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Abstract

In this paper, we assess the accuracy of macroeconomic forecasts at the regional level using a unique 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 including more than 300 international, national and regional indicators. We calculate single–indicator, multi–indicator and pooled forecasts. Our results show that we can significantly increase forecast accuracy compared to an autoregressive benchmark model, both for short- and long-term predictions. Furthermore, our best leading indicators describe the specific regional economic structure better than other indicators.

JEL-Code: C320, C520, C530, E370, R110.

Keywords: leading indicators, regional forecasting, forecast evaluation, forecast combination, data rich environment.

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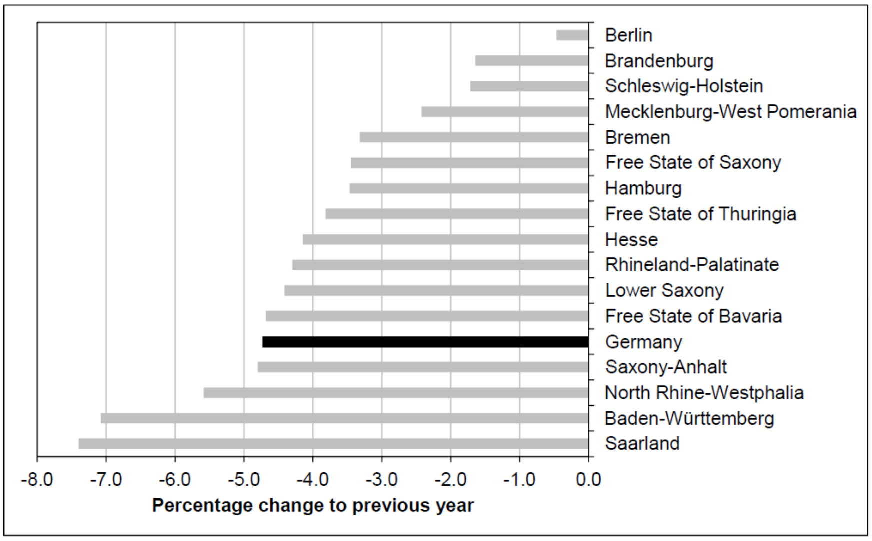
1. Motivation

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

A high heterogeneity among regional units is observable for Germany, for example. The 16 German states are characterized by high disparity in their economic structures. This disparity is explicitly reflected in annual growth rates for real gross domestic product (GDP). Figure 1 shows the annual growth rates of real GDP in 2009. 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%, the GDP growth rate of Berlin, which is characterized by a large amount of different services, lies at -0.5%. The economic recession of 2009 affected the regional units with different intensities. Obviously, the growth rate of Germany (-4.7%) does not seem to be a good approximation for an increase in GDP for all sub-national German regions.[1]

Macroeconomic aggregates beneath national states (e.g., Germany) are difficult to forecast, especially because of data limitations and a low frequency of data publication. For economic forecasts, it is absolutely necessary to know in which phase of the business cycle the whole economy actually is. It is only possible to provide unbiased predictions with such information. With data published at a higher frequency, it is possible to reduce forecast errors and

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

therefore send more accurate signals to regional policy makers.

The literature includes many studies on (supra-)national aggregates, as for the Euro Area (see e.g., Bodo *et al.* (2000), Forni *et al.* (2003) or Carstensen *et al.* (2011)) and Germany (see e.g., Kholodilin and Siliverstovs (2005), Breitung and Schumacher (2008) or Drechsel and Scheufele (2012b)), but only a few attempts have been made 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 between regional units. 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 specifically address the problem of spatial correlation. Second, Schanne *et al.* (2010) forecast unemployment rates for German labor-market districts, using a GVAR model with spatial interactions. The before mentioned studies employ different data frequencies, whereas Bandholz and Funke (2003) and Dreger and Kholodilin (2007) use annual GDP information disaggregated into quarterly data, and Kholodilin *et al.* (2008) and Longhi and Nijkamp (2007) use only annual data. Schanne *et al.* (2010) have instead data on a monthly basis.

Our paper adds to these prominent studies in several ways. First, we overcome the problem of data limitations at the regional level using a unique data set with quarterly national accounts for Eastern Germany, the Free State of Saxony[3] and Baden-Württemberg. Altogether, we have 121 regional indicators, including the Ifo business climate for industry and trade in Saxony or new orders in manufacturing for Baden-Württemberg. Second, we use information from regional, national and international indicators and assess their forecasting performance at the regional level. Most of the previously mentioned studies use only a few regional indicators. Finally, our large data set enables the study of the forecasting accuracy of several pooling strategies for regional target variables. We are most likely the first ones who evaluate the properties of a large set of leading indicators and pooling strategies at the regional level.

We combine different strands of the regional-level forecasting literature. We specifically attempt to determine which indicators are important in forecasting regional GDP. Does early information come from international (World or European Union) or national (Germany) leading indicators? Alternatively, does sub-national or regional information increase forecasting performance? Trading partners such as the US or Europe (France, Poland, etc.) as well as the growing importance of Asian economies creates a stronger linkage between

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

[3]Vogt (2010) studies the properties of a few indicators to forecast regional GDP on a quarterly basis for the Free State of Saxony by combining several outcomes from a VAR-model.

these countries and regional economies. These are two of the 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. In addition, they add comprehensive information from the US economy and find that a set of these variables improves forecasting performance. Banerjee *et al.* (2006) analyses the importance of Euro-area indicators for the prediction of macroeconomic variables for five new Member States.[4] 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 as well as other countries. In our study, we use international and German indicators as well as several variables from the sub-national (Eastern Germany) and regional level (Saxony, Baden-Württemberg). To the best of our knowledge, our study is the first to evaluate these questions from a regional perspective.

