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Working Paper

Boosting and Regional Economic Forecasting: The Case of Germany

CESifo Working Paper, No. 6157

Provided in Cooperation with:

Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

Suggested Citation: Lehmann, Robert; Wohlrabe, Klaus (2016) : Boosting and Regional Economic Forecasting: The Case of Germany, CESifo Working Paper, No. 6157, Center for Economic Studies and ifo Institute (CESifo), Munich

This Version is available at:

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CESIFO WORKING PAPER NO. 6157

CATEGORY 6: FISCAL POLICY, MACROECONOMICS AND GROWTH

OCTOBER 2016

An electronic version of the paper may be downloaded

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ISSN 2364-1428

CESifo

Center for Economic Studies & Ifo Institute

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Abstract

This paper applies component-wise boosting to the topic of regional economic forecasting. Component-wise boosting is a pre-selection algorithm of indicators for forecasting. By using unique quarterly real gross domestic product data for two German states (the Free State of Saxony and Baden-Wuerttemberg) and Eastern Germany for the period from 1997 to 2013, in combination with a large data set of monthly indicators, we show that boosting is generally doing a very good job in regional economic forecasting. We additionally take a closer look into the algorithm and ask which indicators get selected. All in all, boosting outperforms our benchmark model for all the three regions considered. We also find that indicators that mirror the region-specific economy get frequently selected by the algorithm.

JEL-Codes: C530, E170, E370, R110.

Keywords: boosting, regional economic forecasting, gross domestic product.

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This version: October 19, 2016

1. Introduction

The need of region-specific economic forecasts by policy-makers from sub-national entities has increased over the last years. We can identify two major reasons why regional economic forecasts recently become more important. First, these forecasts are the basis for the regional decision-making process, for example, for fiscal policy planning. And second, regional gross domestic product (GDP) often markedly develops in a different way compared to countries as a whole because of specific regional economic structures. A regional economic forecast therefore serves as an additional information source for the policy-maker and as an early warning system.

Not only policy-makers are more interested in region-specific forecasts, but the topic of regional economic forecasting is also increasingly becoming part of literature in this field in recent years. A recent survey on regional economic forecasting is provided by Lehmann and Wohlrabe (2014b). This survey discusses state-of-the-art methodology in regional economic forecasting and names possible future research activities in this field. One of such activities could be examining the forecasting performance of boosting algorithms for regional economic development. In this paper, we fill this gap in the existing literature by looking at the forecasting performance for three regional entities in Germany. It turns out that boosting outperforms the benchmark model, especially in the case of one- and two-quarter-ahead predictions. Additionally, the algorithm mostly selects those variables that mirror the region-specific economic structure.

Boosting is, generally speaking, a multivariate large data set method that is able to pre-select the most relevant predictors for a specific target variable, with respect to all other potential indicators, by simultaneously shrinking the influence of less relevant predictors towards zero (see, among others, Bai and Ng, 2009). Thus, boosting ends up in an either linear or nonlinear function that can easily be handled by standard estimation techniques such as ordinary least squares (OLS) and macroeconomic forecasting issues. Compared to other multivariate large data set methods such as least angle regression (LARS) and least absolute shrinkage selection operator (LASSO), boosting is a 'statistical learning procedure' that works in a similar fashion but is not exactly the same (Efron *et al.*, 2004). Simply speaking, all three models iteratively fit a linear model by regressing the set of potential predictors to the residuals of the former regression step. In each step, the regression coefficients become 'penalized' in order to shrink the influence of less informative indicators towards zero. Closely related to this penalization are the methods elastic net (EN) and non-negative garotte (NNG) which put modified restrictions or criteria on the coefficient estimates. Another way to reduce the number of potential predictors before forecasting economic time series is the classical diffusion index methodology or factor analysis. However, factor models differ in a very essential way from these large data set methods: the indicator reduction is independent from the target series to be forecasted. From the large

set of indicators, the operator extracts a small number of common factors that can be used to forecast each macroeconomic time series (or even any other series of interest). However, this factor extraction can be suboptimal since a set of indicators can have a noisy character or less power in forecasting a specific time series (Bai and Ng, 2009). This noisiness may introduce biases to the forecast. Additionally, it is completely arbitrary how many factors are extracted from the data, therefore test for the optimal number of factors are needed. The last way of dealing with a large set of information are forecast combinations. In contrast to the methods mentioned before where the indicators are filtered first and used for forecasting after, forecast combinations or pooling takes place after the forecasts are generated. Pooling is therefore an aggregation of a large number of different forecasts (for example, from individual indicators) based on a specific aggregation rule (for example, a simple average). Thus, forecast combination is a completely different approach and by no means a pre-selection of indicators.

The existing literature finds that boosting is a well performing alternative. Bai and Ng (2009) focus on the forecasting performance of boosting for four US macroeconomic variables. They find an improvement of boosting over factor-augmented forecasts and simple autoregressive models. Especially for the US industrial production, Buchen and Wohlrabe (2011) certify boosting to be a tough forecasting competitor compared to forecast combinations or factor models. Robinsonov *et al.* (2012) found an improvement of boosting over autoregressive models for German industrial production. A recent study is the one by Zeng (2016). She asks whether boosting is able to filter from a pool of disaggregated variables the most relevant predictors to forecast aggregates. For six euro area macroeconomic variables boosting is doing a very good job to forecast these aggregates. Next to standard macroeconomic variables, boosting has also been used for financial variables. Andrada-Félix and Fernández-Rodríguez (2008) evaluate the performance of boosting in order to forecast the NYSE Composite Indicator. They found a forecast improvement with boosting compared to simple moving average trading rules. The articles by Pierdzioch *et al.* (2016, 2015) focus on gold and silver prices. In both articles boosting is found to have predictive power. The last two papers that are relevant for our study are those by Buchen and Wohlrabe (2014) and Lehmann and Wohlrabe (2016). Whereas the first study sets up a 'simulation' for US, European and German macroeconomic variables in order to find how parameters of the algorithm should optimally be chosen, the second study takes a closer look into the boosting algorithm and asks which indicators are frequently selected. All these studies focus on countries. To the best of our knowledge, studies for regional entities are missing.

This paper is related to Lehmann and Wohlrabe (2016) as well as Kim and Swanson (2014) and has two major contributions. First, we generally ask whether boosting produces lower forecast errors for regional gross domestic product compared to a simple benchmark model. And second, we take a closer look into the boosting procedure. To be more precise, we ask whether there are superior indicators for regional economic forecasting that get selected

into the model by the algorithm. The main focus here lies on the investigation of regional entities. So our paper is by no means a study that compares large data set methods with each other for different regions. It rather focuses on the specific selection of indicators for forecasting regional economic development. We think that it is more fruitful to ask where the information for regional economic forecasting come from, instead of comparing different methodologies with each other. Up to date, the sparse regional economic forecasting literature only applies pooling and factor models as large data set methods (see Lehmann and Wohlrabe, 2015, 2014a). Boosting seems therefore be a promising alternative, so that this study rather complements the existing ones. But why should we use boosting for regional economic forecasting? We see one striking argument: one additional dimension that provides potential indicators. Whereas most of the studies for countries use national and international data, we can add the regional dimension as well. We think that regional economic development is influenced by international economic shocks, nationwide economic linkages and region-specific developments. Thus, the set of potential predictors is even larger than for national studies. Additionally, in comparison to factor models, boosting is an alternative to select indicators. This makes boosting especially interesting for practitioner, since regional economic forecasters want to know on which indicators they should focus on. But we have to state that boosting is a pure time-series-based technique, so that we forecast each regional entity separately. Spatial connections or interdependency are neglected in our case.

The paper is organized as follows: Section 2 introduces the regional data sets, followed by the presentation of the boosting algorithm and forecasting approach. In Section 3 we discuss the results in detail. The final section offers some conclusions.

2. Regional Economic Forecasting and Boosting

2.1. Data

National accounts data for regional entities such as counties or districts are generally only available on an annual basis. Since large data set methods such as boosting only work with a sufficient number of observations, annual information is not suitable for our purposes. However, as in Lehmann and Wohlrabe (2015), we can rely on quarterly gross domestic product (GDP) data for two German states (the Free State of Saxony and Baden-Wuerttemberg) as well as Eastern Germany.¹ Thus, we can compare the performance of boosting for three different regional entities.

¹Eastern Germany comprises the five German states Brandenburg, Mecklenburg-Western Pomerania, Saxony-Anhalt, the Free State of Saxony and the Free State of Thuringia. The German states equal the NUTS-1-classification of Europe.

2.1.1. The Free State of Saxony

Saxony is part of the Eastern German states that joined Germany after its reunification in 1989 and lies in the south-east of Germany. Compared to all German states, the Free State of Saxony had the eighth largest share of total nominal German GDP in 2014 ($\approx 4\%$). If we focus on Eastern Germany (without Berlin) instead, Saxony has the highest nominal GDP compared to all of the other Eastern German states. Additionally, the Free State of Saxony is the Eastern German state with the highest industrial share and the largest export quota.

The quarterly data for Saxony are provided by the German Ifo Institute (Nierhaus, 2007).² The calculations are based on the temporal disaggregation procedure by Chow and Lin (1971) that applies a stable relationship between the target series and a suitable indicator. Thus, a variable with low frequency (here: annual GDP figures) is transformed via specific indicators into a series with higher frequency (quarterly figures as in our case). Official regional statistics such as turnover in manufacturing serve as suitable indicators. This paper uses real quarterly GDP data for Saxony ranging from 1997Q1 to 2013Q4. These figures are calculated according to the latest available classification of national accounts. The series is seasonally adjusted and we apply a year-on-year growth rate transformation to reach stationarity.

