Looking into the Black Box of Boosting: The Case of Germany

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3 November 2015

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Abstract: This paper looks into the 'fine print' of boosting for economic forecasting. By using German industrial production for the period from 1996 to 2014 and a data set consisting of 175 monthly indicators, we evaluate which indicators get selected by the boosting algorithm over time and four different forecasting horizons. It turns out that a number of hard indicators like turnovers, as well as a small number of survey results, get selected frequently by the algorithm and are therefore important to forecasting the performance of the German economy. However, there are indicators such as money supply that never get chosen by the boosting approach at all.

Keywords: boosting, economic forecasting, industrial production

JEL Code: C53, E17, E37

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1. Introduction

Large data set methods such as factor models are widely accepted in the economic forecasting literature. A viable alternative that has attracted a lot of attention in recent years is boosting. While existing literature on this topic generally studies the performance of boosting for industrial production (see Buchen and Wohlrabe, 2011, 2014) or gold and silver returns (see Pierdzioch *et al.*, 2015a,b), only one study exists that takes a closer look at the results of the boosting approach for the US (see Kim and Swanson, 2014). Our paper not only assesses the performance of boosting to forecast industrial production, but also investigates whether there is a stable pattern in which the algorithm selects indicators into the model. In other words, it opens the 'black box' for boosting. We exemplary evaluate this research question for Germany, the largest economy in Europe, in the period from 1996 to 2014. In some ways our paper follows the study by Bańbura and Rünstler (2011) who investigate how single indicator series contribute to the forecast based on a factor model and the role played by publication lags in this context. The paper is organized as follows: Section 2 outlines the boosting algorithm, while Section 3 first presents the data and forecasting methodology, followed by a discussion of the results. The paper ends with a few conclusions.

2. Boosting Algorithm

This paper applies the L_2-boosting approach also used in the corresponding literature (see Buchen and Wohlrabe, 2011; Pierdzioch *et al.*, 2015a,b). 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 $N \geq T$, a pre-selection of variables is necessary to reduce the complexity of the chosen fitting procedure (Bühlmann and Yu, 2003). To achieve this, component-wise boosting estimates a generalized additive model. The well-accepted autoregressive distributed lag (ADL) model is chosen by us and has the following form:

$$\begin{aligned} E(y_t|\mathbf{z}_t, \delta) &=: F(\mathbf{z}_t, \delta) \\ &= \delta' \mathbf{z}_t \\ &= \alpha + \beta_1 y_{t-h} + \sum_{j=1}^{N} \gamma_j x^j_{t-h} \, . \end{aligned} \tag{1}$$

The vector $\mathbf{z} = (y, x^1, \ldots, x^N)$ comprises the lagged target variable to predict (y) and all lagged exogeneous predictors (x). We restrict our analysis to allow only a h-period lag of y or x^j. The number of exogeneous variables is denoted by N. All variables that are not selected by the algorithm obtain a zero restriction. In order to decide the selection, we apply the standard squared error loss (L_2):

$$L(y_t, F(\mathbf{z}_t, \delta)) = \frac{1}{2}(y_t - F(\mathbf{z}_t, \delta))^2 \tag{2}$$

From the pool of $k = 1+N$ potential predictors z_k, the algorithm chooses in every iteration m one variable $z_{k_m^*}$ that yields the smallest sum of squared residuals (SSR). But note that the chosen predictor in a specific iteration does not have to be necessarily different from those of the previous iterations. As the fitting procedure $F(.)$ in every iteration (called base learner) we apply ordinary least squares (OLS) for a linear model. The algorithm proceeds as follows:

1. Initialize $\widehat{f}_{t,0}(.) = \overline{y}$ for each t. Set $m = 0$.
2. Increase m by 1. For $t = 1, \ldots, T$, compute the negative gradient $-\frac{\partial L(y_t, F)}{\partial F}$ and evaluate at $\widehat{f}_{t,m-1}(\mathbf{z}_t, \widehat{\delta}^{[m-1]})$: $u_t = y_t - \widehat{f}_{t,m-1}(\mathbf{z}_t, \widehat{\delta}^{[m-1]})$.
3. For $k = 1, \ldots, 1+N$, regress the negative gradient vector u on z_k and compute $SSR_k = \sum_{t=1}^{T} (u_t - z_{t,k}\widehat{\theta}_k)^2$.
4. Choose $z_{k_m^*}$ such that $SSR_{k_m^*} = \arg\min_{k \in N} SSR_k$.
5. Let $\widehat{f}_{t,m}(.) = z_{t,k_m^*}\widehat{\theta}_{k_m^*}$.
6. For $t = 1, \ldots, T$, update $\widehat{f}_{t,m}(.) = \widehat{f}_{t,m-1}(.) + \nu \widehat{f}_{t,m}(.)$, where $0 < \nu < 1$.
7. Iterate steps 2 to 6 until $m = M^*$.