Furthermore, we add to the existing literature on forecast combinations. The seminal works of Timmermann (2006) and Stock and Watson (2006) show that combining forecast output from different models leads to improved forecast accuracy in comparison to univariate benchmarks or predictions from a single model. 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) or Kuzin *et al.* (2012)). Studies at the regional level are absent. Given our large data set, we evaluate the forecast accuracy of different pooling strategies.

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

2. Data and Empirical Setup

The following section first presents a short overview of our data. Then, we introduce the general empirical model. Afterwards, different combination approaches are briefly described. Finally, our forecast evaluation strategy is presented.

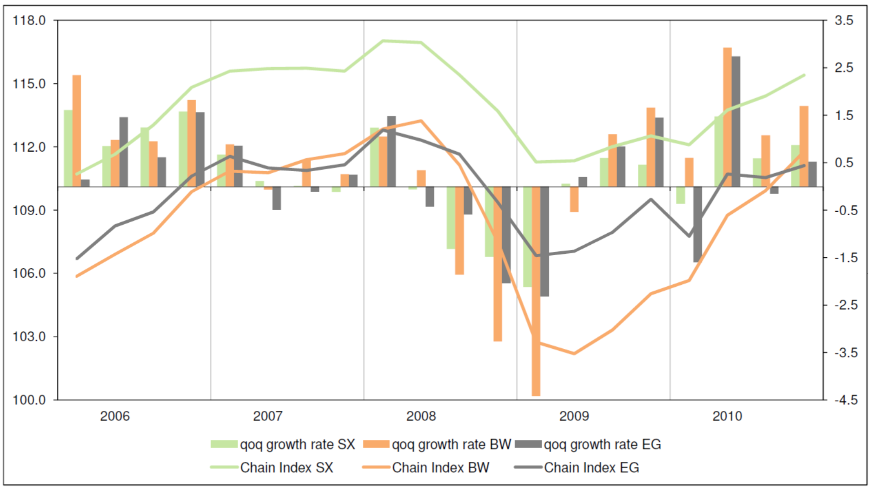
[4] These new Member States are: Czech Republic, Hungary, Poland, Slovakia and Slovenia.

2.1. Data

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 an insufficient number of observations exist. In our paper, we use a new data set which solves these two problems of availability and the length of the time series.

Three different sources exist which provide quarterly national accounts at the German regional or sub-national level. First, Nierhaus (2007) computes quarterly GDP data for the German state Free State of Saxony. He applies the temporal disaggregation method of Chow and Lin (1971), which is 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 data into quarterly data. For this transformation, Nierhaus (2007) uses official German statistics: regional turnovers or quarterly data from national accounts for Germany (e.g., gross value-added). Second, Vullhorst (2008) uses the same temporal disaggregation method as Nierhaus (2007) to calculate quarterly national accounts for the state Baden-Württemberg. Third, the Halle Institute for Economic Research (IWH) provides quarterly data on GDP for Eastern Germany (excluding Berlin).[5] For all three GDP target variables, data are available for the time period 1996:01 to 2010:04.[6] The data are provided in real terms, and we make a seasonal adjustment to obtain quarter-on-quarter (qoq) growth rates or interpretable first differences. Figure 2 shows the Chain Index as well as qoq growth rates for 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), qoq growth rate (right scale, %), seasonally adjusted with Census X-12-ARIMA.
SX: Free State of Saxony, BW: Baden-Württemberg, EG: Eastern Germany
Source: Ifo Institute, Statistical Office of Baden-Württemberg and IWH, author´s calculation and illustration.

[5] A methodical description can be found in Brautzsch and Ludwig (2002).

[6] The data are updated intermittently and are available from the homepage of the Ifo Institute and the IWH. Data for Baden-Württemberg are available from the regional Statistical Office of Baden-Württemberg.

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 qoq 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. With these three and unique time series, we have suitable target variables at the sub-national or regional level.

Our data set contains **368** leading indicators that can be used for the assessment of forecasting performance for our target variables. All indicators come 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 (121).[7] Macroeconomic variables contain industrial production 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 for 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 price 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 and business surveys (Ifo, ZEW, GfK and the European Commission). In addition, composite leading indicators for Germany (e.g., from the OECD) and the Early Bird 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. Last, 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).

The data set is predominantly the same one used by Drechsel and Scheufele (2012a), and we add regional indicators for Eastern Germany (40 indicators), the Free State of Saxony (42 indicators) and Baden-Württemberg (39 indicators). Most of these leading 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 to obtain quarterly data.

If necessary, we transform our data to obtain stationary time series. Table 4 in the Appendix also contains information about the transformation of the indicators.

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

[8]All variables and indicators are seasonally adjusted with Census X-12-ARIMA.

