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Martin Feldkircher, Florian Huber,
Josef Schreiner, Marcel Tirpák,
Peter Tóth, Julia Wörz

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www.nbs.sk
Imricha Karvaša 1
813 25 Bratislava

research@nbs.sk

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Bridging the Information Gap: Small-Scale Nowcasting Models of GDP for Selected CESEE Countries

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Martin Feldkircher, Florian Huber, Josef Schreiner, Marcel Tirpák, Peter Tóth, Julia Wörz[1]

Abstract

In this article, we describe short-term forecasting models of economic activity for seven countries in Central, Eastern and Southeastern Europe (CESEE) and compare their forecasting performance since the outbreak of the Great Recession. To build these models, we use four variants of bridge equations and a dynamic factor model for each country. Given the differences in availability of monthly indicators across countries and the rather short time period over which these indicators are available, we favor small-scale forecasting models. We selected monthly indicators on the basis of expert judgment, correlation analysis and Bayesian model averaging techniques. While our models generally outperform a purely time-series based forecast for all CESEE countries, there is no single technique that consistently produces the best out-of-sample forecast. To maximize forecasting accuracy, we therefore recommend selecting a country-specific suite of well-performing models for every CESEE economy.

JEL classification: C52, C53, E37

Keywords: Nowcasting, bridge equations, dynamic factor models, Bayesian model averaging, Central-, Eastern- and South-Eastern Europe

Referees: Marek Rusnák (Česká národní banka)
Martin Schneider (Österreichische Nationalbank)

[1] Oesterreichische Nationalbank, Foreign Research Division, Martin.Feldkircher@oenb.at, Florian.Huber@oenb.at, Josef.Schreiner@oenb.at, Julia.Woerz@oenb.at; European Central Bank, Convergence and Competitiveness Division, Marcel.Tirpak@ecb.europa.eu; Národná Banka Slovenska, Research Department, Peter.Toth@nbs.sk, (corresponding author). This article should not be reported as representing the views of the European Central Bank (ECB), Národná Banka Slovenska (NBS), OeNB or the Eurosystem. The authors would like to thank Peter Backé, Markus Eller and Martin Schneider (all OeNB); Pavlos Karadeloglou and Vincent Labhard (both ECB); Marek Rusnák (ČNB); Tomáš Slačík (EIB) and Ľuboš Pástor (University of Chicago and NBS) for their useful comments and valuable suggestions.

1. INTRODUCTION

Timely information of high quality about the development of economic activity is a key ingredient of economic policy decisions. However, national accounts data are subject to rather long publication lags[2], compelling macroeconomic forecasters to work with estimates of the current stance and the recent past of the economy. Nowcasting models seek to fill this information gap by using indicators that are available at a higher frequency and with a much lower publication lag than national accounts data or none at all. Banbura at al. (2010) define nowcasting as "the prediction of the present, the very near future and the very recent past." Such models often make use of large data sets and different publication frequencies to predict economic activity. In general, a model-based approach to nowcasting makes it possible to asses which monthly indicators contain valuable information for the estimation of past, current and future real GDP. Beyond improving the accuracy of predicting real GDP growth, such an approach can also improve the identification of business cycle turning points.

A systematic approach to nowcasting has been pioneered by researchers from central banks like the Philadelphia Federal Reserve Bank, the ECB, the Deutsche Bundesbank, the Bank of England and the Banca d'Italia (see Aruoba et al., 2009, Baffigi et al., 2004, Banbura et al., 2010, Giannone et al., 2008, Kuzin et al., 2011, Rünstler and Sédillot, 2003, Trehan, 1989, 1992). Typical high-frequency indicators that are used to predict GDP growth in such models have a monthly frequency and include hard data (such as industrial production indices, turnover or sales data for different sectors of the economy, export figures, price and labor market indicators) as well as soft data from business or consumer surveys (such as the Economic Sentiment Indicator, ESI, of the Directorate General for Economic and Financial Affairs, the Purchasing Managers' Index Markit PMI or order books). Most of the studies mentioned also use financial data, such as exchange rates, interest rates or stock indexes available at a daily or higher frequency.