From steps 2 and 3 it immediately follows that L_2-loss-boosting is just a repeated least squares fitting of residuals. The algorithm converges to a function that represents the sum of M^* base learner estimates multiplied by the constant shrinkage parameter ν:

$$\widehat{F}(\mathbf{z}_t, \widehat{\delta}^{[M^*]}) = \sum_{m=0}^{M^*} \nu \widehat{f}_m(\mathbf{z}_t, \widehat{\theta}^{[m]}) \,. \tag{3}$$

The optimal number of iteration steps M^* minimizes the expected forecast error either estimated by cross-validation or by an information criterion. Friedman (2001) first introduces ν 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.

3. Opening the German Boosting Black Box

3.1. Data

Our data set covers the period from 1996 to 2014 and contains industrial production as the target series, as well as 175 monthly predictors, which we group into the following five categories: macroeconomic (72), finance (12), prices (10), surveys (56) and international (25). The first four categories measure variables at the national level (here: Germany) and include, for example, the Ifo business climate for industry and trade. Since Germany has an economy with a high degree of openness, we suggest that international indicators serve as predictors for German industrial production. Alongside the industrial production of the US, the fifth category also includes leading indicators for a multitude of countries like China and France. All predictors are seasonally adjusted and, if necessary, transformed via first differences or year-to-year growth rates to reach stationarity.

3.2. Forecasting Approach

We generate forecasts for the h-step ahead year-on-year growth rate of German industrial production, where h stands for the forecast horizon: $h = 1, 3, 6$ and 12 months. All forecasts are computed directly and pseudo out-of-sample with an expanding window. The initial estimation window ranges from 1996M01 to 2004M12 and is successively enlarged by one month in every iteration. The first forecast is obtained for January 2005. As the standard measure of forecast accuracy, we use the relative root mean squared forecast errors ($rRMSFEs$), where a boosted autoregressive process of order one serves as the benchmark model:

$$E(y_{t+h}|\mathbf{y}_t) = \alpha + \beta_1 y_{t-h} \tag{4}$$

For the boosting procedure, OLS serves as the base learner and we apply an L_2-loss function. The model is determined with cross-validation, as shown by Buchen and Wohlrabe (2014) to be the best approach. All other parameters are optimally chosen accordingly.

3.3. Results

Before we turn to best performing indicators, we discuss some general findings. Firstly, boosting always produces lower forecast errors than the benchmark. The $rRMSFEs$ are 0.881, 0.809, 0.802 and 0.950 for $h = 1, 3, 6$ and 12. This finding is in line with Buchen and Wohlrabe (2011). Secondly, the composition of the top 10 varies with the forecasting horizons. However, we detect indicators that perform very well for almost each forecasting horizon. Thirdly, there are indicators like money supply that have not been chosen by the algorithm.[1] And lastly, macroeconomic variables as well as survey results for Germany provide the best indicators for forecasting industrial production with the boosting algorithm.

Now let us turn to the details of our analysis. Figure 1 presents the top 5 indicators for each single forecast horizon over time. The upper left (right) panel presents the forecast horizon $h = 1$ ($h = 3$). The two lower panels show the outcome for the longer forecast horizons ($h = 6, 12$). All panels can be interpreted in the same way. We display our forecasting

[1] A complete list of all indicators and their relative frequency can be found in Table 2 in Appendix A.

period in monthly frequency on the x-axes. The y-axes shows the cumulative frequency of an indicator that has been chosen by the boosting algorithm. Thus, the y-axes run from 0% to 100%. If an indicator has been chosen by the algorithm in t then his frequency rises by 1/120. In other words, the slope of each line is $0.8\overline{3}$ percentage points. The indicator's total frequency is then the sum over all forecasting steps where the indicator is part of the boosting model, divided by the length of the evaluation period (in our case: 120). In case the indicator is part of the boosting model in each point in time, the resulting line in Figure 1 will be a 45°-line. If there are phases over time where the indicator has not been chosen by the algorithm, then the line takes a horizontal course.