2.2. Indicator forecasts

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

$$y^k_{t+h} = \alpha + \sum_{i=1}^{p} \beta_i y_{t+1-i} + \sum_{j=1}^{q} \gamma_j x^k_{t+1-j} + \varepsilon^k_t \ , \tag{1}$$

where y^k_{t+h} stands for the h-step-ahead model k of the qoq growth rate of Saxon, Baden-Württemberg or Eastern German real GDP and x^k_t denotes the exogenous leading indicator from the regional, national or international level. Because we use quarterly data, a maximum of 4 lags, both for the lagged dependent and independent variables, is allowed. The optimal length for p and q are determined by the Schwarz Information Criterion (BIC). We apply a recursive forecasting approach with the initial estimation period ranging from 1996:01 to 2002:4 ($T = 28$). This initial period is enlarged 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 single indicator k. As the benchmark, we choose the standard AR(p) process.

There may be an information gain from applying a multi–indicator forecast model. Hence, combining regional with either national or international 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

$$y^k_{t+h} = \alpha + \sum_{i=1}^{p} \beta_i y_{t+1-i} + \sum_{j=1}^{q} \gamma_j r^k_{t+1-j} + \sum_{l=1}^{q} \gamma_j z^k_{t+1-j} + \varepsilon^k_t \tag{2}$$

and we only estimate models for every regional indicator (r^k_t) in combination with an indicator from the national or international level (z^k_t). Therefore, we have the following extra specifications: for Eastern Germany $\mathbf{40 \cdot 248 = 9,880}$, for the Free State of Saxony $\mathbf{42 \cdot 248 = 10,374}$ and for Baden-Württemberg $\mathbf{39 \cdot 248 = 9,633}$.

2.3. Combination strategies

Consistent with the literature on forecast combinations, the following section presents the different pooling strategies that we apply. 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) or 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. 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) as well as Drechsel and Scheufele (2012b) and use 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 models. First, we apply a (v) trimming approach.[9] This weighting scheme filters indicators with a 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 of the other forecasts are combined with equal weights. Second, discounted mean squared forecast errors as weights (vi) are used 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:

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

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

$\lambda_{t+h,k} = \sum_{n=1}^{N} \delta^{t-h-n} \left(FE_{t+h,n}^{k}\right)^2$ represents the sum of discounted (δ) forecast errors of the single–indicator model k. The literature finds no consensus for how the discount rate δ should be chosen. We use different δ ranging from $\delta \in \{0, 0.1, 0.2, ..., 1\}$ and find similar results. To avoid confusing tables, we only show the forecasting performance for $\delta = 0.1$.
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.[10]

2.4. Forecast evaluation

To decide whether an single–indicator or two–indicator model as well as different pooling strategies perform better than the chosen benchmark, we first calculate forecast errors from our forecasting exercise. Let $\widehat{y}_{t+h}^{k}$ denote the h-step-ahead forecast of model k, then the resulting forecast error is: $FE_{t+h}^{k} = y_{t+h}^{k} - \widehat{y}_{t+h}^{k}$. The forecast error for the AR-benchmark is FE_{t+h}^{AR}. In a second step, we use the mean squared forecast error (MSFE) as a loss function to assess the overall performance of a single–indicator model. The MSFE for the h-step-ahead forecast is defined as:

$$MSFE_h^k = \frac{1}{N} \sum_{n=1}^{N} \left(FE_{t+h,n}^{k}\right)^2 . \tag{7}$$

The respective MSFE for the autoregressive benchmark is $MSFE_h^{AR}$. Finally, we construct a relative MSFE (rMSFE)

$$rMSFE_h^k = \frac{MSFE_h^k}{MSFE_h^{AR}} , \tag{8}$$

to decide whether a leading indicator 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 respective horizon h. Otherwise, the simple autoregressive model is preferable.
We apply the test developed by Diebold and Mariano (1995) to decide whether a specific $rMSFE_h^k$ is statistically smaller than one. Because the Diebold-Mariano test could suffer from small sample bias, we use a modification of their test proposed by Harvey *et al.* (1997), which corrects for this issue. The idea of this test is straightforward. Under the null hypothesis, the expected forecast errors of two competing models are equal. In other words, the difference in expected forecast errors is equal to zero. Using our notation, the null could be expressed as:

$$H_0 : E\left[FE_{t+h}^{k} - FE_{t+h}^{AR}\right] = E\left[d_{t+h}^{k}\right] = 0 . \tag{9}$$

[10]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.

The resulting test statistic of this modified Diebold-Mariano (MDM) test proposed by Harvey *et al.* (1997) is the following:

$$MDM^k = \left(\frac{N + 1 - 2h + N^{-1}h(h-1)}{N} \right)^{1/2} \left[\widehat{V}(\overline{d^k}) \right]^{-1/2} \overline{d^k} \,, \tag{10}$$

whereas the last product of Equation (10) is the original Diebold-Mariano test statistic, h represents the forecast horizon and $\overline{d^k}$ is the sample mean of the series d^k_{t+h}. An estimation of the variance of the process d^k_{t+h} is denoted by $\widehat{V}(\overline{d^k})$. Following Harvey *et al.* (1997), the critical values for comparison are obtained from a Student´s t-distribution with $(N-1)$ degrees of freedom.