[2] In the EU, a first or so-called flash estimate of real GDP is usually released six weeks after the end of the reference period. A second estimate of real GDP and its demand components is published with an 11-week lag.

To date, numerous models have been developed to nowcast the GDP growth of the euro area or of large euro area countries. Much less attention has been devoted to countries in Central, Eastern and Southeastern Europe (CESEE). While nowcasting models exist for most of the countries,[3] hardly any study systematically covers CESEE countries as a region. One exception is Ohnsorge and Korniyenko (2011), who develop a set of statistical models for countries from Eastern Europe and Central Asia. The authors compare a range of different models (i.e. bridge equations, a cross-country generalized dynamic factor model, a Bayesian vector auto-regressive model) and expert-based forecasts over a forecast horizon of approximately one to one-and-a-half years, thus focusing on short- to medium-term forecasts. They conclude that model performance varies with data availability, with time series length and with the forecast horizon. Furthermore, they stress the importance of expert judgment for model calibration and the importance of external assumptions.

This article estimates a suite of models with a very short-term horizon for selected CESEE countries: Bulgaria, the Czech Republic, Hungary, Poland, Romania, Slovakia and Slovenia. We are interested not only in forecasts, but also in obtaining accurate backcasts and nowcasts of quarterly real GDP growth. We compare the forecasting performance of different bridge equations and a small dynamic factor model with that of a simple autoregressive process for real GDP growth (our benchmark model) over the period since the Great Recession, which is marked by heightened volatility of economic activity. Our main value added compared to Ohnsorge and Korniyenko (2011) lies in the careful country-specific selection of monthly indicators for the bridge models as well as the dynamic factor model. In addition, we evaluate monthly updates of the model forecasts over a six years period from 2008 to 2014, which allows us to record more than 70 forecast errors. In contrast, the mentioned authors consider only a four years interval with three forecast updates each year, i.e. a relatively small sample of forecast errors.

This article is structured as follows: Section 2 describes competing methodologies and discusses our model choice. In section 3, we present the data sample and our methods to identify high-frequency indicators with good forecasting performance or leading properties, or both. Section 4 evaluates the forecasting accuracy obtained by each model against the preferred benchmark. Section 5 concludes.

[3] For instance, Arnoštová et al. (2011), Benkovskis (2008), Białowolski et al. (2014), Franta et al. (2014), Krajewski (2009), Rogleva (2011), Rusnák (2013) and Rünstler et al. (2009) develop large-scale factor models to nowcast economic activity for individual CESEE countries.

2. MODEL CHOICE: SMALL VERSUS LARGE - BRIDGE VERSUS FACTOR

Baffigi et al. (2004) classify nowcasting models into two types: models that translate the information content of short-term indicators to the lower frequency variables of interest, and models that extract reliable signals from all available higher frequency indicators with the help of complex methods.

The first type of model tries to "bridge" the information gap by combining the dynamic properties of the lower frequency national accounts time series with higher frequency indicators. These are so-called "bridge equation" models (see Baffigi et al., 2004, Rünstler et al., 2009, Trehan, 1989, 1992). In these models, economic activity is predicted by monthly indicators that are converted into quarterly data before use.

For the second type of model, timing properties are important, i.e. whether an indicator is leading, coincident or lagging. The higher frequency of the relevant time series is used to detect business cycle turning points early on. The following models can be subsumed in this category: principal component models, which make use of static factors (see Stock and Watson, 2002, and Giannone et al., 2008), and dynamic factor models, which take account of the dynamics by modeling the extracted static factor by a VAR model in a second step (see Doz et al., 2011, Bai and Ng, 2002, 2007) or more generally by taking into account dynamic correlations directly in the estimation (see Forni et al., 2000, 2004, 2005). The factor MIDAS (Mixed Data Sampling) models combine data at different frequencies using a differentiated weighting scheme.