The best indicator for $h = 1$ are new orders in mechanical engineering goods from domestic firms. This indicator has always been chosen by the algorithm over the whole forecasting period, indicated by the black 45°-line in the upper left panel. The second best indicator for the shortest forecast horizon are production trends obtained from the EU business survey. For $h = 3$ production trends become the best indicator, immediately followed by production expectations of intermediate goods firms obtained from the business survey of the German Ifo Institute. This Ifo indicator is only excluded from the boosting model at the end of 2014. Turning to $h = 6$ we find that the most frequently chosen indicator is the OECD Composite Leading Indicator (CLI) for the Euro Area. As for the two shorter forecasting horizons, the CLI for the Euro Area was part of the model over the whole forecasting period. This pattern changes for the longest forecast horizon: the best indicator (CLI for the whole OECD) was only part of the model in 66.7% of all cases. Between February 2010 and May 2013 the CLI for the OECD has not been chosen by the algorithm, as the horizontal black line indicates. This finding reflects the fact that the lowest $rRMSFE$ is observed for $h = 12$, thus, the relative performance of the benchmark rises with a longer forecast horizon.

But how does the relative frequency of the aforementioned indicators evolve over the forecasting horizons? To answer this question, Table 1 presents the top 10 indicators for each forecast horizon and their specific relative frequency. The best indicator for $h = 1$, new orders in mechanical engineering goods from domestic firms, is not part of the model for forecast horizons longer than one month. The production expectations from the EU survey only occurs in the models for $h = 1, 3$. For the Ifo indicators (production expectations of intermediate goods firms and business expectations in manufacturing) we find an occurrence among the top 10 for $h = 3, 6$. The CLI for the Euro Area only gets selected into the boosting model for the two longest forecasting horizons. The most frequently selected indicator is foreign turnover for energy supply, which is among the top 10 for $h = 1, 3$ and 6.