3. Results

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

The summary tables are divided into two parts. In the upper part, the top 20 single–indicator models from Equation (1) or pooling strategies for every forecasting horizon are shown. The lower part of the tables presents the results for the estimation with more than one indicator. An improvement in forecasting performance is reached if the two–indicator models from Equation (2) produce lower forecasting errors than the minimum of our single–indicator forecasts or pooling. We only show two–indicator models that fulfill this requirement.[11] The minimum for each forecasting horizon is shown in brackets in the lower part of each table. The column Ratio shows the $rMSFE$ from Equation (8). Significant results are indicated with asterisks, presented in the column MDM. To increase readability, we add one column with acronyms for the different sets of indicators. National indicators are denoted with (N), while (I) represents international and (R) regional indicators. Combination strategies are denoted with (C).

3.1. General Results

Tables 1, 2 and 3 present the estimation results for our three regional units.

[11] To save space, we present the five best models for each forecasting horizon. However, the number of models that produce lower forecast errors than the minimum are shown at the end of every table.

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

Target variable: qoq growth rate GDP Free State of Saxony							
Single–indicator forecasts or pooling							
h=1				**h=2**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
MSFE weighted (FS)	(C)	0.743	***	MSFE weighted (FS)	(C)	0.832	***
IFOBEWTSAX	(R)	0.788		WTCHEM	(N)	0.834	
Trimmed 25 (FS)	(C)	0.809	***	Trimmed 25 (FS)	(C)	0.879	***
Trimmed 25 (S)	(C)	0.826	**	GOVBY	(N)	0.895	***
EUBSCONCI	(N)	0.866		Trimmed 25 (S)	(C)	0.901	
YLFBOML	(N)	0.874		IFOEOARS	(N)	0.903	
WTCHEM	(N)	0.876		GFKMPE	(N)	0.947	
TOVEMD	(N)	0.879	*	Trimmed 50 (FS)	(C)	0.951	**
GOVBY	(N)	0.889		GFKWTB	(N)	0.956	
Trimmed 50 (FS)	(C)	0.896	**	GFKPE	(N)	0.958	
Trimmed 50 (S)	(C)	0.902	**	Trimmed 50 (S)	(C)	0.966	*
TOCAPD	(N)	0.912		TOHRSAX	(R)	0.968	
IFOBCITSAX	(R)	0.914		EMMSM1F	(I)	0.973	
EXVALUESAX	(R)	0.922		EMPLWPCTOT	(N)	0.975	
CONFEESAX	(R)	0.923		YLFBOML	(N)	0.975	
GFKPL	(N)	0.924		IFOOOHCON	(N)	0.980	
IPINT	(N)	0.935		CONBPGNRE	(N)	0.989	
YFTBOPB	(N)	0.935		IFOUNFWCON	(N)	0.991	
TRITTOT	(N)	0.939		PCNOSAX	(R)	0.997	
Trimmed 75 (FS)	(C)	0.939	*	YFTBOPB	(N)	0.998	
h=3				**h=4**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
MSFE weighted (FS)	(C)	0.781	***	MSFE weighted (FS)	(C)	0.807	*
Trimmed 25 (FS)	(C)	0.854	***	IFOBERSSAX	(R)	0.902	
IFOEOARS	(N)	0.885		Trimmed 25 (FS)	(C)	0.905	*
Trimmed 25 (S)	(C)	0.885	***	IFOEOARS	(N)	0.908	
TOCAPD	(N)	0.927		TRITTOT	(N)	0.937	
Trimmed 50 (FS)	(C)	0.929	**	Trimmed 25 (S)	(C)	0.948	
PCTOSAX	(R)	0.936	**	TRWIT	(N)	0.981	
Trimmed 50 (S)	(C)	0.937	**	Trimmed 50 (FS)	(C)	0.983	
GFKPE	(N)	0.942		ICTOSAX	(R)	0.994	
GOVBY	(N)	0.942		GFKESL	(N)	0.997	
TRWIT	(N)	0.944		IFOBCRS	(N)	0.999	
NOMANCONGD	(N)	0.947		RSEXC	(N)	1.007	
IFOBCCON	(N)	0.948		GOVBYUS	(I)	1.011	
IFOBCRS	(N)	0.952		Trimmed 50 (S)	(C)	1.013	
WDYAS	(N)	0.959		GFKMPE	(N)	1.021	
IFOBECON	(N)	0.962	*	MSFE weighted (S)	(C)	1.024	
GOYBYUS	(I)	0.965		IFOEMPEWTSAX	(R)	1.026	
EUBSCONCI	(N)	0.966		CONBPGHO	(N)	1.027	
EMMSM3M2F	(I)	0.966	*	PCTOSAX	(R)	1.027	
IFOBERSSAX	(R)	0.968		CLIASAA	(I)	1.029	

Two–indicators models							
h=1 (min=0.743)				**h=2 (min=0.832)**			
Model	Acronym	Ratio	MDM	Model	Acronym	Ratio	MDM
IFOBEWTSAX - EUBSCONCI	(R)-(N)	0.680	**	PCNOSAX - WTCHEM	(R)-(N)	0.735	
IFOBEWTSAX - EUBSSPEIND	(R)-(N)	0.713		HCNOSAX - SDDE	(R)-(N)	0.740	
IFOBEWTSAX - IFOBSCONDUR	(R)-(N)	0.726		TOHRSAX - WTCHEM	(R)-(N)	0.778	
IFOBEWTSAX - WTEXMV	(R)-(N)	0.730		HCNOSAX - EMMSM3M2EP	(R)-(I)	0.785	
IFOBEWTSAX - TOVEMD	(R)-(N)	0.737	*	HCTOSAX - SDDE	(R)-(N)	0.795	
h=3 (min=0.781)				**h=4 (min=0.807)**			
Model	Acronym	Ratio	MDM	Model	Acronym	Ratio	MDM
IFOCUCONSAX - IFOEOARS	(R)-(N)	0.739	*	ICTOSAX - NRCARS	(R)-(N)	0.672	**
-				ICTOSAX - NOCEOD	(R)-(N)	0.737	
-				ICTOSAX - NRTOT	(R)-(N)	0.739	**
-				ICTOSAX - M3MS	(R)-(I)	0.783	
-				ICTOSAX - WSLTOTMTH	(R)-(N)	0.795	*