All models of the second type have some common features. First, they condition the forecasts on a large set of indicators; second, they often involve estimation in two or more steps; and third, they make use of technically demanding methods. However, Camacho and Perez-Quiros (2010) show that more indicators do not necessarily increase forecast accuracy. They propose a small dynamic factor model that takes the form of a state-space model on monthly frequency estimated by a Kalman filter. Foroni et al. (2015) also propose a variant of a factor MIDAS model, an unrestricted MIDAS (U-MIDAS) model, which works with a limited number of indicators.

2.1 BRIDGE EQUATIONS

Bridge equation models use statistical correlations between higher frequency indicators and quarterly real GDP. This type of model was first developed by Trehan (1989, 1992). In the first step, missing monthly observations of the higher frequency indicators x_{it} $(i = 1, \ldots, k)$ within the most recent quarter are extrapolated by simple means or with the help of a simple autoregressive model to deal with the ragged edges problem:

$$x_{it} = \sum_{s=1}^{p_i} \rho_{is} x_{it-s} + u_{it}, \; u_{it} \sim N(0, \sigma_u) \qquad (1)$$

After transforming x_{it} into quarterly frequency (x_{it}^Q), in a second step, the short-term indicators are used as explanatory variables in an ordinary least squares (OLS) model to predict quarterly real GDP (y_t^Q):

$$y_t^Q = \mu + \rho y_{t-1}^Q + \sum_{i=1}^{k} \sum_{s=-q_i}^{q_i} \beta_{is} x_{i\,t-s}^Q + \varepsilon_{it}^Q, \; \varepsilon_{it}^Q \sim N(0, \sigma_\varepsilon) \qquad (2)$$

These bridge equations are entirely driven by the statistical correlation structure – including lags and leads of explanatory variables – between the monthly indicators and quarterly real GDP. Further, it is customary to include an autoregressive term (see, for example, Schumacher 2014).

Since different monthly indicators reflect various aspects of the economy, a variant of this approach – so-called "demand-side" bridge equations – aims at forecasting the respective demand components of real GDP separately and in turn aggregates those predictions to obtain real GDP. In the same vein, "supply-side" bridge models forecast value added by the respective sectors. Finally, under the "direct approach," bridge equations are used to directly forecast real GDP. This is the approach we follow in this article.

Bridge equations are very general and comprise a rather large set of models. Most authors find that bridge equations often show a better forecasting accuracy than univariate or naive models. Another advantage is that bridge equations rely on simple estimation techniques. A drawback is that forecasts of monthly indicators may propagate shocks that are specific only to this indicator. Hence, the forecasting ability of bridge equations seems to rely on picking the "right" higher frequency indicators conditional on the forecast horizon.[4]

[4] Hahn and Skudelny (2008) show that forecasting performance can be improved if different bridge equations are used over the forecast cycle: Depending on the month within a given quarter and the corresponding availability of different higher frequency indicators, the explanatory power of different indicators could vary.

2.2 SMALL DYNAMIC FACTOR MODELS

Dynamic factor models (DFMs) provide an algorithm that uses all available short-term information to forecast real GDP in a transparent and replicable way. These models usually rely on the asymptotical properties and weak orthogonality of idiosyncratic components. They are able to extract a signal from a large set of indicators even when these indicators represent subsets of a common class (i.e. turnover in different activities, sentiment of different agents) and are thus highly correlated. Nevertheless, in practice, DFMs based on large indicator sets do not necessarily perform better than "small" DFMs. This inability of large-scale DFMs to filter out all noise introduced by putting in all available indicators may be related to a breakdown of the theoretical assumptions on which they are based: Time series have to tend to infinity in terms of number and length, idiosyncratic components must be weakly correlated, and the variability of the common component needs to be large. Given that in our country sample, we work with rather short and – compared to the euro area or the U.S.A. – only a limited number of available time series, we opt for a small DFM (see Mariano and Murasawa, 2003, Aruoba et al., 2009, and Camacho and Perez-Quiros, 2010, 2011, for applications of small DFMs).[5]