In the Saxon case, we can rely on a data set that contains 234 monthly indicators. This data set is predominantly the same as in Henzel *et al.* (2015). In order to systematize the indicators, we group them into six categories: macroeconomic (72), prices (11), surveys (56), international (26) and regional (69). The indicators from the first three categories are measured at the national level (here: Germany). Since Saxony can be considered as a small open economy, we expect international indicators to deliver useful information to forecast Saxon GDP. In order to capture region-specific developments, we add indicators that are measured at the regional level (here: Saxony). Of course, the indicators used for disaggregation do not enter the forecasting experiment described later on. All indicators are also seasonally adjusted. Since the potential predictors are measured on a monthly basis, we either apply a three-month-average or the three-month-sum to obtain quarterly data. Whenever indicators are not stationary in levels, we either calculate year-on-year growth rates or first differences to the quarter of the previous year.

2.1.2. Baden-Wuerttemberg

Baden-Wuerttemberg was in terms of GDP per capita the third richest state (excluding the city states Bremen and Hamburg) in Germany in 2014. It lies in the south-west of Germany and hosts large firms such as the Bosch-Group or Mercedes. In 2014, Baden-Wuerttemberg contributed with approximately 15% to total German GDP, which was the third highest share. Baden-Wuerttemberg has also one of the most open economies in Germany; more

²The latest data for Saxony are available upon request from dresden@ifo.de.

than 50% of all industrial turnover are gained in foreign countries. Thus, the structural differences to the Saxon economy makes our analysis even more interesting, since we compare the forecasting performance of boosting for two very different regional entities.

The quarterly GDP data for Baden-Wuerttemberg are also calculated with the method of Chow and Lin (1971) and provided by the Statistical Office of Baden-Wuerttemberg (Vullhorst, 2008).³ As in the Saxon case, the real quarterly GDP data for Baden-Wuerttemberg are available for the period 1997Q1 to 2013Q4, seasonal adjusted and transformed in year-on-year growth rates.

For Baden-Wuerttemberg we use a data set that contains 201 monthly indicators. The distribution between the categories is the same, with one exception: for Baden-Wuerttemberg we can only rely on 36 regional indicators. As before, we only consider indicators that are not used for temporal disaggregation. Again, all monthly indicators are seasonally adjusted and transformed to quarterly as well as stationary information.

2.1.3. Eastern Germany

The five Eastern German states (excluding Berlin) are structural completely different from their Western German counterparts. Eastern Germany is characterized by higher unemployment rates, a lower GDP per capita, tougher demographic developments and missing headquarters (only to name a few problems; see Ragnitz, 2005). We thus suggest to find differences in the forecasting performance of boosting compared to the before mentioned states.

Quarterly GDP data for Eastern Germany are provided by the Halle Institute for Economic Research (abbreviated in German as IWH) and are regularly published under the name ‘Barometer for Economic Activity in East Germany’.⁴ The methodology to generate the quarterly information for Eastern Germany is a bit different to the one used in the case of Saxony and Baden-Wuerttemberg. According to Brautzsch and Ludwig (2002) the quarterly data are generated by their so-called extrapolation method. The basis for disaggregation is not a stable regression relationship between annual information and a suitable indicator as in the case of Chow and Lin (1971), but rather the usage of quarterly shares in the annual aggregate. Both methods have the usage of high-frequency indicators in common. As for Saxony and Baden-Wuerttemberg, the IWH applies German national accounts data if regional information are missing. To compare the results for Eastern Germany with those for Saxony and Baden-Wuerttemberg, we also use real quarterly GDP data for the period from 1997Q1 to 2013Q4 that are seasonally adjusted and transformed into year-on-year growth rates afterwards.

³The latest data for Baden-Wuerttemberg are available upon request from vgr@stala.bw.de.

⁴The data can be downloaded free of charge under <http://www.iwh-halle.de/c/start/prognose/download.asp?lang=e>.

Our set of monthly indicators for Eastern Germany consists of 202 variables. The German and international information remain the same and we can add 37 regional indicators. We again do not take the indicators that are used for disaggregation into account. The same transformation as in the two cases before is applied to the monthly indicators for Eastern Germany.

2.2. Boosting Algorithm

In this paper we apply the component-wise L_2 -boosting approach also used in the corresponding literature (see Buchen and Wohlrabe, 2011, 2014; Lehmann and Wohlrabe, 2016; Pierdzioch *et al.*, 2016, 2015). Generally, boosting follows the idea of iteratively estimating an unknown function in either a linear or nonlinear manner. In applications with large data sets where the number of indicators exceeds the time dimension ($N \geq T$), the complexity of the chosen fitting procedure has to be reduced by a pre-selection of variables (Bühlmann and Yu, 2003). Standard statistical models such as ordinary least squares (OLS) rapidly lose their ability to estimate parameters in such large data set applications. With component-wise boosting we approximate the 'true' model by sequentially estimating nested models that, in the end, are summed up to a generalized model in additive form (forward stage-wise modelling):

$$\hat{f}_M(\mathbf{z}_t) = y_t = \bar{y} + \sum_{m=1}^M b(\mathbf{z}_t; \hat{\beta}_m), \quad (1)$$

where the dependent variable to be forecasted is y_t . The number of iteration steps, and therefore the number of nested models to be estimated, is denoted by $m = 1, 2, \dots, M$ and $b(\mathbf{z}_t; \hat{\beta}_m)$ is called 'learner'. $\mathbf{z}_t$ is the vector with all possible predictors and the corresponding parameter estimates are presented by $\hat{\beta}_m$. For the m -th step, boosting adds the learner with the highest fit to the model from the previous iteration $\hat{f}_{m-1}(\mathbf{z}_t)$ according to a specific loss function $L(y_t, \hat{f}_m(\mathbf{z}_t))$ and without modifying the already estimated parameters.

There are three questions that can immediately be raised from the previous description. How does the fitting procedure work? How is the 'learner' constructed? And how does the loss function look like? These questions are answered subsequently. As indicated at the beginning of this section, we apply component-wise L_2 -boosting. In this context, component-wise means that in each iteration step not a function of predictors $\mathbf{z}_t$ is added to the model, but rather one single predictor z_t from the pool of possible predictors (Bai and Ng, 2009; Buchen and Wohlrabe, 2014). We use the squared error loss (L_2 -loss) that is common in the literature. By applying the squared error loss, the learner is just iteratively fitted to the residuals u_t from the previous stage:

$$\begin{aligned}
L(y_t, \hat{f}_m(z_t)) &= 1/2 (y_t - \hat{f}_m(z_t))^2 \\
&= 1/2 (y_t - \hat{f}_{m-1}(z_t) - b(z_t; \hat{\beta}))^2 \\
&= 1/2 (u_t - b(z_t; \hat{\beta}))^2.
\end{aligned} \tag{2}$$

Before we turn to the description of the boosting-algorithm, we introduce the set of potential predictors $\mathbf{z}_t^r$ for each regional entity r (Saxony [SX], Baden-Wuerttemberg [BW] and Eastern Germany [EG]). The vector $\mathbf{z}_t^r$ comprises p lags of the target variable to predict (y_{t-p}^r) as well as p lags of all N^r potential exogeneous predictors ($x_{N^r, t-p}^r$). The number of potential exogeneous variables that can enter the model for each region were introduced in the former subsection and take the following values: $N^{SX} = 234$, $N^{BW} = 201$ and $N^{EG} = 202$. From the pool of $z_{i,t}^r = 1, 2, \dots, i, \dots, p(1 + N^r)$ potential predictors, the algorithm chooses in every iteration m one 'optimal' variable $z_{i_m^*, t}^r$ that yields the smallest sum of squared residuals (SSR). But it is worth noting that the chosen predictor in a specific iteration does not have to be necessarily different from those of previous iterations, thus, one indicator can be added in linear form more than once. To be more concrete, the algorithm proceeds as follows:

1. Set $m = 0$ and initialize the algorithm with the simple average of the target series $\hat{f}_0^r(\mathbf{z}_t) = \bar{y}^r$.
2. For each iteration step $m = 1$ to M repeat:
 - (a) Calculate the actual residuals $u_{m,t}^r = y_{m-1,t}^r - \hat{f}_{m-1}^r(\mathbf{z}_t)$.
 - (b) For $z_{i_m, t}^r = 1, 2, \dots, i, \dots, p(1 + N^r)$, regress the residuals $u_{m,t}^r$ on $z_{i_m, t}^r$ and compute the $SSR_{i_m}^r = \sum_{t=1}^T (u_{m,t}^r - b(z_{i_m, t}^r; \hat{\beta}_{i_m}^r))^2$.
 - (c) Choose the 'optimal' indicator $z_{i_m^*, t}^r$ that yields the smallest sum of squared residuals: $SSR_{i_m^*}^r = \min SSR_{i_m}^r$.
 - (d) Update $\hat{f}_m^r(\mathbf{z}_t) = \hat{f}_{m-1}^r(\mathbf{z}_t) + \nu^r b(z_{i_m^*, t}^r; \hat{\beta}_{i_m^*}^r)$, with $0 < \nu^r < 1$. The 'learner' from the previous iteration step is left untouched.

Friedman (2001) first introduces ν^r as an additional regularization parameter next to M . The main reason for the introduction is to reduce the learner's variance, thus, improving the prediction performance of boosting. The algorithm converges to a function that represents the sum of M base learner estimates multiplied by the constant shrinkage parameter ν^r :

$$\hat{f}_M^r(\mathbf{z}_t) = \bar{y}^r + \sum_{m=1}^M \nu^r b(z_{i_m^*, t}^r; \hat{\beta}_{i_m^*}^r). \tag{3}$$

From Equation (3) one can immediately see why boosting can handle large data sets. This equation cannot be estimated with standard techniques, but applying the boosting algorithm

enables us to densify the most relevant information for forecasting from the pool of indicators $\mathbf{z}_t^r$. All variables that are not selected by the algorithm obtain a zero restriction on their coefficient. As one can see, the number of iteration steps can be arbitrary chosen. Thus, we need to find a rule in order to calculate the optimal number of iteration steps M^* . The most commonly used rules in the existing literature that minimize the expected forecast errors are cross-validation or information criteria (for example, the corrected Akaike Information Criterion). How the forecasting model looks like and which parameter we choose in practice, is described in the next subsection.

