables, domestic		1.5	1
TOCONNDURF	TO: consumer non-durables, foreign		1.5	1
TOINTD	TO: intermediate goods, domestic		1.5	1
TOINTF	TO: intermediate goods, foreign		1.5	1
TOCONGD	TO: consumer goods, domestic		1.5	1
TOCONGF	TO: consumer goods, foreign		1.5	1
TOCEOD	TO: computer, electronic and optical products, domestic		1.5	1
TOCEOF	TO: computer, electronic and optical products, foreign		1.5	1
TOCHEMD	TO: chemicals, domestic		1.5	1
TOCHEMF	TO: chemicals, foreign		1.5	1
TOMECHD	TO: mechanical engineering, domestic		1.5	1
TOMECHF	TO: mechanical engineering, foreign		1.5	1
TOVEMD	TO: motor vehicles, trailers etc., domestic		1.5	1
TOVEMF	TO: motor vehicles, trailers etc., foreign		1.5	1
TOEGSD	TO: energy, gas etc. supply, domestic		1.5	1
TOEGSF	TO: energy, gas etc. supply, foreign		1.5	1
NOCON	new orders (NO): construction	**X**	1.5	1
NOMANTOT	NO: manufacturing total	**X**	1.5	1
NOMANTOTD	NO: manufacturing total, domestic	**X**	1.5	1
NOMANTOTF	NO: manufacturing total, foreign	**X**	1.5	1
NOMANCAP	NO: capital goods	**X**	1.5	1
NOMANCAPD	NO: capital goods, domestic	**X**	1.5	1
NOMANCAPF	NO: capital goods, foreign	**X**	1.5	1
NOMANCONG	NO: consumer goods	**X**	1.5	1
NOMANCONGD	NO: consumer goods, domestic	**X**	1.5	1
NOMANCONGF	NO: consumer goods, foreign	**X**	1.5	1
NOMANINT	NO: intermediate goods	**X**	1.5	1
NOMANINTD	NO: intermediate goods, domestic	**X**	1.5	1
NOMANINTF	NO: intermediate goods, foreign	**X**	1.5	1
NOCHEMD	NO: chemicals, domestic	**X**	1.5	1
NOCHEMF	NO: chemicals, foreign	**X**	1.5	1
NOMECHD	NO: mechanical engineering, domestic	**X**	1.5	1
NOMECHF	NO: mechanical engineering, foreign	**X**	1.5	1
NOVEMD	NO: motor vehicles, trailers etc., domestic	**X**	1.5	1
NOVEMF	NO: motor vehicles, trailers etc., foreign	**X**	1.5	1
NOCEOD	NO: computer, electronic and optical products, domestic	**X**	1.5	1
NOCEOF	NO: computer, electronic and optical products, foreign	**X**	1.5	1
CONEMPL	construction: total employment		1.5	1
CONTOT	construction: permits issued, total		1.5	1
CONHOPE	construction: housing permits issued for building		2	1

Continued on next page...