Figure 1: Five most frequently selected indicators for each forecast horizon

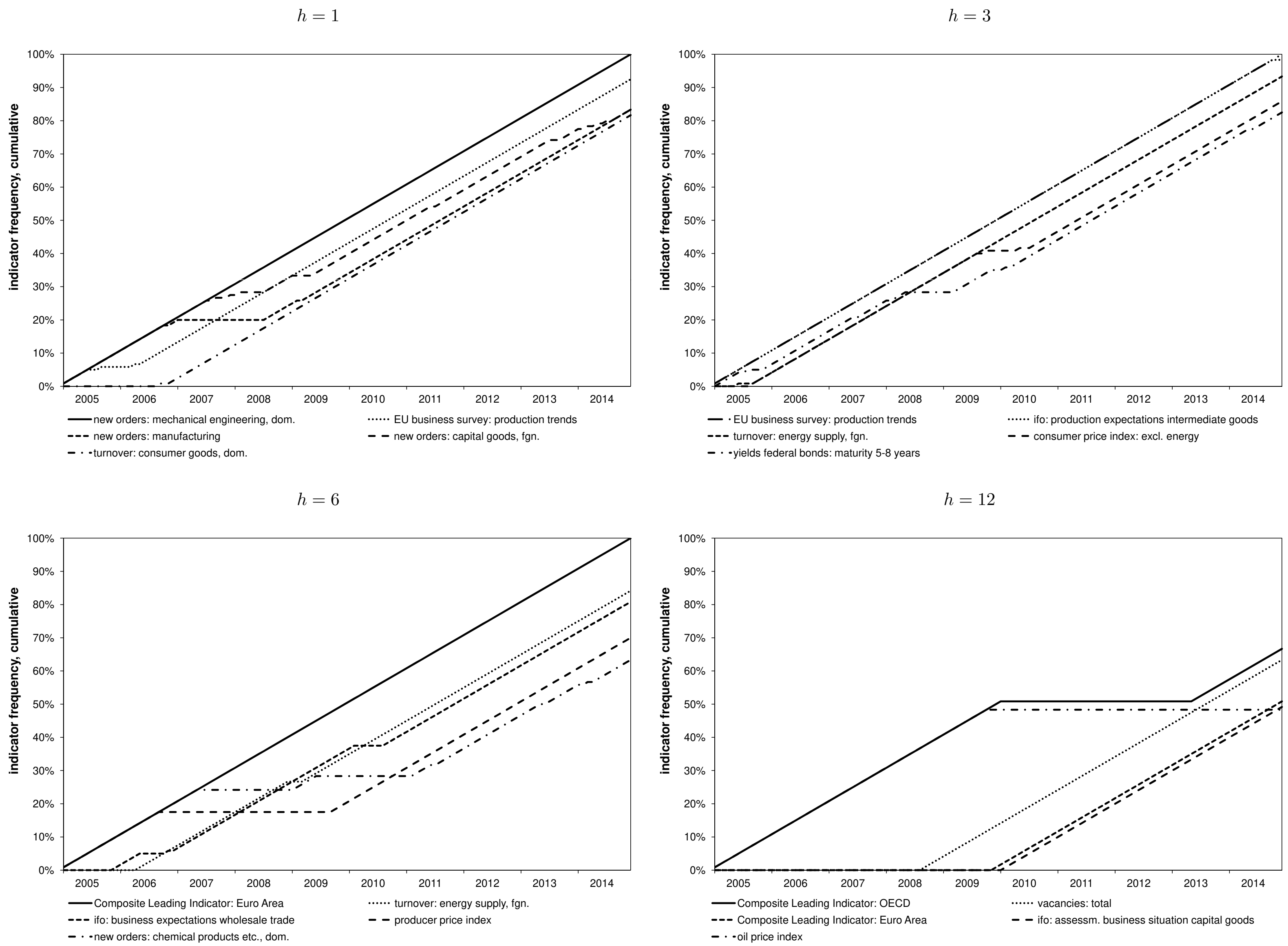

Table 1: Top 10 indicators for each forecast horizon

$h = 1$		$h = 3$	
new orders: mechanical engineering, dom.	100.0%	EU business survey: production trends	100.0%
EU business survey: production trends	92.5%	ifo: production expectations intermediate goods	98.3%
new orders: manufacturing	83.3%	turnover: energy supply, fgn.	93.3%
new orders: capital goods, fgn.	83.3%	consumer price index: excl. energy	85.8%
turnover: consumer goods, dom.	81.7%	yields federal bonds: maturity 5-8 years	82.5%
EU business survey: confidence indicator industry	78.3%	ifo: business expectations retail sales	66.7%
new orders: manufacturing, dom.	77.5%	turnover: consumer goods, dom.	62.5%
turnover: energy supply, fgn.	69.2%	ifo: business expectations manufacturing	60.0%
ifo: production expectations consumer durables	69.2%	new orders: manufacturing, dom.	57.5%
new orders: motor vehicles etc., fgn.	64.2%	ifo: business expectations consumer goods	57.5%
$h = 6$		$h = 12$	
Composite Leading Indicator: Euro Area	100.0%	Composite Leading Indicator: OECD	66.7%
turnover: energy supply, fgn.	84.2%	vacancies: total	63.3%
ifo: business expectations wholesale trade	80.8%	Composite Leading Indicator: Euro Area	50.8%
producer price index	70.0%	ifo: assessm. business situation capital goods	49.2%
new orders: chemical products etc., dom.	63.3%	oil price index	48.3%
ifo: business expectations manufacturing	57.5%	new registrations: heavy trucks	45.8%
new orders: motor vehicles etc., dom.	55.0%	yields federal bonds: maturity 5-8 years	44.2%
new orders: consumer goods	52.5%	industrial production: motor vehicles etc.	39.2%
ifo: construction activity	52.5%	turnover: wholesale trade, machinery	39.2%
ifo: production expectations intermediate goods	51.7%	wholesale trade price index	38.3%

Note: The table presents the relative frequencies of the top 10 indicators in our sample for the different forecasting horizons. A value of 100% is reached if an indicator gets chosen by the algorithm 120 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.