2.3. Forecasting Approach

After the introduction of the boosting algorithm in general, we describe the applied forecasting framework in the following. As in Buchen and Wohlrabe (2014) we apply ordinary least squares (OLS) for a linear model as the base 'learner' $b(z_{i,t}^r; \beta_i^r)$. We restrict our analysis to allow only a one-period lag⁵ of y^r and $\mathbf{z}^r$, thus, $p = 1$. Taking the parameters and the setting together, our boosting model ends up in a boosted autoregressive distributed lag (ADL) model of the following form:

$$\begin{aligned} y_t^r &= \hat{\alpha}^r + \sum_{m=1}^M \nu^r \hat{\beta}_{i_m^*}^r z_{i_m^*, t-h}^r + \varepsilon_t^r \\ &= \hat{\alpha}^r + \sum_{m=1}^M \nu^r \hat{\gamma}_{i_m^*}^r y_{i_m^*, t-h}^r + \sum_{m=1}^M \nu^r \hat{\delta}_{i_m^*}^r x_{i_m^*, t-h}^r + \varepsilon_t^r \\ &\text{with } i^* \in \{1, \dots, (1 + N^r)\} \text{ and } \hat{\gamma}_{i_m^*}^r, \hat{\delta}_{i_m^*}^r \in \hat{\beta}_{i_m^*}^r. \end{aligned} \quad (4)$$

The forecasting horizon for the three target series is denoted by h , which we restrict to $h \in \{1, 2\}$, since most of the variables are short-term indicators.⁶ Because of the shortness of the data sets, we apply an pseudo out-of-sample expanding window approach, thus, the initial estimation window ranging from 1997Q1 to 2005Q4 ($T_E = 36$) is successively enlarged by one quarter in every timely iteration. After the enlargement each parameter is re-estimated and the algorithm is newly applied. The forecasting experiment is implemented in a direct-step fashion, thus, the forecasting equation is adjusted in such a way that forecasts for $h = 2$ do not depend on forecasts for $h = 1$. We, therefore, generate $T_F = 32$ forecasts for both horizons. The first forecast is obtained for 2006Q1; the last forecast is calculated for 2013Q4. For each regional entity, the regularization parameter is set to $\nu^r = \nu = 0.1$, which is fairly standard in the existing literature. The maximum number of boosting iterations M^r for each region is selected by us via a small 'simulation study'. In the range of $M \in \{1, 2, \dots, 100\}$,

⁵We also experimented with a maximum of $p = 4$, but the resulting forecast errors were larger compared to the ones produced with only one lag.

⁶For forecast horizons of three- or four-quarter-ahead ($h = 3, 4$) we found that boosting loses its power compared to the benchmark model.

we choose that M where the algorithm produces the lowest forecast error for $h = 1$. Because of the shortness of the time series and the regional focus of our study, no study in style of Buchen and Wohlrabe (2014) exists that recommends a maximum number of iterations. The 'simulation study' reveals the following maximum number of iterations: $M^{SX} = 25$, $M^{BW} = 100$ and $M^{EG} = 30$. In the end, the optimal model is selected according to the corrected Akaike Information Criterion (see Buchen and Wohlrabe, 2014; Bühlmann, 2006).⁷

As the benchmark model, by which we assess the performance of boosting, we choose a boosted autoregressive process of order one:

$$y_t^r = \hat{\alpha}^r + \sum_{m=1}^M \nu^r \hat{\beta}_{i_m^*}^r y_{i_m^*, t-h}^r + \varepsilon_t^r. \quad (5)$$

An autoregressive benchmark is pretty standard in the forecasting literature, thus, our results are comparable with existing studies.⁸ As the measure of forecast accuracy, we apply the root mean squared forecast error (RMSFE). Let $FE_{t+h}^{r, Boost} = y_{t+h}^r - \hat{y}_{t+h}^{r, Boost}$ denote the h -step-ahead forecast error resulting from boosting for regional GDP (y^r) and period t , then the $RMSFE_h^{r, Boost}$ is defined as:

$$RMSFE_h^{r, Boost} = \sqrt{\frac{1}{T_F} \sum_{k=1}^{T_F} \left(FE_{t+h,k}^{r, Boost} \right)^2}. \quad (6)$$

The respective RMSFE for the benchmark model is $RMSFE_h^{r, AR(1)}$. In order to decide whether boosting is performing better than the autoregressive process, we calculate the relative RMSFE (rRMSFE):

$$rRMSFE_h^r = \frac{RMSFE_h^{r, Boost}}{RMSFE_h^{r, AR(1)}}. \quad (7)$$

If this ratio is smaller than one, boosting with a large set of indicators produces lower forecast errors compared to the benchmark model on average. The opposite holds for ratios larger one.

3. Results

3.1. General results

We start by presenting the overall performance of boosting for the three regions under consideration. Table 1 shows the RMSFE (in percentage points) for boosting and the benchmark

⁷Cross-validation is an alternative of obtaining the optimal model. However, our small sample prevents us from using this selection criterion.

⁸Nevertheless, other benchmarks are also imaginable, for example, a random walk or a boosted autoregressive process with a higher order than one. Since we implement the boosting algorithm with a maximum number of one lag, the boosted autoregressive process of order is the fairest competitor.

model as well as the resulting rRMSFE for both forecast horizons and the three regional entities. A rRMSFE smaller than one is set in bold face.

Table 1: Overall performance of boosting

Region	h = 1			h = 2		
	Boosting (RMSFE)	Benchmark (RMSFE)	Ratio (rRMSFE)	Boosting (RMSFE)	Benchmark (RMSFE)	Ratio (rRMSFE)
Free State of Saxony	1.908	2.135	0.894	2.812	2.753	1.021
Baden-Wuerttemberg	2.319	3.284	0.706	3.893	5.139	0.757
Eastern Germany	1.585	2.008	0.790	2.291	2.562	0.894

Note: The table presents the root mean squared forecast errors (RMSFE, in percentage points) for boosting and the AR(1) benchmark model as well as the resulting relative root mean squared forecast errors (rRMSFE). A ratio smaller than one is set in bold face. The forecasting period runs from 2006Q1 to 2013Q4.

With the exception of $h = 2$ in the Saxon case ($rRMSFE = 1.021$), boosting outperforms the autoregressive benchmark model. The largest improvement over the benchmark can be found for Baden-Wuerttemberg for the shorter forecast horizon ($rRMSFE = 0.706$). As indicated in Footnote 6 we also tested the performance of boosting for forecast horizons up to one year ($h = 3, 4$). The two ratios for Saxony and Eastern Germany are larger than one. Only for Baden-Wuerttemberg boosting is able to beat the autoregressive benchmark for longer forecast horizons.

In the next step we ask whether there are region-specific indicators that get regularly selected by the algorithm. We can generally state that the composition of best indicators varies with the forecast horizon. However, there are indicators that show up for almost all horizons. At the opposite end of the scale, we have indicators in the sample such as price indices that never get selected by the procedure.⁹ In order to determine the most frequently chosen indicators, we introduce Table 2 that shows the top 10 for each forecast horizon and region. Each top-10-indicator is assigned a percentage value that can be interpreted as follows. The percentage value presents the cumulative frequency of an indicator that has been chosen by the boosting algorithm. Thus, it runs from 0% to 100%. If an indicator gets chosen in period $t \in T_F$, then the cumulative frequency rises by $1/32$, with 32 as the length of our forecasting period (T_F). An indicator's total frequency is then the sum of all forecasting steps where the indicator is part of the boosting model, divided by the length of the evaluation period.

In general, we find remarkable differences in the indicator selection for the three regional entities. However, there are some 'overlapping' indicators that provide forecasting signals for at least two of the three regions. First, the Composite Leading Indicators by the OECD, especially the one for China, get selected by the algorithm in the Saxon and Eastern German case. Second, indicators from the sector of construction play a crucial role for economic forecasting for Saxon and Eastern German GDP. This finding is triggered by the economic

⁹A complete list of all indicators for each regional entity and their relative frequency can be found in the Appendix.

structure of both regions and we will elaborate more on this issue in the following subsections. Third, indicators from the industrial sector of automotive engineering get selected in all three regional cases. This is due to the fact that automotive engineering is the key branch in Germany, with firms like BMW, Mercedes and Volkswagen. We will discuss the region-specific results in more detail in the following subsections, compare these results with those found in existing studies and bring forward explanations why differences or similarities emerge.

Table 2: Top 10 indicators for each region and forecast horizon

$h = 1$		$h = 2$	
Free State of Saxony			
gross domestic product: SX	100.0%	ifo SX: busin. expect. wholesale trade	78.1%
new orders: industr. construct. Saxony	90.6%	UK average brent oil price	59.4%
ifo SX: busin. expect. wholesale trade	75.0%	new orders: consumer goods	56.3%
new orders: consumer goods	62.5%	Composite Leading Indicator: China	56.3%
Composite Leading Indicator: China	62.5%	ifo SX: busin. climate chemicals	56.3%
Composite Leading Indicator: US	59.4%	new orders: motor veh., trail. etc., dom.	43.8%
new orders: motor veh., trail. etc., dom.	37.5%	new orders: chemicals, dom.	40.6%
industr. production: construct.	28.1%	turnover: industr. construct. SX	34.4%
turnover: industr. construct. SX	21.9%	new car registrations	31.3%
turnover: energy supply, dom.	18.8%	vacancies total	31.3%
Baden-Wuerttemberg			
vacancies total	100.0%	vacancies total	100.0%
number of working days	96.9%	ifo: production expect. consumer dur.	100.0%
new orders: consumer goods, fgn.	90.6%	number of working days	84.4%
ifo: production expect. consumer dur.	90.6%	new car registrations	68.8%
industr. production: consumer dur.	84.4%	turnover: energy supply, fgn.	62.5%
new orders: consumer goods	81.3%	new orders: motor veh., trail. etc., dom.	62.5%
new orders: public construct. BW	81.3%	new orders: total manuf., fgn.	62.5%
ifo BW: busin. expect. retail sales	71.9%	EU busin. survey: price expect. manuf.	59.4%
new orders: motor veh., trail. etc., fgn.	68.8%	ifo BW: busin. expect. retail sales	59.4%
EU busin. survey: confid. indic. ret. sal.	68.8%	working hours: industr. construct. BW	59.4%
Eastern Germany			
Composite Leading Indicator: US	100.0%	vacancies total	93.8%
vacancies total	96.9%	Composite Leading Indicator: China	59.4%
Composite Leading Indicator: OECD	71.9%	ifo: production expect. consumer dur.	53.1%
industr. production: construct.	65.6%	turnover: consumer non-dur., dom.	50.0%
gross domestic product: EG	62.5%	new car registrations	50.0%
Composite Leading Indicator: China	62.5%	Composite Leading Indicator: US	50.0%
new orders: consumer goods	59.4%	Composite Leading Indicator: OECD	43.8%
ifo: production expect. consumer dur.	50.0%	new orders: motor veh., trail. etc., dom.	40.6%
retail sales: cars	43.8%	new orders: industr. construct. EG	34.4%
Composite Leading Indicator: Asia	40.6%	EU busin. survey: price expect. manuf.	28.1%

Note: The table presents the cumulative frequencies of the top 10 indicators in our sample for the different forecasting horizons and regions. A value of 100% is reached if an indicator gets chosen by the algorithm 32 times, thus, for the length of our forecasting period.