In general, DFMs assume that comovements among macroeconomic variables have a common element that can be extracted and used for forecasting. The model is cast in a state-space form on monthly frequency, where real GDP is observed only in one month of each quarter and is treated as unobserved in the remaining two months. A typical small DFM is specified on the monthly frequency as follows:

$$x_{it} = \alpha_i f_{t+K_i} + \eta_{it} \tag{3}$$

$$y_t = \gamma f_t + \omega_t \tag{4}$$

$$f_t = \varphi f_{t-1} + e_t. \tag{5}$$

Each time series is decomposed into two orthogonal components: an unobserved common factor (f_t) and the idiosyncratic behavior of each series (η_{it} and ω_t in equations (3) and (4))[6]. The common factor (f_t) of the monthly indicators (x_{it}) and GDP (y_t) is treated as a latent variable and is estimated by the Kalman filter.[7,8] Note that y_t is observed only in the

[5] Also, Bai and Ng (2008) show that careful variable selection (corresponding to a reduction on model size by zero loads on variables in large-scale models) can improve model performance.

[6] The idiosyncratic terms in equations (3)-(5) are assumed to be i.i.d. processes originating from the normal distribution with a zero mean. Their variances are estimated parameters.

[7] Note that different release dates of monthly indicators do not pose a problem here. Hence, the method can deal with ragged edges in the data while using all available information in the monthly series.

[8] All data entering the model were normalized to have a zero mean and unit variance. Following the related literature, the variance of e_t was set to 0.1 so that the estimates can be identified. To further

last months of each quarter and that we interpolate the first two months using a cubic polynomial.[9]

Our approach differs from the rest of the small DFM literature in three minor respects. First, we use three-month growth rates in equation (3) instead of monthly growth rates. This makes the otherwise rather volatile x_{it} indicators somewhat smoother. Second, our variable transformation[10] allows for a simpler specification of equation (4). In the literature, a decomposition introduced by Mariano and Murasawa (2003) is typically assumed. This means linking the quarterly growth rates of y_t to the weighted average of monthly f_t and its four lags. In other words, by using three-month growth rates of x_{it}, we can drop the lagged values of f_t in (4). Third, our setup differs from the standard approach in the manual selection of lags and leads, K_i, in equation (3). We do this based on correlations between x_{it+Ki} and y_t, whereas the common approach in the literature is to set K_i=0.

The main advantage of small DFMs as opposed to their large-scale counterparts lies in a convenient one-step estimation procedure: The unobserved factor $\mathrm{f_t}$, the missing values of $\mathrm{x_{it}}$ and $\mathrm{y_t}$ and the parameters of the model ($\alpha_\mathrm{i}, \gamma$ and φ) are estimated in a single step.[11] In contrast, large factor models with a large number of predictors are typically estimated in at least two steps. In the first step, the first few principal components are derived from the monthly series, which approximate the common factors. In the next step, the factors are linked to real GDP growth in a quarterly model. The advantage of large DFMs, however, can be attributed to their ability to condition the GDP forecast on virtually all available higher frequency indicators.

aid the identification and interpretability of the parameters, φ was set to 0.9. This ensures that the variance of the factor f_t is one, like that of all the other variables in the model. At the same time it is a practical assumption to make sure that the numerical estimator converges even in case of more volatile data.

[9] Alternative approaches in the literature use random numbers, sample averages or the Kalman filter to interpolate y_t. Our time series are probably too short for using the Kalman filter to interpolate y_t. The same conclusion could be drawn from an application of the small DFM for Slovakia by Tóth (2014), who interpolated y_t by the Kalman filter at the expense of having to calibrate the error variances in (3)-(5) in order the maximum likelihood estimator to converge.