Are there, however, any indicators that get selected repeatedly for each forecasting horizon? We identify six indicators: (i) domestic turnover consumer goods, (ii) the consumer price index (excl. energy), (iii) total turnover wholesale trade (excl. motor vehicles) and (iv) chemical products, (v) the CLI for the US economy and (vi) US industrial production. These six indicators are selected at least once for each forecast horizon. As indicated by Figure 1 and Table 1, indicators (i) and (ii) are even among the top 10 indicators.

4. Conclusion

Boosting is a viable method for forecasting German industrial production. We open the boosting 'black box' in order to identify systematic patterns and which indicators get selected by the algorithm. For short term forecasts, macroeconomic variables like turnover from energy supply or from machinery goods are regularly selected by the algorithm. Additionally, survey results from the Ifo Institute play a major role in forecasting industrial production three or sixth months ahead. For the longest forecast horizon (one year), the Composite Leading Indicator for the Euro Area is often part of the boosting model. However, there are indicators like money supply that do not get selected.

Future research activities should focus on the evaluation of different economic variables like employment or the unemployment rate. We expect different results and patterns for these variables. In addition, follow-up studies could compare, for example, boosting methods with factor models, and evaluate whether there are phases or indicators that lead to a superior forecasting performance of one of these techniques.

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A. Indicator List

Table 2: List of indicators and relative frequency

Indicator	h = 1	h = 3	h = 6	h = 12
Macroeconomic variables				
industrial production (IP): total (incl. construction)	2.5%	0.0%	0.0%	0.0%
IP manufacturing: total	0.0%	0.0%	0.0%	0.0%
IP manufacturing: intermediate goods	6.7%	0.0%	0.0%	0.0%
IP manufacturing: consumer goods	8.3%	45.0%	10.8%	0.0%
IP manufacturing: capital goods	0.0%	0.0%	0.0%	2.5%
IP manufacturing: consumer durables	0.0%	25.0%	0.0%	0.0%
IP manufacturing: consumer non-durables	30.8%	0.8%	21.7%	0.0%
IP manufacturing: mining and quarrying	0.0%	0.0%	0.0%	0.0%
IP manufacturing: chemicals	14.2%	18.3%	5.8%	0.0%
IP manufacturing: basic metals	0.0%	0.0%	0.0%	20.0%
IP manufacturing: mechanical engineering	0.0%	0.0%	0.0%	29.2%
IP manufacturing: motor vehicles, trailers	0.0%	0.0%	8.3%	39.2%
IP construction: total	0.0%	7.5%	17.5%	1.7%
IP energy supply: total	56.7%	19.2%	18.3%	0.0%
turnover (TO): manufacturing total, domestic	44.2%	0.0%	0.0%	0.0%
TO: manufacturing total, foreign	0.0%	0.0%	0.0%	0.0%
TO: intermediate goods, domestic	48.3%	0.0%	0.0%	0.0%
TO: intermediate goods, foreign	0.0%	0.0%	0.0%	0.0%
TO: consumer goods, domestic	81.7%	62.5%	17.5%	7.5%
TO: consumer goods, foreign	0.0%	0.0%	0.0%	0.0%
TO: capital goods, domestic	0.0%	0.0%	0.0%	3.3%
TO: capital goods, foreign	0.0%	0.0%	0.0%	0.0%
TO: consumer durables, domestic	0.0%	22.5%	0.0%	0.0%
TO: consumer durables, foreign	0.0%	0.0%	0.0%	28.3%
TO: consumer non-durables, domestic	51.7%	0.0%	11.7%	13.3%
TO: consumer non-durables, foreign	0.0%	0.0%	0.0%	0.0%
TO: mining and quarrying, domestic	38.3%	0.0%	0.0%	0.0%
TO: mining and quarrying, foreign	0.0%	0.0%	0.0%	0.0%
TO: energy, gas etc. supply, domestic	0.0%	0.0%	0.0%	0.0%
TO: energy, gas etc. supply, foreign	69.2%	93.3%	84.2%	0.0%
TO: chemicals, domestic	10.0%	0.0%	0.0%	0.0%
TO: chemicals, foreign	0.0%	0.0%	0.0%	0.0%
TO: mechanical engineering, domestic	0.0%	0.0%	0.0%	15.0%
TO: mechanical engineering, foreign	0.0%	0.0%	0.0%	0.0%
TO: motor vehicles, trailers etc., domestic	0.8%	6.7%	8.3%	0.0%
TO: motor vehicles, trailers etc., foreign	0.0%	0.0%	0.0%	0.0%
TO: comp., electr. and opt. prod., domestic	0.0%	0.0%	0.0%	0.0%
TO: comp., electr. and opt. prod., foreign	0.0%	0.0%	0.0%	0.0%
new orders (NO): manufacturing total	83.3%	54.2%	0.0%	0.0%
NO: manufacturing total, domestic	77.5%	57.5%	30.0%	0.0%
NO: manufacturing total, foreign	3.3%	0.0%	0.0%	0.0%
NO: intermediate goods	0.0%	5.0%	0.0%	0.0%
NO: intermediate goods, domestic	50.0%	57.5%	13.3%	0.0%
NO: intermediate goods, foreign	0.0%	0.0%	17.5%	0.0%
NO: consumer goods	0.0%	0.0%	52.5%	0.0%
NO: consumer goods, domestic	0.0%	0.0%	10.8%	7.5%
NO: consumer goods, foreign	0.0%	0.0%	0.0%	0.0%
NO: capital goods	0.0%	0.8%	1.7%	0.0%
NO: capital goods, domestic	0.0%	0.0%	0.0%	0.0%
NO: capital goods, foreign	83.3%	1.7%	0.0%	0.0%