3.2. Free State of Saxony

The most frequent selected indicator for $h = 1$ are the autoregressive terms of the target variable, followed by new orders of Saxon industrial construction firms and the Ifo business expectations for Saxon wholesaling. Thus, regional indicators dominate the 'forecasting picture' for the Free State. We find similar results as in Lehmann and Wohlrabe (2014a) and Henzel *et al.* (2015), where the Ifo business expectations for Saxon wholesaling played a crucial role in forecasting total Saxon gross value added. Additionally, the construction sector is traditionally overrepresented in Eastern German states since large infrastructural investments were introduced after reunification (see Ragnitz, 2005) leading to a construction 'boom'. This may describe why indicators from the Saxon construction sector frequently get selected by the algorithm. Another interesting result is that domestic new orders of motor vehicles and trailers in Germany get frequently selected by the algorithm for $h = 1$. Such a result is straightforward and in line with the structure of the Saxon economy. Vehicle manufacturing is the most important sector for the Saxon economy. In 2014, almost 30% of total Saxon industrial turnover was generated in the vehicle manufacturing sector. Unfortunately, official statistics provide no long time series on new orders of the Saxon vehicle manufacturing sector. We suggest that such an indicator will be selected very frequently by the algorithm.

For $h = 2$ the most frequent selected indicator is again the Ifo business expectations for the Saxon wholesale trade, which reinforces the important role of regional indicators. Domestic new orders of motor vehicles and trailers in Germany are again among the top 10 indicators; we additionally find that new car registrations get frequently selected, which strengthens the argument on the structure of the Saxon economy. Next to vehicle manufacturing also regional survey results from the chemical industry in Saxony as well as new orders for German chemical products are part of the boosting model. This result is also straightforward, since the chemical industry has the fifth largest share (over 5% in 2014) of total manufacturing turnover in Saxony. The last important indicator, which is also among the top five for $h = 1$, is the OECD Composite Leading Indicator (CLI) for China. The People's Republic of China plays a crucial role for Saxon firms. In 2014, almost 18% of all Saxon exports were demanded by China, followed by the United States with a share of approximately 10% and Poland with 5%. In general, the Saxon economy has the highest export quota (2014: $\approx 38\%$ of total turnover in manufacturing were generated abroad) among the Eastern German states. These results are also in line with Henzel *et al.* (2015).

3.3. Baden-Wuerttemberg

The top 3 selected indicators for $h = 1$ are total vacancies, the number of working days and foreign new orders of consumer goods. Compared to the study of Lehmann and Wohlrabe (2015), the results are somewhat different. The explanation is, however, straightforward.

First, we use year-on-year growth rates instead of quarter-on-quarter growth rates in this study. And second, the time period under investigation varies. To the best of our knowledge, no other study exists to which we can compare our results. Among the top 10 indicators for $h = 1$ we find foreign new orders for German vehicle manufacturing. The Daimler AG is located in Baden-Wuerttemberg, which describes this emerging result. In comparison to Saxony, regional indicators are not that dominant. One possible explanation is that important industrial indicators such as production are missing at the regional level. We expect that especially these missing indicators deliver important forecasting signals.

The top 3 indicators for $h = 2$ are almost the same as for the shorter forecast horizon. Now, the Ifo production expectations for consumer durables always get selected by the indicator. Again, the vehicle manufacturing sector, together with new car registrations, are among the top 10 indicators. These findings can also be explained by the presence of the Daimler AG in Stuttgart, the capital city of Baden-Wuerttemberg. This view is also supported by new orders from abroad in total manufacturing. The economic structure of Baden-Wuerttemberg also delivers important hints for this result. With more than 30% since 2010, Baden-Wuerttemberg has the highest share of manufacturing in gross value added among the German states. Next to vehicle manufacturing, capital goods producers with a high potential for new innovations such as the Bosch Group are located in the German state Baden-Wuerttemberg.

3.4. Eastern Germany

Turning to the last region of Eastern Germany, we find that the CLI for the US and OECD as well as total vacancies build the top 3 indicators for $h = 1$. One of the most frequent selected indicators is industrial production in the construction sector. As stated in the 'General results' section, the Eastern German economy faced a construction 'boom' after reunification that led to an important position of the construction sector afterwards (Ragnitz, 2005). Another important results is the emergence of new orders of consumer goods. This is described by the key markets of Eastern German firms: they mainly operate on domestic markets and show a lower export quota compared to Western German firms (Ragnitz, 2009).

For $h = 2$ the most relevant indicators are total vacancies, the OECD CLI for China and the Ifo production expectations for consumer durables. As for the Free State of Saxony, China holds an important position for the Eastern German exports. In 2014, almost 10% of all Eastern German exports were demanded by China (for comparison: Western Germany $\approx 7\%$, Baden-Wuerttemberg $\approx 8\%$). This important position of China may explain why the CLI also gets selected by the algorithm in the Eastern German case. The last interesting results, for which we also find a suitable explanation, is the selection of new orders for Eastern German industrial construction firms. Next to the argumentation mentioned earlier and brought forward by Ragnitz (2005), the importance of industrial construction in Eastern

Germany becomes obvious by looking at turnover figures. In 2014, industrial construction had the largest share in total Eastern German turnovers in 2014 (more than 37%). Public construction had a share of almost 33% and building construction of nearly 30%. Together with the fact that the share of construction in total gross value added in 2014 was 7% in Eastern Germany and 4% in the Western part, these turnover figures underpin the important position of construction for Eastern German economic development. Such a fact should be kept in mind if it comes to forecasting Eastern German GDP in practice.

4. Conclusion

With boosting we are able to calculate more precise forecasts of GDP for three German regions separately compared to a simple benchmark model. A closer look into the boosting procedure reveals interesting results for regional economic forecasting and therefore practitioner. Especially regional indicators that mirror the region-specific economic structure regularly get selected by the algorithm. However, a large number of variables, such as price indices, are never part of the boosting model.

Classical business cycle indicators such as GDP come with one disadvantage at the regional level: a low frequency. Or they are, in the case of industrial production, completely missing. A viable alternative can be labor market indicators such as employment development or unemployment rates. Future research activities can concentrate on these variables since we hypothesize that different indicators play a crucial role compared to GDP. If the focus of regional forecasters lie on labor market outcomes, a systematic study that applies boosting seems fruitful.

Another field of research can concentrate on different methodological issues. By investigating regional entities, we quickly think in terms of spatial applications such as spatial lag or spatial error models. Since boosting is a pure time series approach, future research activities can investigate methodological comparisons. How does boosting perform compared to simple spatial models? Is there any cross-section time-dimension trade-off for which one method is superior to the other? Such questions can also easily extended by other methods such as pooling or factor models.

Acknowledgments. We thank Udo Ludwig for his very helpful comments and Lisa Giani Contini for editing this text.

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A. Indicator List

Table 3: List of indicators and cumulative frequency for the Free State of Saxony

Indicator	h = 1	h = 2
Target variable		
gross domestic product (GDP): Free State of Saxony	100.0%	15.6%
Macroeconomic variables		
industrial production (IP): total (incl. construction)	0.0%	0.0%
IP manufacturing: total	0.0%	0.0%
IP manufacturing: intermediate goods	0.0%	0.0%
IP manufacturing: consumer goods	0.0%	0.0%
IP manufacturing: capital goods	0.0%	0.0%
IP manufacturing: consumer durables	3.1%	0.0%
IP manufacturing: consumer non-durables	0.0%	9.4%
IP manufacturing: mining and quarrying	0.0%	0.0%
IP manufacturing: chemicals	0.0%	0.0%
IP manufacturing: basic metals	0.0%	0.0%
IP manufacturing: mechanical engineering	0.0%	0.0%
IP manufacturing: motor vehicles, trailers etc.	0.0%	0.0%
IP construction: total	28.1%	6.3%
IP energy supply: total	0.0%	0.0%
turnover (TO): manufacturing total, domestic	0.0%	0.0%
TO: manufacturing total, foreign	0.0%	0.0%
TO: intermediate goods, domestic	0.0%	6.3%
TO: intermediate goods, foreign	0.0%	0.0%
TO: consumer goods, domestic	0.0%	0.0%
TO: consumer goods, foreign	0.0%	0.0%
TO: capital goods, domestic	0.0%	0.0%
TO: capital goods, foreign	0.0%	0.0%
TO: consumer durables, domestic	0.0%	0.0%
TO: consumer durables, foreign	0.0%	0.0%
TO: consumer non-durables, domestic	0.0%	0.0%
TO: consumer non-durables, foreign	0.0%	0.0%
TO: mining and quarrying, domestic	3.1%	0.0%
TO: mining and quarrying, foreign	0.0%	0.0%
TO: energy, gas etc. supply, domestic	18.8%	3.1%
TO: energy, gas etc. supply, foreign	0.0%	6.3%
TO: chemicals, domestic	0.0%	0.0%
TO: chemicals, foreign	0.0%	0.0%
TO: mechanical engineering, domestic	0.0%	0.0%
TO: mechanical engineering, foreign	0.0%	0.0%
TO: motor vehicles, trailers etc., domestic	0.0%	0.0%
TO: motor vehicles, trailers etc., foreign	0.0%	0.0%
TO: comp., electr. and opt. prod., domestic	0.0%	0.0%
TO: comp., electr. and opt. prod., foreign	0.0%	0.0%
new orders (NO): manufacturing total	0.0%	0.0%
NO: manufacturing total, domestic	3.1%	6.3%
NO: manufacturing total, foreign	0.0%	0.0%
NO: intermediate goods	0.0%	0.0%
NO: intermediate goods, domestic	0.0%	0.0%
NO: intermediate goods, foreign	0.0%	0.0%
NO: consumer goods	62.5%	56.3%
NO: consumer goods, domestic	0.0%	0.0%