Note: This table reports the best 20 indicators due to the smallest rMSFE for single–indicators forecasts or pooling. The lower part shows the best 5 two–indicator outcomes with a smaller rMSFE than the minimum of the single–indicator forecasts or pooling. MDM presents significance due to the modified Diebold-Mariano test.
Number of models better than the minimum: h = 1 (**5**), h = 2 (**8**), h = 3 (**1**), h = 4 (**7**).
Acronyms: FS: Full Sample and S: Saxony. (I) international, (N) national, (R) regional indicators and (C) combinations.
Table 4 in the appendix shows the acronyms used for the different indicators.
***, ** and * indicates rMSFE is significant smaller than one at the 1%, 5% and 10% level.
Source: author´s calculations.

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

Target variable: qoq growth rate GDP Baden-Württemberg							
Single–indicator forecasts or pooling							
h=1				**h=2**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
NOMANBWTOTF	(R)	0.511	*	MSFE weighted (FS)	(C)	0.655	**
KIBW	(R)	0.591	*	GFKPL	(N)	0.731	*
NOMANBWTOTD	(R)	0.597		Trimmed 25 (FS)	(C)	0.776	**
IFOBCITBW	(R)	0.664	*	Trimmed 25 (BW)	(C)	0.794	**
CLIEUNORM	(I)	0.673		EMMSM1EP	(I)	0.811	
MSFE weighted (FS)	(C)	0.684	**	KIBW	(R)	0.816	
Trimmed 25 (FS)	(C)	0.689	**	MMRDTD	(I)	0.816	*
Trimmed 25 (BW)	(C)	0.702	**	NOMANCAPD	(N)	0.828	
CLIEUAA	(I)	0.708		MMRTM	(I)	0.834	*
CLIEUTR	(I)	0.709		TOMAND	(N)	0.836	
IFOBCMANBW	(R)	0.769	*	IPMET	(N)	0.837	*
IFOBEITBW	(R)	0.737	*	IPMOT	(N)	0.840	*
IPMANBWTOT	(R)	0.752		IPVEM	(N)	0.840	*
TOCAPD	(N)	0.764	*	TOMQD	(N)	0.842	
IFOBEMANBW	(R)	0.769	*	TOCONDURF	(N)	0.859	**
GFKPL	(N)	0.784	*	NOVEMF	(N)	0.860	
CLITR	(I)	0.789		IFOUNFWCON	(N)	0.862	**
TOVEMD	(N)	0.792	**	Trimmed 50 (FS)	(C)	0.863	**
MSFE weighted (BW)	(C)	0.796	**	TOVEMD	(N)	0.864	*
Trimmed 50 (FS)	(C)	0.804	**	TOVEMF	(N)	0.865	
h=3				**h=4**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
NOMANBWTOTD	(R)	0.735		NOMANBWTOTD	(R)	0.744	*
NOMANCAPD	(N)	0.805	*	NOMANTOTD	(N)	0.761	
Trimmed 25 (FS)	(C)	0.806	**	TOCAPD	(N)	0.767	
IPMOT	(N)	0.807	*	NOMANCAPD	(N)	0.777	
IPVEM	(N)	0.807	*	TRVATIM	(N)	0.783	*
MSFE weighted (FS)	(C)	0.824	***	Trimmed 25 (FS)	(C)	0.787	**
NOMANTOTD	(N)	0.824	*	TOMECHD	(N)	0.800	
TRVATIM	(N)	0.828	*	TOCONDURF	(N)	0.804	*
TOCONDURF	(N)	0.834	*	MSFE weighted (FS)	(C)	0.808	***
TOMAND	(N)	0.834	*	IPMOT	(N)	0.809	*
IPMET	(N)	0.835		IPVEM	(N)	0.809	*
TOVEMF	(N)	0.841		TOVEMF	(N)	0.814	*
TOCAPD	(N)	0.841		IPCAP	(N)	0.817	
Trimmed 25 (BW)	(C)	0.843	**	IPMET	(N)	0.817	
EMMSM1F	(I)	0.848		IPMANBWTOT	(R)	0.826	*
TOMQD	(N)	0.851	*	TOMAND	(N)	0.827	
NOVEMF	(N)	0.856		Trimmed 25 (BW)	(C)	0.829	*
MMRDTD	(I)	0.863	*	MMRDTD	(I)	0.834	
NOVEMD	(N)	0.870		EMMSM2M1F	(I)	0.841	
TOCHEMD	(N)	0.870		TOCAPF	(N)	0.845	