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Table 2: List of indicators and relative frequency – continued

Indicator	**h = 1**	**h = 3**	**h = 6**	**h = 12**
NO: chemicals, domestic	53.3%	42.5%	63.3%	0.0%
NO: chemicals, foreign	43.3%	0.0%	0.0%	0.0%
NO: mechanical engineering, domestic	100.0%	0.0%	0.0%	0.0%
NO: mechanical engineering, foreign	0.0%	0.0%	13.3%	0.0%
NO: motor vehicles, trailers etc., domestic	8.3%	0.0%	55.0%	0.0%
NO: motor vehicles, trailers etc., foreign	64.2%	45.0%	0.0%	0.8%
NO: comp., electr. and opt. prod., domestic	6.7%	15.8%	0.0%	0.0%
NO: comp., electr. and opt. prod., foreign	0.0%	42.5%	45.0%	0.0%
wholesale trade (WT): turnover, total (excl. Cars)	35.8%	34.2%	37.5%	36.7%
WT: turnover, chemicals	51.7%	37.5%	9.2%	20.8%
WT: turnover, machinery	0.0%	29.2%	19.2%	39.2%
WT: total employment	0.0%	8.3%	30.0%	0.0%
retail sales (RS): turnover, total (excl. cars)	0.0%	0.0%	0.0%	0.0%
new registrations (NR): all vehicles	0.0%	11.7%	0.0%	2.5%
NR: cars	0.0%	0.0%	0.0%	7.5%
NR: heavy trucks	0.0%	0.0%	1.7%	45.8%
exports: volume index, basis 2005	0.0%	0.0%	0.0%	0.0%
imports: volume index, basis 2005	0.0%	0.0%	0.0%	0.0%
unemployed persons (UNP): total, % of civilian labor	0.0%	0.0%	0.0%	26.7%
employed persons (EMPL): residence concept, total	0.0%	0.0%	0.0%	0.0%
EMPL: work-place concept, total	0.0%	45.8%	0.0%	0.0%
working days: total	57.5%	0.0%	0.0%	0.0%
vacancies: total	0.0%	12.5%	5.8%	63.3%
Finance				
discount rate - short term euro repo rate	0.0%	11.7%	0.0%	0.0%
Euro-Coin real time estimates	0.0%	0.0%	0.0%	0.0%
M1, overnight deposits	0.0%	0.0%	0.0%	0.0%
M2, money supply	0.0%	0.0%	0.0%	0.0%
M3, money supply	0.0%	0.0%	0.0%	0.0%
EM money supply: M1, ep	0.0%	0.0%	0.0%	0.0%
yields on fully taxed bonds outst. (YFTBO): public	0.0%	10.0%	0.8%	0.0%
yields on listed fed. bonds outst. mat. (YLFBOM): 3-5 years	0.0%	22.5%	0.0%	7.5%
yields on listed fed. bonds outst. mat. (YLFBOM): 5-8 years	0.0%	82.5%	3.3%	44.2%
DAX share price index	0.0%	0.0%	19.2%	2.5%
german price compet.: 37 industr. countr., basis: cpi	3.3%	9.2%	0.0%	0.0%
nominal effective exchange rate	0.0%	7.5%	44.2%	0.0%
Prices				
consumer price index	0.0%	0.0%	46.7%	30.0%
consumer price index (excl. energy)	2.5%	85.8%	30.0%	23.3%
producer price index	0.0%	18.3%	70.0%	20.8%
wholesale trade price index, 2010=100	5.0%	0.0%	0.0%	38.3%
export price index	0.0%	0.0%	0.0%	20.8%
import price index	8.3%	0.0%	0.0%	0.0%
HWWA index of world market prices: eurozone, energy	0.0%	0.0%	0.0%	0.0%
HWWA index of world market prices: eurozone, excl. energy	20.8%	41.7%	21.7%	0.0%
oil prices, euro per barrel	0.0%	0.0%	0.0%	48.3%
London gold price, per US $	0.0%	0.0%	17.5%	14.2%
Surveys				
ZEW: economic sentiment indicator	0.0%	0.0%	0.0%	0.0%
ZEW: present economic situation	0.0%	0.0%	0.0%	0.0%
ifo business climate industry and trade	0.0%	0.0%	0.0%	0.0%
ifo: assessm. of business situation industry and trade	0.0%	0.0%	0.0%	0.0%
ifo: business expectations industry and trade	0.0%	0.0%	0.0%	0.0%