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Table 3: List of indicators and cumulative frequency for the Free State of Saxony – continued

Indicator	h = 1	h = 2
NO: consumer goods, foreign	0.0%	0.0%
NO: capital goods	0.0%	0.0%
NO: capital goods, domestic	0.0%	0.0%
NO: capital goods, foreign	0.0%	0.0%
NO: chemicals, domestic	0.0%	40.6%
NO: chemicals, foreign	0.0%	0.0%
NO: mechanical engineering, domestic	0.0%	0.0%
NO: mechanical engineering, foreign	0.0%	0.0%
NO: motor vehicles, trailers etc., domestic	37.5%	43.8%
NO: motor vehicles, trailers etc., foreign	0.0%	0.0%
NO: comp., electr. and opt. prod., domestic	0.0%	0.0%
NO: comp., electr. and opt. prod., foreign	0.0%	0.0%
wholesale trade (WT): total employment	0.0%	0.0%
retail sales (RS): turnover, total (excl. cars)	6.3%	9.4%
new registrations (NR): all vehicles	0.0%	31.3%
NR: cars	0.0%	0.0%
NR: heavy trucks	0.0%	0.0%
exports: volume index, basis 2005	0.0%	0.0%
imports: volume index, basis 2005	0.0%	0.0%
unemployed persons (UNP): total, % of civilian labor	0.0%	0.0%
employed persons (EMPL): residence concept, total	0.0%	0.0%
EMPL: work-place concept, total	0.0%	0.0%
working days: total	0.0%	0.0%
vacancies: total	0.0%	31.3%
wages and salaries (WS): total economy, hourly basis	0.0%	0.0%
WS: total economy, per employed person	0.0%	0.0%
Euro-Coin real time estimates	0.0%	0.0%
Prices		
consumer price index	0.0%	0.0%
consumer price index (excl. energy)	0.0%	0.0%
producer price index	0.0%	0.0%
wholesale trade price index, 1975=100	0.0%	0.0%
export price index	0.0%	0.0%
import price index	0.0%	0.0%
HWWA index of world market prices: eurozone, energy	3.1%	0.0%
HWWA index of world market prices: eurozone, excl. energy	0.0%	6.3%
oil prices, euro per barrel	0.0%	0.0%
UK average brent oil price	0.0%	59.4%
London gold price, per US \$	18.8%	28.1%
Surveys		
ZEW: economic sentiment indicator	0.0%	0.0%
ZEW: present economic situation	0.0%	0.0%
ifo business climate industry and trade	0.0%	0.0%
ifo: assessm. of business situation industry and trade	0.0%	0.0%
ifo: business expectations industry and trade	0.0%	0.0%
ifo: business climate manufacturing	0.0%	0.0%
ifo: assessment of business situation manufacturing	0.0%	0.0%
ifo: business expectations manufacturing	0.0%	0.0%
ifo: inventory of finished goods manufacturing	0.0%	0.0%
ifo: orders on hand manufacturing	0.0%	0.0%
ifo: foreign orders on hand manufacturing	0.0%	0.0%
ifo: export expectations next 3 months manufacturing	0.0%	0.0%
ifo: business climate intermediate goods	0.0%	0.0%

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Table 3: List of indicators and cumulative frequency for the Free State of Saxony – continued

Indicator	h = 1	h = 2
ifo: assessm. of business sit. intermediate goods	3.1%	0.0%
ifo: production expectations intermediate goods	0.0%	0.0%
ifo: business climate consumer goods	0.0%	0.0%
ifo: assessment of business situation consumer goods	0.0%	0.0%
ifo: business expectations consumer goods	0.0%	0.0%
ifo: business climate capital goods	0.0%	0.0%
ifo: assessment of business situation capital goods	0.0%	0.0%
ifo: production expectations capital goods	0.0%	0.0%
ifo: business climate consumer durables	0.0%	0.0%
ifo: assessment of business situation consumer durables	0.0%	0.0%
ifo: production expectations consumer durables	0.0%	25.0%
ifo: business climate consumer non-durables	9.4%	0.0%
ifo: assessm. of business sit. consumer non-durables	0.0%	0.0%
ifo: production expectations consumer non-durables	6.3%	3.1%
ifo: business climate construction	0.0%	0.0%
ifo: assessment of business situation construction	0.0%	0.0%
ifo: business expectations construction	0.0%	0.0%
ifo: construction unfavourable weather	0.0%	0.0%
ifo: orders on hand construction	0.0%	0.0%
ifo: business climate wholesale trade	0.0%	0.0%
ifo: assessment of business situation wholesale trade	0.0%	0.0%
ifo: business expectations wholesale trade	0.0%	0.0%
ifo: assessment of inventories wholesale trade	0.0%	0.0%
ifo: expect. with regard to order activ. next 3 months WT	0.0%	0.0%
ifo: business climate retail sales	0.0%	0.0%
ifo: assessment of inventories retail sales	0.0%	0.0%
ifo: business expectations retail sales	0.0%	0.0%
ifo: expect. with regard to order activ. next 3 months RS	0.0%	0.0%
EU consumer survey (EUCS): unemploy. expect. next 12 months	0.0%	0.0%
EUCS: statement on financial situation	0.0%	0.0%
EUCS: consumer confidence indicator	0.0%	0.0%
EUCS: economic sentiment indicator	0.0%	0.0%
EU business survey (EUBS): product. trends recent month, ind.	0.0%	12.5%
EUBS: assessment of order-book levels, industry	0.0%	0.0%
EUBS: assessment of export order-books level, industry	0.0%	0.0%
EUBS: assessment of stocks of finished products, industry	0.0%	0.0%
EUBS: production expectations for the month ahead, industry	0.0%	0.0%
EUBS: selling price expectations for the month ahead, industry	0.0%	9.4%
EUBS: employment expectations for the month ahead, industry	0.0%	0.0%
EUBS: industrial confidence indicator	0.0%	0.0%
EUBS: service sector confidence indicator	0.0%	0.0%
EUBS: retail trade confidence indicator	0.0%	0.0%
EUBS: construction confidence indicator	0.0%	0.0%
International		
Bulgarian business indicator survey, whole economy	0.0%	3.1%
Bulgarian business indicator survey, manufacturing	0.0%	9.4%
EUCS: economic sentiment indicator, France	0.0%	0.0%
EUCS: economic sentiment indicator, Spain	0.0%	0.0%
EUCS: economic sentiment indicator, Poland	0.0%	0.0%
EUCS: economic sentiment indicator, Czech Republic	0.0%	0.0%
EUCS: economic sentiment indicator, Italy	0.0%	0.0%
EUCS: economic sentiment indicator, United Kingdom	0.0%	0.0%
University of Michigan consumer sentiment	0.0%	0.0%

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Table 3: List of indicators and cumulative frequency for the Free State of Saxony – continued

Indicator	h = 1	h = 2
IP: United States, total	0.0%	0.0%
OECD Composite Leading Indicator (CLI): OECD, ampl. adj.	0.0%	0.0%
CLI: OECD, trend restored	0.0%	0.0%
CLI: OECD, normalised	15.6%	0.0%
CLI: Asia, amplitude adjusted	0.0%	0.0%
CLI: Asia, trend restored	0.0%	0.0%
CLI: Asia, normalised	0.0%	0.0%
CLI: China, amplitude adjusted	0.0%	0.0%
CLI: China, trend restored	0.0%	0.0%
CLI: China, normalised	62.5%	56.3%
CLI: Euro Area, amplitude adjusted	0.0%	0.0%
CLI: Euro Area, trend restored	0.0%	0.0%
CLI: Euro Area, normalised	0.0%	6.3%
CLI: United States, amplitude adjusted	6.3%	0.0%
CLI: United States, trend restored	0.0%	0.0%
CLI: United States, normalised	59.4%	0.0%
Regional		
ifo business climate industry and trade, Saxony	0.0%	0.0%
ifo SAX: assessm. of business situation industry and trade	0.0%	0.0%
ifo SAX: business expectations industry and trade	0.0%	0.0%
ifo SAX: business climate manufacturing	0.0%	0.0%
ifo SAX: assessment of business situation manufacturing	0.0%	0.0%
ifo SAX: business expectations manufacturing	0.0%	0.0%
ifo SAX: export expectations manufacturing	0.0%	0.0%
ifo SAX: business climate intermediate goods	0.0%	0.0%
ifo SAX: assessm. of business sit. intermediate goods	0.0%	0.0%
ifo SAX: business expectations intermediate goods	0.0%	0.0%
ifo SAX: business climate consumer goods	0.0%	0.0%
ifo SAX: assessment of business situation consumer goods	0.0%	0.0%
ifo SAX: business expectations consumer goods	0.0%	0.0%
ifo SAX: business climate capital goods	0.0%	0.0%
ifo SAX: assessment of business situation capital goods	0.0%	0.0%
ifo SAX: business expectations capital goods	0.0%	0.0%
ifo SAX: business climate consumer non-durables	0.0%	0.0%
ifo SAX: assessm. of business sit. consumer non-durables	0.0%	0.0%
ifo SAX: business expectations consumer non-durables	0.0%	0.0%
ifo SAX: business climate food, beverage and tobacco	0.0%	0.0%
ifo SAX: assessm. of business sit. food, beverage and tobacco	0.0%	0.0%
ifo SAX: business expectations food, beverage and tobacco	0.0%	28.1%
ifo SAX: business climate chemicals	0.0%	56.3%
ifo SAX: assessm. of business sit. chemicals	12.5%	0.0%
ifo SAX: business expectations chemicals	0.0%	25.0%
ifo SAX: business climate mechanical engineering	6.3%	0.0%
ifo SAX: assessm. of business sit. mechanical engineering	0.0%	15.6%
ifo SAX: business expectations mechanical engineering	0.0%	0.0%
ifo SAX: business climate motor vehicles, trailers etc.	0.0%	0.0%
ifo SAX: assessm. of business sit. motor vehicles, trailers etc.	0.0%	0.0%
ifo SAX: business expectations motor vehicles, trailers etc.	0.0%	0.0%
ifo SAX: business climate construction	0.0%	0.0%
ifo SAX: assessment of business situation construction	0.0%	0.0%
ifo SAX: business expectations construction	0.0%	0.0%
ifo SAX: business climate building construction	0.0%	0.0%
ifo SAX: assessm. of business sit. building construction	0.0%	0.0%