Two–indicators models							
h=1 (min=0.511)				**h=2 (min=0.655)**			
Model	Acronym	Ratio	MDM	Model	Acronym	Ratio	MDM
NOMANBWTOTD - USISMP	(R)-(I)	0.423	*	NOMANBWTOTF - TOCEOF	(R)-(N)	0.615	
KIBW - TOMANF	(R)-(N)	0.427	*		–		
KIBW - TOMQF	(R)-(N)	0.431	*		–		
KIBW - CLIUSAA	(R)-(I)	0.440	*		–		
KIBW - CLIUSNORM	(R)-(I)	0.440	*		–		
h=3 (min=0.735)				**h=4 (min=0.744)**			
Model	Acronym	Ratio	MDM	Model	Acronym	Ratio	MDM
NOMANBWTOTD - EMPLRCTOT	(R)-(N)	0.601		IFOBEMANBW - MMRDTD	(R)-(I)	0.658	**
NOMANBWTOTD - EMPLWPCTOT	(R)-(N)	0.603		IFOBCWTBW - NOMANTOTD	(R)-(N)	0.685	
NOMANBWTOTD - IFOAOIWT	(R)-(N)	0.637		IFOBCMANBW - MMRDTD	(R)-(I)	0.700	*
NOMANBWTOTD - GFKFSE	(R)-(N)	0.648		IFOBSWTBW - IPTOT	(R)-(N)	0.702	*
NOMANBWTOTD - GFKCCC	(R)-(N)	0.651		IFOBEWTBW - NOMANCAPD	(R)-(N)	0.703	*

Note: This table reports the best 20 indicators due to the smallest rMSFE for single–indicators forecasts or pooling. The lower part shows the best 5 two–indicator outcomes with a smaller rMSFE than the minimum of the single–indicator forecasts or pooling. MDM presents significance due to the modified Diebold-Mariano test.
Number of models better than the minimum: $h = 1$ (**57**), $h = 2$ (**1**), $h = 3$ (**17**), $h = 4$ (**27**).
Acronyms: FS: Full Sample and BW: Baden-Württemberg. (I) international, (N) national, (R) regional indicators and (C) combinations. Table 4 in the appendix shows the acronyms used for the different indicators.
***, ** and * indicates rMSFE is significant smaller than one at the 1%, 5% and 10% level.
Source: author´s calculations.

Table 3: **Results for Eastern Germany**

Target variable: qoq growth rate GDP Eastern Germany							
Single–indicator forecasts or pooling							
h=1				**h=2**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
IWHOLKMANEG	(R)	0.805		GFKMPE	(N)	0.816	
Trimmed 25 (FS)	(C)	0.809	**	MSFE weighted (FS)	(C)	0.891	***
IFOBSMANEG	(R)	0.819		Trimmed 25 (FS)	(C)	0.896	***
Trimmed 25 (EG)	(C)	0.819	**	Trimmed 25 (EG)	(C)	0.909	***
GFKMPE	(N)	0.823	*	GFKFSL	(N)	0.910	
MSFE weighted (FS)	(C)	0.829	***	GFKPE	(N)	0.911	
IFOBEMANEG	(R)	0.846	*	TOCONGD	(N)	0.934	
CLICNORM	(I)	0.863		YFTBOPB	(N)	0.938	
CLICAA	(I)	0.866		YLFBOML	(N)	0.940	
IFOBCMANEG	(R)	0.869		Trimmed 50 (FS)	(C)	0.947	**
IFOBCITEG	(R)	0.872		IFOUNFWCON	(N)	0.948	
MMRTM	(I)	0.885		YLFBOMS	(N)	0.956	
TOCAPD	(N)	0.888		Trimmed 50 (EG)	(C)	0.959	**
GFKFSL	(N)	0.889	*	CLINORM	(I)	0.961	
IPMECH	(N)	0.891		EUBSRTCI	(N)	0.962	
Trimmed 50 (FS)	(C)	0.894	**	EMPLWPCTOT	(N)	0.966	
Trimmed 50 (EG)	(C)	0.903	*	GFKWTB	(N)	0.971	
YFTBOCB	(N)	0.904		EMMSM1F	(I)	0.972	
IPCAP	(N)	0.904		MMRDTD	(I)	0.972	
TRVATIM	(N)	0.907	*	EUBSSPEIND	(N)	0.973	
h=3				**h=4**			
Indicator or strategy	Acronym	Ratio	MDM	Indicator or strategy	Acronym	Ratio	MDM
MSFE weighted (FS)	(C)	0.906	**	MSFE weighted (FS)	(C)	0.860	**
IPCONG	(N)	0.910		Trimmed 25 (FS)	(C)	0.878	**
Trimmed 25 (FS)	(C)	0.918	**	TRITTOT	(C)	0.891	**
Trimmed 25 (EG)	(C)	0.943	**	Trimmed 25 (EG)	(C)	0.903	**
ICNOEG	(R)	0.950		TOMECHD	(N)	0.909	
TRVATIM	(N)	0.954		TOCAPD	(N)	0.919	
TRWIT	(N)	0.960		MMRTM	(I)	0.941	
EMMSM1F	(I)	0.960		Trimmed 50 (FS)	(C)	0.943	**
Trimmed 50 (FS)	(C)	0.966	*	NRCARS	(N)	0.947	
TRITTOT	(N)	0.977		Trimmed 50 (EG)	(C)	0.953	**
DREUROREPO	(I)	0.979		MMRDTD	(I)	0.955	
Trimmed 50 (EG)	(C)	0.981		TRVATTOT	(N)	0.956	
GFKSP	(N)	0.985		COMBAEB	(N)	0.956	*
IFOCUCONEG	(R)	0.991		NOCEOD	(N)	0.958	
Trimmed 75 (FS)	(C)	0.993		GFKESL	(N)	0.959	
IFOAOIRS	(N)	0.995		TOINTD	(N)	0.959	
EMPLWPCTOT	(N)	0.996		TRWIT	(N)	0.963	
EMMSM3M2F	(I)	0.996		YLFBOML	(N)	0.964	
EMPLRCTOT	(N)	0.996		TOMAND	(N)	0.966	
WTEXMV	(N)	0.996		NOMANCONG	(N)	0.967	