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Table 2: List of indicators and relative frequency – continued

Indicator	**h = 1**	**h = 3**	**h = 6**	**h = 12**
ifo: business climate manufacturing	0.0%	0.0%	0.0%	0.0%
ifo: assessment of business situation manufacturing	0.0%	0.0%	0.0%	0.0%
ifo: business expectations manufacturing	0.0%	60.0%	57.5%	0.0%
ifo: inventory of finished goods manufacturing	11.7%	5.0%	0.0%	0.0%
ifo: orders on hand manufacturing	0.0%	0.0%	0.0%	0.0%
ifo: foreign orders on hand manufacturing	62.5%	1.7%	0.0%	0.0%
ifo: export expectations next 3 months manufacturing	0.0%	0.0%	0.0%	0.0%
ifo: business climate intermediate goods	41.7%	41.7%	0.0%	0.0%
ifo: assessm. of business sit. intermediate goods	0.0%	0.0%	0.0%	0.0%
ifo: production expectations intermediate goods	5.0%	98.3%	51.7%	0.0%
ifo: business climate consumer goods	9.2%	0.0%	0.0%	0.0%
ifo: assessment of business situation consumer goods	0.0%	0.0%	0.0%	0.0%
ifo: business expectations consumer goods	59.2%	57.5%	16.7%	0.0%
ifo: business climate capital goods	0.0%	0.0%	0.0%	0.0%
ifo: assessment of business situation capital goods	0.0%	0.0%	0.0%	49.2%
ifo: production expectations capital goods	0.0%	3.3%	0.0%	0.0%
ifo: business climate consumer durables	10.8%	7.5%	15.0%	0.0%
ifo: assessment of business situation consumer durables	0.0%	6.7%	0.0%	0.0%
ifo: production expectations consumer durables	69.2%	4.2%	5.0%	0.0%
ifo: business climate consumer non-durables	0.0%	0.0%	0.0%	0.0%
ifo: assessm. of business sit. consumer non-durables	0.0%	0.0%	0.0%	0.0%
ifo: production expectations consumer non-durables	0.0%	0.0%	6.7%	13.3%
ifo: business climate construction	0.0%	0.0%	0.0%	0.0%
ifo: assessment of business situation construction	0.0%	0.0%	0.0%	0.0%
ifo: business expectations construction	0.0%	0.0%	0.0%	0.0%
ifo: construction activity	41.7%	22.5%	52.5%	0.0%
ifo: orders on hand construction	0.0%	0.0%	0.0%	0.0%
ifo: business climate wholesale trade	5.0%	0.0%	0.0%	0.0%
ifo: assessment of business situation wholesale trade	0.0%	0.0%	0.0%	0.0%
ifo: business expectations wholesale trade	8.3%	49.2%	80.8%	0.0%
ifo: assessment of inventories wholesale trade	0.0%	0.0%	0.0%	0.0%
ifo: expect. with regard to order activ. next 3 months WT	6.7%	0.0%	9.2%	0.0%
ifo: business climate retail sales	0.8%	0.0%	0.0%	0.0%
ifo: assessment of inventories retail sales	0.0%	0.0%	0.0%	0.0%
ifo: business expectations retail sales	0.0%	66.7%	23.3%	8.3%
ifo: expect. with regard to order activ. next 3 months RS	0.8%	0.0%	0.0%	0.0%
EU consumer survey (EUCS): unemploym. expect. next 12 months	0.0%	0.0%	0.0%	0.0%
EUCS: statement on financial situation	0.0%	2.5%	0.0%	0.0%
EUCS: consumer confidence indicator	0.0%	0.0%	0.0%	0.0%
EUCS: economic sentiment indicator	0.0%	0.0%	0.0%	0.0%
EU business survey (EUBS): product. trends recent month, ind.	92.5%	100.0%	5.8%	0.0%
EUBS: assessment of order-book levels, industry	0.0%	0.0%	0.0%	0.0%
EUBS: assessment of export oder-books level, industry	0.0%	0.0%	0.0%	0.0%
EUBS: assessment of stocks of finished products, industry	0.0%	0.0%	0.0%	0.0%
EUBS: production expectations for the month ahead, industry	20.0%	11.7%	0.0%	0.0%
EUBS: selling price expectations for the month ahead, industry	0.0%	0.0%	0.0%	0.0%
EUBS: employment expectations for the month ahead, industry	0.0%	0.0%	0.0%	0.0%
EUBS: industrial confidence indicator	78.3%	1.7%	0.0%	0.0%
EUBS: service sector confidence indicator	0.0%	0.0%	0.0%	0.0%
EUBS: retail sales confidence indicator	0.0%	5.0%	0.0%	0.0%
EUBS: construction confidence indicator	0.0%	0.0%	0.0%	0.0%
International				
Bulgarian business indicator survey, whole economy	0.0%	0.0%	0.0%	0.0%
Bulgarian business indicator survey, manufacturing	0.0%	0.0%	0.0%	0.0%
EUCS: economic sentiment indicator, France	0.0%	0.0%	0.0%	0.0%