Table 4: **Indicators, Acronyms and Transformations – continued**

Acronym	**Indicator**	**Multi**	**Lag**	**Transformation**
CONNREPE	construction: non-residential permits		2	1
CONBPGTOT	construction: building permits granted, total		2	1
CONBPGHO	construction: building permits granted, new homes		2	1
CONBPGNRE	construction: building permits granted, non-residentials		2	1
CONHW	construction: hours worked		2	1
WTEXMV	wholesale trade (WT): total (excl. motor vehicles)		1.5	1
WTCLFW	WT: clothing and footwear		1.5	1
WTCHEM	WT: chemicals		1.5	1
WTCONMA	WT: construction machinery		1.5	1
WTSLGF	WT: solid, liquid, gaseous fuels etc.		1.5	1
WTEMPL	WT: total employment		1.5	1
RSEXC	retail sales (RS): total (excl. cars)		1	1
NRTOT	new registrations (NR): all vehicles	**X**	0.5	1
NRCARS	NR: cars	**X**	0.5	1
NRHT	NR: heavy trucks	**X**	0	1
EXVOL	exports: volume index, basis 2005	**X**	1.5	1
IMVOL	imports: volume index, basis 2005	**X**	1.5	1
UNPTOT	unemployed persons (UNP): total, % of civilian labor		0	2
EMPLRCTOT	employed persons (EMPL): residence concept, total		1	1
EMPLWPCTOT	EMPL: work-place concept, total		1	1
WDAYS	working days: total		0	1
VACTOT	vacancies: total		0	1
MANHW	manufacturing: hours worked (excl. construction)		1.5	1
TREUCD	tax revenues (TR): EU customs duties		1.5	1
TRITTOT	TR: income taxes, total		1.5	1
TRVAT	TR: value added tax		1.5	1
TRVATIM	TR: value added tax on imports		1.5	1
TRVATTOT	TR: value added tax, total		1.5	1
TRWIT	TR: wage income tax		1.5	1
Finance				
MMRDTD	money market rate (MMR): day-to-day, monthly average		0	2
MMRTM	MMR: three-month, monthly average		0	2
DREUROREPO	discount rate - short term euro repo rate		0	2
GOVBY	long term government bond yield, 9-10 years		0	2
YFTBOPB	yields on fully taxed bonds outstanding (YFTBO): public bonds		0	2
YFTBOCB	YFTBO: corporate bonds		0	2
YLFBOMS	yields on listed fed. bonds outstand. mat. (YLFBOM): 3-5 years		0	2
YLFBOML	yields on listed fed. bonds outstand. mat. (YLFBOM): 5-8 years		0	2
TSPI	term spread (TS): 10 years, policy inst		0	0
TSDAY	TS: 10 years, 1Day		0	0
TSMTH	TS: 10 years, 3Month		0	0
SPRDAYPR	1Day - policy rates		0	0
SPRCTB	corporate - treasury bond		0	0
GPC23CPI	german price competition: 23 industrialized countries, basis: cpi		0	1
DAXSPI	DAX share price index		0	1
NEER	nominal effective exchange rate		0	1
VDAXNVI	VDAX: new volatility index, price index		0	2
VDAXOVI	VDAX: old volatility index, price index		0	2
M1OD	M1, overnight deposits		1	1
M2MS	M2, money supply		1	1
M3MS	M3, money supply		1	1
EMMSM1EP	EM money supply: M1, ep		1	1
EMMSM1F	EM money supply: M1, flows		1	2
EMMSM2M1I	EM money supply: M2-M1, index		1	1
EMMSM2M1F	EM money supply: M2-M1, flows		1	2
EMMSM3M2EP	EM money supply: M3-M2, ep		1	1
EMMSM3M2F	EM money supply: M3-M2, flows		1	2
BLDNB	bank lending to domestic non-banks, short term		1.5	1
BLDEI	banl lending to enterprises and individuals, short term		1.5	1
TDDE	time deposits of domestic enterprises		1.5	1
SDDE	saving deposits of domestic enterprises		1.5	1
Prices				
CPI	consumer price index		0	1
CPIEE	consumer price index (excl. energy)		0.5	1
HWWAPITOT	HWWA index of world market prices: eurozone, total		0.5	1
HWWAPIEY	HWWA index of world market prices: eurozone, energy		0.5	1
HWWAPIEEY	HWWA index of world market prices: eurozone, excl. energy		0.5	1
OIL	oil prices, euro per barrel		0	1
OILUK	brent oil price, UK average		0	1
LGP	London gold price, per US $		0	1
IMPI	import price index		1	1
EXPI	export price index		1	1
WTPI	wholesale trade price index, 1975=100		0.5	1
PPI	producer price index		0.5	1

Continued on next page...