Two–indicators models							
h=1 (min=0.805)				**h=2 (min=0.816)**			
Model	Acronym	Ratio	MDM	Model	Acronym	Ratio	MDM
IFOBEMANEG - IFOOOHCON	(R)-(N)	0.705	*	IFOBCMANEG - GFKMPE	(R)-(N)	0.765	*
IWHOLKMANEG - NOCHEMD	(R)-(N)	0.705		IFOBEMANEG - GFKMPE	(R)-(N)	0.770	**
IFOBCITEG - IPINT	(R)-(N)	0.710	*	IFOEMPEWTEG - GFKMPE	(R)-(N)	0.791	
IFOEMPECONEG - GFKMPE	(R)-(N)	0.713	*	IWHSITMANEG - GFKMPE	(R)-(N)	0.796	
IFOBCMANEG - IFOOOHCON	(R)-(N)	0.715	**	IFOBSMANEG - GFKMPE	(R)-(N)	0.815	
h=3 (min=0.906)				**h=4 (min=0.860)**			
Model	Acronym	Ratio	MDM	Model	Acronym	Ratio	MDM
ICNOEG - TRVATIM	(R)-(N)	0.885	*		–		
IFOBCCONEG - IPCONDUR	(R)-(N)	0.889			–		
IFOBSCONEG - IPCONDUR	(R)-(N)	0.893			–		
ICWHEG - NRCARS	(R)-(N)	0.905			–		
ICWHEG - IFOEOARS	(R)-(N)	0.905			–		

Note: This table reports the best 20 indicators due to the smallest rMSFE for single–indicators forecasts or pooling. The lower part shows the best 5 two–indicator outcomes with a smaller rMSFE than the minimum of the single–indicator forecasts or pooling. MDM presents significance due to the modified Diebold-Mariano test.

Number of models better than the minimum: $h = 1$ (**64**), $h = 2$ (**5**), $h = 3$ (**5**), $h = 4$ (**0**).

Acronyms: FS: Full Sample and EG: Eastern Germany. (I) international, (N) national, (R) regional indicators and (C) combinations. Table 4 in the appendix shows the acronyms used for the different indicators.

***, ** and * indicates rMSFE is significant smaller than one at the 1%, 5% and 10% level.

Source: author´s calculations.

For all three GDP target variables, we are able to beat the AR(p) benchmark model significantly. This result holds true for all considered forecasting horizons because we find $rMSFE$ in all three tables that are smaller than one. All three tables show that regional, national and international indicators have important information for the prediction of regional GDP. Whereas regional indicators are relevant for the short term (see $h = 1$ in all three tables), signals for the long term predominantly come from international or national indicators (see $h = 4$ in Table 1, 2 and 3). Forecasting differences also exist for our regional units. For Saxony, national and regional indicators produce lower forecast errors than the benchmark model. International indicators are relatively negligible for the prediction of Saxon GDP. In contrast, international indicators are more important for Baden-Württemberg and Eastern Germany. The best performance of regional indicators can be found for Baden-Württemberg. Combining regional with national or international indicators improves forecasting accuracy, as the lower parts of Tables 1, 2 and 3 suggest (see the results for the two–indicator models in the lower parts of the tables). We can conclude that the forecasting power of single–indicator models can be increased for all forecasting horizons except in the long term for Eastern Germany. If we want to forecast GDP in Eastern Germany for the next four quarters ($h = 4$), no model with two indicators beats the minimum of our single–indicator forecast exercise or the outcome of pooling.
Pooling strategies also perform very well at the regional level (see the indicators denoted with (C)). MSFE weights or trimming (25% or 50% as well as for the full sample or only with regional indicators) significantly beat the outcome of the autoregressive benchmark. For Saxony, pooling produces the lowest forecast errors for all horizons. The results for Baden-Württemberg show that pooling is important in the medium term ($h = 2$). In the long term, several weighting schemes increase forecasting performance for Eastern German GDP.