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Table 3: List of indicators and cumulative frequency for the Free State of Saxony – continued

Indicator	h = 1	h = 2
ifo SAX: business expectations building construction	0.0%	0.0%
ifo SAX: business climate underground construction	0.0%	0.0%
ifo SAX: assessm. of business sit. underground construction	0.0%	0.0%
ifo SAX: business expectations underground construction	0.0%	0.0%
ifo SAX: employment expectations construction	0.0%	0.0%
ifo SAX: business climate wholesale trade	3.1%	0.0%
ifo SAX: assessment of business situation wholesale trade	0.0%	0.0%
ifo SAX: business expectations wholesale trade	75.0%	78.1%
ifo SAX: employment expectations wholesale trade	0.0%	0.0%
ifo SAX: business climate retail sales	0.0%	0.0%
ifo SAX: assessment of business situation retail sales	0.0%	0.0%
ifo SAX: business expectations retail sales	0.0%	0.0%
ifo SAX: employment expectations retail sales	0.0%	0.0%
turnover (TO): housing construction, Saxony	0.0%	0.0%
TO: commercial construction, Saxony	21.9%	34.4%
TO: public construction, Saxony	0.0%	0.0%
new orders (NO): manufacturing total, Saxony	0.0%	0.0%
NO: construction total, Saxony	0.0%	0.0%
NO: housing construction, Saxony	0.0%	0.0%
NO: commercial construction, Saxony	90.6%	3.1%
NO: public construction, Saxony	12.5%	0.0%
exports: values, Saxony	0.0%	3.1%
imports: values, Saxony	0.0%	0.0%
working hours (WH): construction total, Saxony	0.0%	0.0%
WH: housing construction, Saxony	0.0%	0.0%
WH: commercial construction, Saxony	0.0%	0.0%
WH: public construction, Saxony	0.0%	0.0%
number of firms, construction total, Saxony	0.0%	9.4%
number of employed persons, construction total, Saxony	0.0%	0.0%
compensations, construction total, Saxony	0.0%	0.0%
consumer price index, Saxony	0.0%	0.0%
capacity utilization, construction total, Saxony	0.0%	0.0%
range of orders on hand, construction total, Saxony	0.0%	0.0%

Note: The table presents the relative frequencies of all indicators in our sample for the different forecasting horizons. A value of 100% is reached if an indicator gets chosen by the algorithm 32 times, thus, for the length of our forecasting period. An indicator is assigned with 0% if this indicator is not chosen over the forecasting period at all.

Table 4: List of indicators and cumulative frequency for Baden-Wuerttemberg

Indicator	h = 1	h = 2
Target variable		
gross domestic product (GDP): Baden-Wuerttemberg	18.8%	0.0%
Macroeconomic variables		
industrial production (IP): total (incl. construction)	0.0%	0.0%
IP manufacturing: total	0.0%	0.0%
IP manufacturing: intermediate goods	0.0%	0.0%
IP manufacturing: consumer goods	12.5%	6.3%
IP manufacturing: capital goods	0.0%	0.0%
IP manufacturing: consumer durables	84.4%	6.3%
IP manufacturing: consumer non-durables	3.1%	46.9%
IP manufacturing: mining and quarrying	0.0%	0.0%
IP manufacturing: chemicals	0.0%	0.0%
IP manufacturing: basic metals	0.0%	0.0%
IP manufacturing: mechanical engineering	0.0%	0.0%
IP manufacturing: motor vehicles, trailers etc.	0.0%	0.0%
IP construction: total	9.4%	0.0%
IP energy supply: total	3.1%	0.0%
turnover (TO): manufacturing total, domestic	0.0%	0.0%
TO: manufacturing total, foreign	0.0%	0.0%
TO: intermediate goods, domestic	21.9%	0.0%
TO: intermediate goods, foreign	0.0%	0.0%
TO: consumer goods, domestic	12.5%	6.3%
TO: consumer goods, foreign	0.0%	0.0%
TO: capital goods, domestic	0.0%	0.0%
TO: capital goods, foreign	0.0%	0.0%
TO: consumer durables, domestic	25.0%	12.5%
TO: consumer durables, foreign	0.0%	0.0%
TO: consumer non-durables, domestic	3.1%	25.0%
TO: consumer non-durables, foreign	0.0%	0.0%
TO: mining and quarrying, domestic	0.0%	0.0%
TO: mining and quarrying, foreign	0.0%	0.0%
TO: energy, gas etc. supply, domestic	9.4%	0.0%
TO: energy, gas etc. supply, foreign	46.9%	62.5%
TO: chemicals, domestic	0.0%	31.3%
TO: chemicals, foreign	0.0%	0.0%
TO: mechanical engineering, domestic	0.0%	37.5%
TO: mechanical engineering, foreign	21.9%	0.0%
TO: motor vehicles, trailers etc., domestic	3.1%	3.1%
TO: motor vehicles, trailers etc., foreign	9.4%	0.0%
TO: comp., electr. and opt. prod., domestic	15.6%	0.0%
TO: comp., electr. and opt. prod., foreign	0.0%	0.0%
new orders (NO): manufacturing total	0.0%	0.0%
NO: manufacturing total, domestic	0.0%	0.0%
NO: manufacturing total, foreign	0.0%	0.0%
NO: intermediate goods	0.0%	0.0%
NO: intermediate goods, domestic	46.9%	0.0%
NO: intermediate goods, foreign	0.0%	0.0%
NO: consumer goods	81.3%	6.3%
NO: consumer goods, domestic	0.0%	3.1%
NO: consumer goods, foreign	90.6%	56.3%
NO: capital goods	0.0%	0.0%

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Table 4: List of indicators and cumulative frequency for Baden-Wuerttemberg – continued

Indicator	h = 1	h = 2
NO: capital goods, domestic	0.0%	0.0%
NO: capital goods, foreign	0.0%	0.0%
NO: chemicals, domestic	0.0%	3.1%
NO: chemicals, foreign	0.0%	0.0%
NO: mechanical engineering, domestic	0.0%	6.3%
NO: mechanical engineering, foreign	0.0%	0.0%
NO: motor vehicles, trailers etc., domestic	31.3%	62.5%
NO: motor vehicles, trailers etc., foreign	68.8%	12.5%
NO: comp., electr. and opt. prod., domestic	37.5%	40.6%
NO: comp., electr. and opt. prod., foreign	3.1%	0.0%
wholesale trade (WT): total employment	0.0%	12.5%
retail sales (RS): turnover, total (excl. cars)	15.6%	9.4%
new registrations (NR): all vehicles	3.1%	9.4%
NR: cars	25.0%	68.8%
NR: heavy trucks	0.0%	0.0%
exports: volume index, basis 2005	0.0%	0.0%
imports: volume index, basis 2005	0.0%	0.0%
unemployed persons (UNP): total, % of civilian labor	0.0%	0.0%
employed persons (EMPL): residence concept, total	0.0%	0.0%
EMPL: work-place concept, total	0.0%	0.0%
working days: total	96.9%	84.4%
vacancies: total	100.0%	100.0%
wages and salaries (WS): total economy, hourly basis	0.0%	0.0%
WS: total economy, per employed person	0.0%	0.0%
Euro-Coin real time estimates	0.0%	0.0%
Prices		
consumer price index	0.0%	0.0%
consumer price index (excl. energy)	0.0%	31.3%
producer price index	0.0%	15.6%
wholesale trade price index, 1975=100	0.0%	0.0%
export price index	0.0%	0.0%
import price index	0.0%	3.1%
HWWA index of world market prices: eurozone, energy	0.0%	0.0%
HWWA index of world market prices: eurozone, excl. energy	25.0%	0.0%
oil prices, euro per barrel	0.0%	0.0%
UK average brent oil price	0.0%	25.0%
Zdon gold price, per US \$	6.3%	6.3%
Surveys		
ZEW: economic sentiment indicator	0.0%	0.0%
ZEW: present economic situation	31.3%	0.0%
ifo business climate industry and trade	0.0%	0.0%
ifo: assessm. of business situation industry and trade	0.0%	0.0%
ifo: business expectations industry and trade	0.0%	0.0%
ifo: business climate manufacturing	0.0%	0.0%
ifo: assessment of business situation manufacturing	0.0%	0.0%
ifo: business expectations manufacturing	0.0%	0.0%
ifo: inventory of finished goods manufacturing	0.0%	0.0%
ifo: orders on hand manufacturing	0.0%	0.0%
ifo: foreign orders on hand manufacturing	0.0%	0.0%
ifo: export expectations next 3 months manufacturing	0.0%	0.0%
ifo: business climate intermediate goods	0.0%	0.0%
ifo: assessm. of business sit. intermediate goods	0.0%	0.0%
ifo: production expectations intermediate goods	0.0%	0.0%
<i>Continued on next page...</i>		

Table 4: List of indicators and cumulative frequency for Baden-Wuerttemberg – continued