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Table 2: List of indicators and relative frequency – continued

Indicator	**h = 1**	**h = 3**	**h = 6**	**h = 12**
EUCS: economic sentiment indicator, Spain	0.0%	0.0%	0.0%	0.0%
EUCS: economic sentiment indicator, Poland	0.0%	0.0%	0.0%	0.0%
EUCS: economic sentiment indicator, Czech Republic	0.0%	0.0%	0.0%	0.0%
EUCS: economic sentiment indicator, Italy	0.0%	0.0%	0.0%	0.0%
EUCS: economic sentiment indicator, United Kingdom	0.0%	0.0%	0.0%	0.0%
University of Michigan consumer sentiment	0.0%	0.0%	0.0%	0.0%
IP: United States, total	5.0%	0.8%	27.5%	20.8%
OECD Composite Leading Indicator (CLI): OECD, ampl. adj.	0.0%	0.0%	0.0%	0.0%
CLI: OECD, trend restored	2.5%	0.0%	34.2%	66.7%
CLI: OECD, normalised	0.0%	0.0%	0.0%	0.0%
CLI: Asia, amplitude adjusted	0.0%	0.0%	0.0%	0.0%
CLI: Asia, trend restored	0.0%	0.0%	0.0%	0.0%
CLI: Asia, normalised	0.0%	0.0%	0.0%	0.0%
CLI: China, amplitude adjusted	0.0%	0.0%	0.0%	0.0%
CLI: China, trend restored	27.5%	0.0%	0.0%	20.0%
CLI: China, normalised	0.0%	0.0%	0.0%	0.0%
CLI: Euro Area, amplitude adjusted	0.0%	0.0%	0.0%	0.0%
CLI: Euro Area, trend restored	0.0%	6.7%	100.0%	50.8%
CLI: Euro Area, normalised	0.0%	0.0%	0.0%	0.0%
CLI: United States, amplitude adjusted	0.0%	0.0%	0.0%	0.0%
CLI: United States, trend restored	35.0%	55.8%	41.7%	19.2%
CLI: United States, normalised	0.0%	0.0%	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 120 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.