3.2. Detailed regional results

3.2.1. Free State of Saxony

Surveys (consumer or business) and macroeconomic variables yield the best results for Saxon GDP (see Table 1). The Ifo business expectations and the Ifo business climate for industry and trade in Saxony (IFOBCITSAX, $rMSFE = 0.914$) produce lower forecasting errors than the benchmark model. These results are consistent with a body of German forecasting literature. One of the most important leading indicators for German GDP is the Ifo business climate for industry and trade.[12] This phenomenon is also the case for Saxony (Lehmann *et al.*, 2010). Furthermore, exports (EXVALUE, $rMSFE = 0.922$) improve the forcasting accuracy. Within the Eastern German states, the Saxon economy has the highest degree of openness (approximately 40% of all turnovers in the manufacturing sector are gained

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

from abroad). Another highlight is the importance of national indicators such as domestic turnovers from selling motor vehicles and trailers (TOVEMD) and industrial production of intermediate goods (IPINT). These results are straightforward, because Saxon industry is predominantly described by these two sectors. The top-selling industry in Saxony is vehicle manufacturing. Subcompanies of Volkswagen and BMW are located in Saxony. More than 21% of all turnovers in 2011 are gained in this sector and approximately 39% from the group of intermediate goods producers. Saxon firms are strongly linked to the Western German economy; therefore, national indicators are useful for predicting Saxon GDP.

3.2.2. Baden-Württemberg

In comparison to the Free State of Saxony, the results for Baden-Württemberg are even better. The best indicators predict GDP one quarter ahead almost 50% more accurately then the AR benchmark (see e.g., KIBW in Table 2). Foreign new orders in manufacturing produce lower forecast errors in the short term than the autoregressive model (NOMANBWTOTF, $rMSFE = 0.511$). Additionally, turnovers of German capital goods producers (TOCAPD) yield significantly better results than the benchmark. The results from these two separate indicators are consistent with the economic structure of Baden-Württemberg. Baden-Württemberg has the highest share of manufacturing of the German states; approximately 30% of nominal gross value-added is generated in this sector. Manufacturing of motor vehicles (e.g., Daimler AG), 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. In addition to macroeconomic indicators, regional surveys play a major role for predicting GDP in Baden-Württemberg. The Ifo business climate for industry and trade in Baden-Württemberg (IFOBCITBW, $rMSFE = 0.664$) significantly beats the benchmark model. As mentioned previously, international indicators such as the composite leading indicator for the Euro Area (CLIEUNORM) and the OECD countries (CLITR) perform well. 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, which also explains the results from our two–indicator models. A combination of regional indicators with, for example, the ISM Purchasing Manager Index for the US reduces forecast errors significantly in comparison to the autoregressive benchmark model (NOMANBWTOTD - USISMP, $rMSFE = 0.423$). 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) and the IWH are able to predict Eastern German GDP better than the autoregressive benchmark in the short term. An indicator on business expectations in the manufacturing sector and the Ifo business climate for industry and trade in Eastern Germany are very helpful. Considering macroeconomic variables, we also find results that are consistent with the Eastern German economic structure. Domestic turnovers of capital and intermediate goods producers have a higher forecast accuracy than the benchmark (TOINTD, TOCAPD). 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)). Therefore, it is not surprising that a combination of the regional business climate for manufacturing and an indicator based on a consumer survey (GFKMPE) produce significantly lower forecast errors than the AR process. Accordingly, the sentiment of consumers sends important signals for Eastern German GDP. 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 qoq GDP growth in Eastern Germany. From the short forecasting horizon ($h = 1$), we can conclude that international indicators also play a role. The composite leading indicator of China decreases forecast errors (CLICNORM). China was the third most important trading partner for Eastern German firms in 2011.

4. Conclusion

This paper analyzes the forecasting performance of leading indicators and pooling techniques 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. Whereas domestic indicators play a major role in Eastern Germany, international indicators and new orders from foreign countries produce lower forecast errors for GDP in Baden-Württemberg. Furthermore, we can conclude that regional indicators have a high forecasting power, especially in the short and medium term. If it is possible to use regional indicators, a forecaster should not approximate them with national indicators.

As we use a large data set, pooling strategies can improve forecasting accuracy. For all three regional units, trimming or MSFE weights outperforms all other weighting schemes and single–indicator forecasts. Hence, pooling in a regional context is just as important as on the national level.

Finally, we have shown that adding national and international indicators to regional ones leads in most cases to a better forecasting performance than the best single–indicator forecast or pooling technique. Due to data limitations, it is not possible to add more variables. 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, EU, etc.) and aggregation levels. It would be interesting to know if it is better to predict regional GDP directly or its different components. This issue was analyzed for Germany as a whole by Drechsel and Scheufele (2012a), but no regional study exists.

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A. Indicators

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

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

Continued on next page...

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

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

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

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

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

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

Continued on next page...

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

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

Continued on next page...

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

Acronym	**Indicator**	**Transformation**
PCNOBW	public construction (PC): new orders Baden-Württemberg	1
PCWHBW	PC: working hours Baden-Württemberg	1
PCTOBW	PC: turnover Baden-Württemberg	1
CONNOBW	construction: new orders Baden-Württemberg	1
CONWHBW	construction: working hours Baden-Württemberg	1
CONTOBW	construction: turnover Baden-Württemberg	1
CONFIRMBW	construction: firms Baden-Württemberg	1
CONEMPBW	construction: employed people Baden-Württemberg	1
CONFEEBW	construction: fees Baden-Württemberg	1
IFOCUCONBW	Ifo: capacity utilization construction, Baden-Württemberg	2
CPIBW	consumer price index, Baden-Württemberg	1
KIBW	business cycle indicator of Baden-Württemberg	1

Note: 0 = three-month-average in levels; 1 = three-month-average and qoq growth rate; 2 = three-month-average and Δ
Source: Drechsel and Scheufele (2012a), author´s extensions and calculations.