Indicator	h = 1	h = 2
ifo: business climate consumer goods	0.0%	0.0%
ifo: assessment of business situation consumer goods	0.0%	0.0%
ifo: business expectations consumer goods	0.0%	0.0%
ifo: business climate capital goods	0.0%	0.0%
ifo: assessment of business situation capital goods	0.0%	0.0%
ifo: production expectations capital goods	0.0%	0.0%
ifo: business climate consumer durables	6.3%	0.0%
ifo: assessment of business situation consumer durables	0.0%	0.0%
ifo: production expectations consumer durables	90.6%	100.0%
ifo: business climate consumer non-durables	0.0%	6.3%
ifo: assessm. of business sit. consumer non-durables	0.0%	0.0%
ifo: production expectations consumer non-durables	0.0%	0.0%
ifo: business climate construction	0.0%	0.0%
ifo: assessment of business situation construction	0.0%	0.0%
ifo: business expectations construction	0.0%	0.0%
ifo: construction unfavourable weather	0.0%	0.0%
ifo: orders on hand construction	0.0%	0.0%
ifo: business climate wholesale trade	0.0%	0.0%
ifo: assessment of business situation wholesale trade	0.0%	0.0%
ifo: business expectations wholesale trade	0.0%	0.0%
ifo: assessment of inventories wholesale trade	0.0%	0.0%
ifo: expect. with regard to order activ. next 3 months WT	0.0%	0.0%
ifo: business climate retail sales	0.0%	0.0%
ifo: assessment of inventories retail sales	0.0%	0.0%
ifo: business expectations retail sales	0.0%	0.0%
ifo: expect. with regard to order activ. next 3 months RS	0.0%	0.0%
EU consumer survey (EUCS): unemploy. expect. next 12 months	0.0%	0.0%
EUCS: statement on financial situation	0.0%	0.0%
EUCS: consumer confidence indicator	0.0%	0.0%
EUCS: economic sentiment indicator	0.0%	0.0%
EU business survey (EUBS): product. trends recent month, ind.	0.0%	0.0%
EUBS: assessment of order-book levels, industry	0.0%	0.0%
EUBS: assessment of export order-books level, industry	0.0%	0.0%
EUBS: assessment of stocks of finished products, industry	0.0%	0.0%
EUBS: production expectations for the month ahead, industry	0.0%	0.0%
EUBS: selling price expectations for the month ahead, industry	62.5%	59.4%
EUBS: employment expectations for the month ahead, industry	0.0%	0.0%
EUBS: industrial confidence indicator	0.0%	0.0%
EUBS: service sector confidence indicator	6.3%	6.3%
EUBS: retail trade confidence indicator	68.8%	0.0%
EUBS: construction confidence indicator	0.0%	0.0%
International		
Bulgarian business indicator survey, whole economy	3.1%	0.0%
Bulgarian business indicator survey, manufacturing	0.0%	0.0%
EUCS: economic sentiment indicator, France	0.0%	0.0%
EUCS: economic sentiment indicator, Spain	0.0%	0.0%
EUCS: economic sentiment indicator, Poland	0.0%	0.0%
EUCS: economic sentiment indicator, Czech Republic	0.0%	0.0%
EUCS: economic sentiment indicator, Italy	0.0%	0.0%
EUCS: economic sentiment indicator, United Kingdom	0.0%	0.0%
University of Michigan consumer sentiment	0.0%	0.0%
IP: United States, total	0.0%	0.0%
OECD Composite Leading Indicator (CLI): OECD, ampl. adj.	0.0%	0.0%

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Table 4: List of indicators and cumulative frequency for Baden-Wuerttemberg – continued

Indicator	h = 1	h = 2
CLI: OECD, trend restored	0.0%	0.0%
CLI: OECD, normalised	6.3%	0.0%
CLI: Asia, amplitude adjusted	0.0%	9.4%
CLI: Asia, trend restored	0.0%	0.0%
CLI: Asia, normalised	0.0%	3.1%
CLI: China, amplitude adjusted	31.3%	0.0%
CLI: China, trend restored	0.0%	0.0%
CLI: China, normalised	62.5%	59.4%
CLI: Euro Area, amplitude adjusted	31.3%	0.0%
CLI: Euro Area, trend restored	0.0%	0.0%
CLI: Euro Area, normalised	0.0%	50.0%
CLI: United States, amplitude adjusted	0.0%	0.0%
CLI: United States, trend restored	0.0%	0.0%
CLI: United States, normalised	0.0%	0.0%
Regional		
ifo business climate manufacturing, Baden-Wuerttemberg	0.0%	0.0%
ifo BW: assessment of business situation manufacturing	0.0%	0.0%
ifo BW: business expectations manufacturing	0.0%	0.0%
ifo BW: business climate construction	0.0%	0.0%
ifo BW: assessment of business situation construction	0.0%	0.0%
ifo BW: business expectations construction	0.0%	0.0%
ifo BW: employment expectations construction	0.0%	0.0%
ifo BW: business climate wholesale trade	0.0%	0.0%
ifo BW: assessment of business situation wholesale trade	0.0%	0.0%
ifo BW: business expectations wholesale trade	12.5%	3.1%
ifo BW: employment expectations wholesale trade	0.0%	0.0%
ifo BW: business climate retail sales	0.0%	0.0%
ifo BW: assessment of business situation retail sales	0.0%	0.0%
ifo BW: business expectations retail sales	71.9%	59.4%
ifo BW: employment expectations retail sales	0.0%	0.0%
industrial production (IP): total (incl. construction), BW	3.1%	6.3%
turnover (TO): construction total, BW	15.6%	0.0%
TO: housing construction, BW	0.0%	6.3%
TO: commercial construction, BW	25.0%	0.0%
TO: public construction, BW	12.5%	21.9%
new orders (NO): manufacturing domestic, BW	62.5%	6.3%
NO: manufacturing foreign, BW	3.1%	62.5%
NO: construction total, BW	15.6%	3.1%
NO: housing construction, BW	0.0%	6.3%
NO: commercial construction, BW	21.9%	15.6%
NO: public construction, BW	81.3%	31.3%
working hours (WH): construction total, BW	0.0%	0.0%
WH: housing construction, BW	0.0%	0.0%
WH: commercial construction, BW	0.0%	59.4%
WH: public construction, BW	53.1%	0.0%
number of firms, construction total, BW	0.0%	0.0%
number of employed persons, construction total, BW	0.0%	0.0%
compensations, construction total, BW	0.0%	0.0%
consumer price index, BW	0.0%	0.0%
capacity utilization, construction total, BW	0.0%	0.0%
business cycle indicator BW	0.0%	46.9%

Note: The table presents the relative frequencies of all indicators in our sample for the different forecasting horizons. A value of 100% is reached if an indicator gets chosen by the algorithm 32 times, thus, for the length of our forecasting period. An indicator is assigned with 0% if this indicator is not chosen over the forecasting period at all.

Table 5: List of indicators and cumulative frequency for Eastern Germany

Indicator	h = 1	h = 2
Target variable		
gross domestic product (GDP): Eastern Germany	62.5%	0.0%
Macroeconomic variables		
industrial production (IP): total (incl. construction)	0.0%	0.0%
IP manufacturing: total	0.0%	0.0%
IP manufacturing: intermediate goods	0.0%	0.0%
IP manufacturing: consumer goods	0.0%	12.5%
IP manufacturing: capital goods	0.0%	0.0%
IP manufacturing: consumer durables	25.0%	0.0%
IP manufacturing: consumer non-durables	0.0%	3.1%
IP manufacturing: mining and quarrying	0.0%	0.0%
IP manufacturing: chemicals	0.0%	0.0%
IP manufacturing: basic metals	0.0%	0.0%
IP manufacturing: mechanical engineering	0.0%	15.6%
IP manufacturing: motor vehicles, trailers etc.	0.0%	0.0%
IP construction: total	65.6%	25.0%
IP energy supply: total	0.0%	0.0%
turnover (TO): manufacturing total, domestic	0.0%	0.0%
TO: manufacturing total, foreign	0.0%	0.0%
TO: intermediate goods, domestic	28.1%	0.0%
TO: intermediate goods, foreign	0.0%	0.0%
TO: consumer goods, domestic	0.0%	0.0%
TO: consumer goods, foreign	0.0%	0.0%
TO: capital goods, domestic	0.0%	0.0%
TO: capital goods, foreign	0.0%	0.0%
TO: consumer durables, domestic	6.3%	0.0%
TO: consumer durables, foreign	0.0%	0.0%
TO: consumer non-durables, domestic	0.0%	50.0%
TO: consumer non-durables, foreign	0.0%	0.0%
TO: mining and quarrying, domestic	0.0%	0.0%
TO: mining and quarrying, foreign	0.0%	0.0%
TO: energy, gas etc. supply, domestic	0.0%	9.4%
TO: energy, gas etc. supply, foreign	0.0%	0.0%
TO: chemicals, domestic	0.0%	21.9%
TO: chemicals, foreign	0.0%	0.0%
TO: mechanical engineering, domestic	0.0%	0.0%
TO: mechanical engineering, foreign	0.0%	0.0%
TO: motor vehicles, trailers etc., domestic	3.1%	0.0%
TO: motor vehicles, trailers etc., foreign	3.1%	0.0%
TO: comp., electr. and opt. prod., domestic	0.0%	0.0%
TO: comp., electr. and opt. prod., foreign	0.0%	0.0%
new orders (NO): manufacturing total	0.0%	0.0%
NO: manufacturing total, domestic	3.1%	0.0%
NO: manufacturing total, foreign	0.0%	0.0%
NO: intermediate goods	0.0%	0.0%
NO: intermediate goods, domestic	9.4%	0.0%
NO: intermediate goods, foreign	0.0%	0.0%
NO: consumer goods	59.4%	18.8%
NO: consumer goods, domestic	6.3%	0.0%

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Table 5: List of indicators and cumulative frequency for Eastern Germany – continued