Table 4: **Indicators, Acronyms and Transformations – continued**

Acronym	Indicator	Multi	Lag	Transformation
Wages				
WSLTOTHOU	wage and salary level (WSL): overall economy, basis: hours		1.5	1
WSLTOTMTH	WSL: overall economy, basis: monthly		1.5	1
WSLMANHOU	WSL: manufacturing, basis: hours		1.5	1
WSLMANMTH	WSL: manufacturing, basis: monthly		1.5	1
Surveys				
ZEWPS	ZEW: present economic situation	x	0	0
ZEWES	ZEW: economic sentiment indicator	x	0	0
IFOBCIT	Ifo business climate industry and trade, index	x	0	0
IFOBEIT	Ifo: business expextations industry and trade, index	x	0	0
IFOBSIT	Ifo: assessment of business situation industry and trade, index	x	0	0
IFOBCMAN	Ifo: business climate manufacturing, index	x	0	0
IFOBEMAN	Ifo: business expextations manufacturing, index	x	0	0
IFOBSMAN	Ifo: assessment of business situation manufacturing, index	x	0	0
IFOEXEMAN	Ifo: export expectations next 3 months manufacturing, balance	x	0	0
IFOOOHMAN	Ifo: orders on hand manufacturing, balance	x	0	0
IFOFOOHMAN	Ifo: foreign orders on hand manufacturing, balance	x	0	0
IFOIOFGMAN	Ifo: inventory of finished goods manufacturing, balance	x	0	0
IFOBCCAP	Ifo: business climate capital goods, balance	x	0	0
IFOBECAP	Ifo: business expectations capital goods, balance	x	0	0
IFOBSCAP	Ifo: assessment of business situation capital goods, balance	x	0	0
IFOBCCONDUR	Ifo: business climate consumer durables, balance	x	0	0
IFOBECONDUR	Ifo: business expectations consumer durables, balance	x	0	0
IFOBSCONDUR	Ifo: assessment of business situation consumer durables, balance	x	0	0
IFOBCCONNDUR	Ifo: business climate consumer non-durables, balance	x	0	0
IFOBECONNDUR	Ifo: business expectations consumer non-durables, balance	x	0	0
IFOBSCONNDUR	Ifo: assessment of business situation consumer non-durables, balance	x	0	0
IFOBCINT	Ifo: business climate intermediate goods, balance	x	0	0
IFOBEINT	Ifo: business expectations intermediate goods, balance	x	0	0
IFOBSINT	Ifo: assessment of business situation intermediate goods, balance	x	0	0
IFOBCCONG	Ifo: business climate consumer goods, balance	x	0	0
IFOBECONG	Ifo: business expectations consumer goods, balance	x	0	0
IFOBSCONG	Ifo: assessment of business situation consumer goods, balance	x	0	0
IFOBCCON	Ifo: business climate construction, index	x	0	0
IFOBECON	Ifo: business expectations construction, index	x	0	0
IFOBSCON	Ifo: assessment of business situation construction, index	x	0	0
IFOOOHCON	Ifo: orders on hand construction, balacne	x	0	0
IFOUNFWCON	Ifo: unfavourable weather situation	x	0	0
IFOBCWT	Ifo business climate wholesale trade, index	x	0	0
IFOBEWT	Ifo: business expextations wholesale trade, index	x	0	0
IFOBSWT	Ifo: assessment of business situation wholesale trade, index	x	0	0
IFOAOIWT	Ifo: assessment of inventories wholesale trade, balance	x	0	0
IFOEOAWT	Ifo: expect. with regard to order activity next 3 months WT, balance	x	0	0
IFOBCRS	Ifo business climate retail sales, index	x	0	0
IFOBERS	Ifo: business expextations retail sales, index	x	0	0
IFOAOIRS	Ifo: assessment of inventories retail sales, balance	x	0	0
IFOEOARS	Ifo: expect. with regard to order activity next 3 months RS, balance	x	0	0
GFKBCE	GfK consumer survey (GfK): business cycle expectations	x	0	0
GFKIE	GfK: income expectations	x	0	0
GFKWTB	GfK: willingness to buy	x	0	0
GFKPL	GfK: prices over the last 12 months	x	0	0
GFKPE	GfK: prices over the next 12 months	x	0	0
GFKUE	GfK: unemployment situation over next 12 months	x	0	0
GFKFSL	GfK: financial situation over the last 12 months	x	0	0
GFKFSE	GfK: financial situation over the next 12 months	x	0	0
GFKESL	GfK: economic situation over the last 12 months	x	0	0
GFKESE	GfK: economic situation over the next 12 months	x	0	0
GFKMPP	GfK: major purchases at present	x	0	0
GFKMPE	GfK: major purchases over the next 12 months	x	0	0
GFKSP	GfK: savings at present	x	0	0
GFKSE	GfK: savings over the next 12 months	x	0	0
GFKCCI	GfK: consumer confidence, index	x	0	0
GFKCCC	GfK: consumer confidence climate, balance	x	0	0
GFKCCIN	GfK: consumer confidence indicator	x	0	0
EUCSUE	EU consumer survey (EUCS): unemploy. expect. over next 12 months	x	0	0
EUCSFSP	EUCS: statement on financial situation	x	0	0
EUCSCCI	EUCS: consumer confidence indicator	x	0	0
EUCSESI	EUCS: economic sentiment indicator	x	0	0
EUBSPTIND	EU business survey (EUBS): prod. trends recent month, industry	x	0	0
EUBSOBLIND	EUBS: assessment of order-book levels, industry	x	0	0
EUBSEXOBLIND	EUBS: assessment of export oder-books level, industry	x	0	0
EUBSSFGIND	EUBS: assessment of stocks of finished products, industry	x	0	0
EUBSPEIND	EUBS: production expectations for the month ahead, industry	x	0	0
EUBSSPEIND	EUBS: selling price expectations for the month ahead, industry	x	0	0
EUBSEMPEIND	EUBS: employment expectations for the month ahead, industry	x	0	0

Continued on next page...

Table 4: **Indicators, Acronyms and Transformations – continued**

Acronym	Indicator	Multi	Lag	Transformation
EUBSINDCI	EUBS: industrial confidence indicator	X	0	0
EUBSSSCI	EUBS: service sector confidence indicator	X	0	0
EUBSRTCI	EUBS: retail trade confidence indicator	X	0	0
EUBSCONCI	EUBS: construction confidence indicator	X	0	0
COMBAEB	Commerzbank EarlyBird	X	0.5	0
International				
BGBIS	Belgium business indicator survey, whole economy		0	0
BGBISMAN	Belgium business indicator survey, manufacturing (not smoothed)		0	0
UMCS	University of Michigan US consumer sentiment, expectations		0	0
USISMP	US ISM production		0	0
EUCSFRESI	EUCS: economic sentiment indicator, France		0	0
EUCSESESI	EUCS: economic sentiment indicator, Spain		0	0
EUCSPOESI	EUCS: economic sentiment indicator, Poland		0	0
EUCSCZESI	EUCS: economic sentiment indicator, Czech Republic		0	0
EUCSITESI	EUCS: economic sentiment indicator, Italy		0	0
EUCSUKESI	EUCS: economic sentiment indicator, United Kingdom		0	0
DJESI50	EM Dow Jones EUROSTOXX index, benchmark 50		0	1
DJIPRI	Dow Jones industrials, price index		0	1
SPUSSPI	Standard & Poor´s 500 stock price index		0	1
GOVBYUK	government bond yield long term, United Kingdom		0	2
GOVBYUS	government bond yield long term, United States		0	2
USIPTOT	IP: United States, total		1	1
CLIAA	OECD Composite Leading Indicator (CLI): OECD, amplitude adjusted		1.5	0
CLITR	CLI: OECD, trend restored		1.5	1
CLINORM	CLI: OECD, normalised		1.5	0
CLIASAA	CLI: Asia, amplitude adjusted		1.5	0
CLIASTR	CLI: Asia, trend restored		1.5	1
CLIASNORM	CLI: Asia, normalised		1.5	0
CLICAA	CLI: China, amplitude adjusted		1.5	0
CLICTR	CLI: China, trend restored		1.5	1
CLICNORM	CLI: China, normalised		1.5	0
CLIEUAA	CLI: Euro Area, amplitude adjusted		1.5	0
CLIEUTR	CLI: Euro Area, trend restored		1.5	1
CLIEUNORM	CLI: Euro Area, normalised		1.5	0
CLIUSAA	CLI: United States, amplitude adjusted		1.5	0
CLIUSTR	CLI: United States, trend restored		1.5	1
CLIUSNORM	CLI: United States, normalised		1.5	0
ECRTE	Euro-Coin real time estimates		0	0
Regional – Eastern Germany				
IFOBCITEG	Ifo business climate industry and trade Eastern Germany, balance		0	0
IFOBEITEG	Ifo: business expectations industry and trade Eastern Germany, balance		0	0
IFOBSITEG	Ifo: assess. of business sit. indust. and trade Eastern Germany, balance		0	0
IFOBCMANEG	Ifo: business climate manufacturing Eastern Germany, balance		0	0
IFOBEMANEG	Ifo: business expectations manufacturing Eastern Germany, balance		0	0
IFOBSMANEG	Ifo: assessment of business sit. manufacturing Eastern Germany, balance		0	0
IFOBCCONEG	Ifo: business climate construction Eastern Germany, balance		0	0
IFOBECONEG	Ifo: business expectations construction Eastern Germany, balance		0	0
IFOBSCONEG	Ifo: assessment of business sit. construction Eastern Germany, balance		0	0
IFOEMPECONEG	Ifo: employ. expect. next 3 months constr. Eastern Germany, balance		0	0
IFOBCWTEG	Ifo business climate wholesale trade Eastern Germany, balance		0	0
IFOBEWTEG	Ifo: business expectations wholesale trade Eastern Germany, balance		0	0
IFOBSWTEG	Ifo: assessment of business situation WT Eastern Germany, balance		0	0
IFOEMPEWTEG	Ifo: employ. expect. over next 3 months WT Eastern Germany, balance		0	0
IFOBCRSEG	Ifo business climate retail sales Eastern Germany, balance		0	0
IFOBERSEG	Ifo: business expectations retail sales Eastern Germany, balance		0	0
IFOBSRSEG	Ifo: assessment of business situation RS Eastern Germany, balance		0	0
IFOEMPERSEG	Ifo: employ. expect. over next 3 months RS Eastern Germany, balance		0	0
HCNOEG	housing construction (HC): new orders Eastern Germany		2.5	1
HCWHEG	HC: working hours Eastern Germany		2.5	1
HCTOEG	HC: turnover Eastern Germany		2.5	1
ICNOEG	industry construction (IC): new orders Eastern Germany		2.5	1
ICWHEG	IC: working hours Eastern Germany		2.5	1
ICTOEG	IC: turnover Eastern Germany		2.5	1
PCNOEG	public construction (PC): new orders Eastern Germany		2.5	1
PCWHEG	PC: working hours Eastern Germany		2.5	1
PCTOEG	PC: turnover Eastern Germany		2.5	1
CONNOEG	construction: new orders Eastern Germany		2.5	1
CONTOEG	construction: turnover Eastern Germany		2.5	1
CONFIRMEG	construction: firms Eastern Germany		2.5	1
CONEMPEG	construction: employed people Eastern Germany		2.5	1
CONFEEEG	construction: fees Eastern Germany		2.5	1
IFOCUCONEG	Ifo: capacity utilization construction, Eastern Germany		0	2
CPIEG	consumer price index, Eastern Germany		1	1
IWHSITMANEG	IWH Industry Survey (IWH): business sit. manuf., Eastern Germany		0	0
IWHOLKMANEG	IWH: business outlook manufacturing, Eastern Germany		0	0