Indicator	h = 1	h = 2
NO: consumer goods, foreign	0.0%	0.0%
NO: capital goods	0.0%	0.0%
NO: capital goods, domestic	0.0%	0.0%
NO: capital goods, foreign	0.0%	0.0%
NO: chemicals, domestic	0.0%	0.0%
NO: chemicals, foreign	0.0%	0.0%
NO: mechanical engineering, domestic	0.0%	0.0%
NO: mechanical engineering, foreign	0.0%	0.0%
NO: motor vehicles, trailers etc., domestic	37.5%	40.6%
NO: motor vehicles, trailers etc., foreign	0.0%	0.0%
NO: comp., electr. and opt. prod., domestic	0.0%	0.0%
NO: comp., electr. and opt. prod., foreign	0.0%	0.0%
wholesale trade (WT): total employment	0.0%	0.0%
retail sales (RS): turnover, total (excl. cars)	43.8%	6.3%
new registrations (NR): all vehicles	0.0%	50.0%
NR: cars	0.0%	18.8%
NR: heavy trucks	0.0%	21.9%
exports: volume index, basis 2005	0.0%	0.0%
imports: volume index, basis 2005	0.0%	0.0%
unemployed persons (UNP): total, % of civilian labor	0.0%	0.0%
employed persons (EMPL): residence concept, total	0.0%	0.0%
EMPL: work-place concept, total	0.0%	0.0%
working days: total	0.0%	3.1%
vacancies: total	96.9%	93.8%
wages and salaries (WS): total economy, hourly basis	0.0%	0.0%
WS: total economy, per employed person	0.0%	0.0%
Euro-Coin real time estimates	0.0%	0.0%
Prices		
consumer price index	0.0%	0.0%
consumer price index (excl. energy)	0.0%	0.0%
producer price index	3.1%	0.0%
wholesale trade price index, 1975=100	0.0%	18.8%
export price index	0.0%	6.3%
import price index	0.0%	0.0%
HWWA index of world market prices: eurozone, energy	0.0%	0.0%
HWWA index of world market prices: eurozone, excl. energy	0.0%	0.0%
oil prices, euro per barrel	0.0%	0.0%
UK average brent oil price	0.0%	15.6%
London gold price, per US \$	0.0%	18.8%
Surveys		
ZEW: economic sentiment indicator	0.0%	0.0%
ZEW: present economic situation	0.0%	0.0%
ifo business climate industry and trade	0.0%	0.0%
ifo: assessm. of business situation industry and trade	0.0%	0.0%
ifo: business expectations industry and trade	0.0%	0.0%
ifo: business climate manufacturing	0.0%	0.0%
ifo: assessment of business situation manufacturing	0.0%	0.0%
ifo: business expectations manufacturing	0.0%	0.0%
ifo: inventory of finished goods manufacturing	0.0%	0.0%
ifo: orders on hand manufacturing	0.0%	0.0%
ifo: foreign orders on hand manufacturing	0.0%	0.0%
ifo: export expectations next 3 months manufacturing	0.0%	0.0%
ifo: business climate intermediate goods	0.0%	0.0%
<i>Continued on next page...</i>		

Table 5: List of indicators and cumulative frequency for Eastern Germany – continued

Indicator	h = 1	h = 2
ifo: assessm. of business sit. intermediate goods	0.0%	3.1%
ifo: production expectations intermediate goods	15.6%	0.0%
ifo: business climate consumer goods	0.0%	0.0%
ifo: assessment of business situation consumer goods	0.0%	0.0%
ifo: business expectations consumer goods	0.0%	0.0%
ifo: business climate capital goods	0.0%	0.0%
ifo: assessment of business situation capital goods	0.0%	0.0%
ifo: production expectations capital goods	0.0%	0.0%
ifo: business climate consumer durables	0.0%	0.0%
ifo: assessment of business situation consumer durables	0.0%	0.0%
ifo: production expectations consumer durables	50.0%	53.1%
ifo: business climate consumer non-durables	0.0%	0.0%
ifo: assessm. of business sit. consumer non-durables	0.0%	0.0%
ifo: production expectations consumer non-durables	9.4%	0.0%
ifo: business climate construction	0.0%	0.0%
ifo: assessment of business situation construction	0.0%	3.1%
ifo: business expectations construction	0.0%	0.0%
ifo: construction unfavourable weather	0.0%	25.0%
ifo: orders on hand construction	0.0%	0.0%
ifo: business climate wholesale trade	0.0%	0.0%
ifo: assessment of business situation wholesale trade	0.0%	0.0%
ifo: business expectations wholesale trade	0.0%	0.0%
ifo: assessment of inventories wholesale trade	0.0%	0.0%
ifo: expect. with regard to order activ. next 3 months WT	0.0%	0.0%
ifo: business climate retail sales	0.0%	0.0%
ifo: assessment of inventories retail sales	0.0%	0.0%
ifo: business expectations retail sales	0.0%	0.0%
ifo: expect. with regard to order activ. next 3 months RS	0.0%	0.0%
EU consumer survey (EUCS): unemploy. expect. next 12 months	0.0%	0.0%
EUCS: statement on financial situation	0.0%	0.0%
EUCS: consumer confidence indicator	0.0%	0.0%
EUCS: economic sentiment indicator	0.0%	0.0%
EU business survey (EUBS): product. trends recent month, ind.	0.0%	0.0%
EUBS: assessment of order-book levels, industry	0.0%	0.0%
EUBS: assessment of export order-books level, industry	0.0%	15.6%
EUBS: assessment of stocks of finished products, industry	0.0%	0.0%
EUBS: production expectations for the month ahead, industry	0.0%	0.0%
EUBS: selling price expectations for the month ahead, industry	0.0%	28.1%
EUBS: employment expectations for the month ahead, industry	0.0%	0.0%
EUBS: industrial confidence indicator	0.0%	0.0%
EUBS: service sector confidence indicator	3.1%	6.3%
EUBS: retail trade confidence indicator	0.0%	0.0%
EUBS: construction confidence indicator	0.0%	0.0%
International		
Bulgarian business indicator survey, whole economy	0.0%	0.0%
Bulgarian business indicator survey, manufacturing	0.0%	9.4%
EUCS: economic sentiment indicator, France	0.0%	0.0%
EUCS: economic sentiment indicator, Spain	0.0%	0.0%
EUCS: economic sentiment indicator, Poland	0.0%	0.0%
EUCS: economic sentiment indicator, Czech Republic	0.0%	0.0%
EUCS: economic sentiment indicator, Italy	0.0%	0.0%
EUCS: economic sentiment indicator, United Kingdom	0.0%	0.0%
University of Michigan consumer sentiment	0.0%	0.0%

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Table 5: List of indicators and cumulative frequency for Eastern Germany – continued

Indicator	h = 1	h = 2
IP: United States, total	0.0%	0.0%
OECD Composite Leading Indicator (CLI): OECD, ampl. adj.	3.1%	0.0%
CLI: OECD, trend restored	0.0%	0.0%
CLI: OECD, normalised	71.9%	43.8%
CLI: Asia, amplitude adjusted	40.6%	3.1%
CLI: Asia, trend restored	0.0%	0.0%
CLI: Asia, normalised	0.0%	0.0%
CLI: China, amplitude adjusted	0.0%	0.0%
CLI: China, trend restored	0.0%	0.0%
CLI: China, normalised	62.5%	59.4%
CLI: Euro Area, amplitude adjusted	0.0%	0.0%
CLI: Euro Area, trend restored	0.0%	6.3%
CLI: Euro Area, normalised	0.0%	6.3%
CLI: United States, amplitude adjusted	21.9%	0.0%
CLI: United States, trend restored	0.0%	18.8%
CLI: United States, normalised	100.0%	50.0%
Regional		
ifo EG: business climate manufacturing	0.0%	0.0%
ifo EG: assessment of business situation manufacturing	0.0%	0.0%
ifo EG: business expectations manufacturing	9.4%	0.0%
ifo EG: business climate construction	0.0%	0.0%
ifo EG: assessment of business situation construction	0.0%	0.0%
ifo EG: business expectations construction	0.0%	0.0%
ifo EG: employment expectations construction	0.0%	0.0%
ifo EG: business climate wholesale trade	0.0%	0.0%
ifo EG: assessment of business situation wholesale trade	0.0%	0.0%
ifo EG: business expectations wholesale trade	34.4%	21.9%
ifo EG: employment expectations wholesale trade	0.0%	0.0%
ifo EG: business climate retail sales	0.0%	0.0%
ifo EG: assessment of business situation retail sales	0.0%	0.0%
ifo EG: business expectations retail sales	0.0%	0.0%
ifo EG: employment expectations retail sales	0.0%	0.0%
turnover (TO): manufacturing, EG	0.0%	0.0%
TO: construction total, EG	0.0%	0.0%
TO: housing construction, EG	0.0%	0.0%
TO: commercial construction, EG	0.0%	15.6%
TO: public construction, EG	0.0%	0.0%
new orders (NO): construction total, EG	0.0%	0.0%
NO: housing construction, EG	3.1%	0.0%
NO: commercial construction, EG	0.0%	34.4%
NO: public construction, EG	0.0%	0.0%
working hours (WH): construction total, EG	0.0%	0.0%
WH: housing construction, EG	0.0%	0.0%
WH: commercial construction, EG	0.0%	0.0%
WH: public construction, EG	0.0%	0.0%
number of firms, construction total, EG	0.0%	0.0%
number of employed persons, construction total, EG	0.0%	0.0%
compensations, construction total, EG	0.0%	0.0%
consumer price index, EG	0.0%	0.0%
capacity utilization, construction total, EG	0.0%	0.0%
IWH business survey: business situation manufacturing, EG	0.0%	0.0%
IWH: business expectations manufacturing, EG	0.0%	0.0%
IWH: business situation construction, EG	25.0%	25.0%

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Table 5: List of indicators and cumulative frequency for Eastern Germany – continued

Indicator	h = 1	h = 2
IWH: business expectations construction, EG	0.0%	0.0%

Note: The table presents the relative frequencies of all indicators in our sample for the different forecasting horizons. A value of 100% is reached if an indicator gets chosen by the algorithm 32 times, thus, for the length of our forecasting period. An indicator is assigned with 0% if this indicator is not chosen over the forecasting period at all.