Continued on next page...

Table 4: **Indicators, Acronyms and Transformations – continued**

Acronym	Indicator	Multi	Lag	Transformation
IWHSITCONEG	IWH: business situation construction, Eastern Germany		0	0
IWHOLKCONEG	IWH: business outlook construction, Eastern Germany		0	0
Regional – Free State of Saxony				
IFOBCITSAX	Ifo business climate industry and trade Saxony, balance		0	0
IFOBEITSAX	Ifo: business expectations industry and trade Saxony, balance		0	0
IFOBSITSAX	Ifo: assessment of business sit. indus. and trade Saxony, balance		0	0
IFOBCMANSAX	Ifo: business climate manufacturing Saxony, balance		0	0
IFOBEMANSAX	Ifo: business expectations manufacturing Saxony, balance		0	0
IFOBSMANSAX	Ifo: assessment of business sit. manufacturing Saxony, balance		0	0
IFOBCCONSAX	Ifo: business climate construction Saxony, balance		0	0
IFOBECONSAX	Ifo: business expectations construction Saxony, balance		0	0
IFOBSCONSAX	Ifo: assessment of business situation construction Saxony, balance		0	0
IFOEMPECONSAX	Ifo: employment expect. over next 3 months constr. Saxony, balance		0	0
IFOBCWTSAX	Ifo business climate wholesale trade Saxony, balance		0	0
IFOBEWTSAX	Ifo: business expectations wholesale trade Saxony, balance		0	0
IFOBSWTSAX	Ifo: assessment of business situation wholesale trade Saxony, balance		0	0
IFOEMPEWTSAX	Ifo: employment expect. over next 3 months WT Saxony, balance		0	0
IFOBCRSSAX	Ifo business climate retail sales Saxony, balance		0	0
IFOBERSSAX	Ifo: business expect. retail sales Saxony, balance		0	0
IFOBSRSSAX	Ifo: assessment of business situation retail sales Saxony, balance		0	0
IFOEMPERSSAX	Ifo: employment expect. over next 3 months RS Saxony, balance		0	0
NOMANSAXTOT	NO: manufacturing Saxony, total		2.5	1
HCNOSAX	housing construction (HC): new orders Saxony		2.5	1
HCWHSAX	HC: working hours Saxony		2.5	1
HCTOSAX	HC: turnover Saxony		2.5	1
ICNOSAX	industry construction (IC): new orders Saxony		2.5	1
ICWHSAX	IC: working hours Saxony		2.5	1
ICTOSAX	IC: turnover Saxony		2.5	1
PCNOSAX	public construction (PC): new orders Saxony		2.5	1
PCWHSAX	PC: working hours Saxony		2.5	1
PCTOSAX	PC: turnover Saxony		2.5	1
CONNOSAX	construction: new orders Saxony		2.5	1
CONWHSAX	construction: working hours Saxony		2.5	1
CONFIRMSAX	construction: firms Saxony		2.5	1
CONEMPSAX	construction: employed people Saxony		2.5	1
CONFEESAX	construction: fees Saxony		2.5	1
IFOCUCONSAX	Ifo: capacity utilization construction, Saxony		0	2
IFOOOHCONSAX	Ifo: orders on hand construction, Saxony		0	0
CPISAX	consumer price index, Saxony		2	1
EXVALUESAX	exports: value, Saxony		2.5	1
IMVALUESAX	imports: value, Saxony		2.5	1
Regional – Baden-Württemberg				
IFOBCITBW	Ifo business climate industry and trade BW, balance		0	0
IFOBEITBW	Ifo: business expect. industry and trade BW, balance		0	0
IFOBSITBW	Ifo: assess. of busin. sit. indust. and trade BW, balance		0	0
IFOBCMANBW	Ifo: business climate manufacturing BW, balance		0	0
IFOBEMANBW	Ifo: business expect. manufacturing BW, balance		0	0
IFOBSMANBW	Ifo: assessment of busin. sit. manufacturing BW, balance		0	0
IFOBCCONBW	Ifo: business climate construction BW, balance		0	0
IFOBECONBW	Ifo: business expectations construction BW, balance		0	0
IFOBSCONBW	Ifo: assessment of business sit. construction BW, balance		0	0
IFOEMPECONBW	Ifo: employ. expect. next 3 months constr. BW, balance		0	0
IFOBCWTBW	Ifo business climate wholesale trade BW, balance		0	0
IFOBEWTBW	Ifo: business expectations wholesale trade BW, balance		0	0
IFOBSWTBW	Ifo: assessment of business situation WT BW, balance		0	0
IFOEMPEWTBW	Ifo: employ. expect. over next 3 months WT BW, balance		0	0
IFOBCRSBW	Ifo business climate retail sales BW, balance		0	0
IFOBERSBW	Ifo: business expectations retail sales BW, balance		0	0
IFOBSRSBW	Ifo: assessment of business situation RS BW, balance		0	0
IFOEMPERSBW	Ifo: employ. expect. over next 3 months RS BW, balance		0	0
NOMANBWTOTD	NO: manufacturing Baden-Württemberg, domestic		2.5	1
NOMANBWTOTF	NO: manufacturing Baden-Württemberg, foreign		2.5	1
IPMANBWTOT	IP: manufacturing Baden-Württemberg, total		2.5	1
HCNOBW	housing construction (HC): new orders Baden-Württemberg		2.5	1
HCWHBW	HC: working hours Baden-Württemberg		2.5	1
HCTOBW	HC: turnover Baden-Württemberg		2.5	1
ICNOBW	industry construction (IC): new orders Baden-Württemberg		2.5	1
ICWHBW	IC: working hours Baden-Württemberg		2.5	1
ICTOBW	IC: turnover Baden-Württemberg		2.5	1
PCNOBW	public construction (PC): new orders Baden-Württemberg		2.5	1
PCWHBW	PC: working hours Baden-Württemberg		2.5	1
PCTOBW	PC: turnover Baden-Württemberg		2.5	1
CONNOBW	construction: new orders Baden-Württemberg		2.5	1
CONWHBW	construction: working hours Baden-Württemberg		2.5	1
CONFIRMBW	construction: firms Baden-Württemberg		2.5	1

Continued on next page...

Table 4: **Indicators, Acronyms and Transformations – continued**

Acronym	Indicator	Multi	Lag	Transformation
CONEMPBW	construction: employed people Baden-Württemberg		2.5	1
CONFEEBW	construction: fees Baden-Württemberg		2.5	1
IFOCUCONBW	Ifo: capacity utilization construction, Baden-Württemberg		0	2
CPIBW	consumer price index, Baden-Württemberg		1	1
KIBW	business cycle indicator of Baden-Württemberg		2.5	1

Note: 0 = three-month-average in levels; 1 = three-month-average and qoq growth rate; 2 = three-month-average and first difference.
X indicates that the particular indicator is used for multi–indicator models.
Source: Drechsel and Scheufele (2012a), author´s extensions and calculations.