[10] We are aware of the fact that by using three-month growth rates we may potentially introduce serial correlation in the errors of (3)-(5), which is a trade-off for the mentioned advantages of our approach.

[11] Note that the two-step and other iterative estimation procedures used in case of large DFMs are not directly applicable to small-scale DFMs, as those methods require a large set of indicators. Therefore we cannot compare the efficiency of the mentioned estimation procedures.

3. SELECTION OF INDICATORS

The data used in this article are taken from eight large datasets compiled for CESEE countries and the euro area. The datasets comprise 90 series for each country (71 monthly and 19 quarterly indicators). The series include composite indicators as well as their components (i.e. total industrial production in addition to separate time series for production in mining, manufacturing, etc.). In addition, we consider three indicators of world prices as well as the German Ifo Business Climate Index and its two components, namely the assessment of the business situation and business expectations. See annex 1 for detailed information on the variables used in this article.

Our analysis focuses on a relatively broad set of CESEE economies, but the availability of monthly indicators significantly differs across countries and over time. Therefore, rather than making use of the largest possible number of high-frequency indicators available, we build on the result obtained by Camacho and Perez-Quiros (2010) and opt for models based on a limited number of indicators. Indicator selection may reduce noise and address theoretical shortcomings, therefore it can improve estimation results. However, it has to be done very carefully as it also entails some drawbacks. In particular the ragged end pattern of the data has to be taken into account. Since different indicators carry important information depending on the forecasting horizon (i.e. survey data become less important when other data like industrial production become available), the preselection has to match the exact forecast horizon. This is not always trivial as selection based on correlation neglects the ragged ends problem and potential dynamic cross-correlation between different variables. Further, the predictive content of individual variables is not stable over time. Therefore, the selection should be repeated in every forecasting round. Finally, indicator selection might result in the exclusion of variables that are of key interest to policymakers.

In our case, the selection of indicators depends on the type of forecasting model – we estimate four variants of bridge equations and a small DFM for each CESEE country. We describe the different approaches used to select the indicators for each model below.

3.1 BRIDGE EQUATIONS WITH THE "USUAL SUSPECTS"

Our first set of bridge equations works with high frequency indicators. These could be used to forecast real GDP on their own, as they are potentially very informative with respect to economic activity. The indicators could be labeled the "usual suspects" and comprise the following: First, the Economic Sentiment Indicator (ESI) published by Eurostat in the last week of every month. The ESI index collects data on the perceptions and expectations of economic agents in four major economic sectors (industry, construction, retail trade and services) as well as consumers' expectations. We use the ESI in our first bridge equation. Our second bridge equation augments the autoregressive quarterly GDP model by the index of industrial production (IP), which measures changes in the volume of output in industry on a monthly basis. The third "usual suspects" model replaces the industrial production index, IP index, by the subcomponent measuring changes in the volume of output in manufacturing (IP manuf). Eurostat publishes both IP indices with a six-week lag. Hence, this first set of bridge equations always uses one high frequency indicator at a time.

3.2 BAYESIAN MODEL AVERAGING

To identify the variables with the greatest explanatory power for our fourth bridge equation, we conducted a Bayesian Model Averaging (BMA) exercise. This exercise allowed us to take advantage of the relatively large set of potential explanatory variables in our dataset, including country-specific, euro area-wide and world price indicators as well as the Ifo Business Climate Index for Germany. We excluded indicators that are almost perfectly correlated among each other and included a lag of the dependent variable.[12] This implies approximately 1.6e^32 different models per country that can potentially yield good nowcasts for real GDP growth. The challenge is to select the models that yield the best forecasts, accounting for interdependence among the variables. The BMA is a natural choice to sort through the model space.

[12] We tested the data for a unit root by means of an augmented Dickey Fuller test. Variables that show a unit root behavior (tested at the 10% significance level) were transformed by taking first differences. In general, all variables with a strictly positive support are in logarithmic transform.

We apply two variants of BMA. First, in a standard BMA framework, the models are evaluated based on the underlying marginal likelihood. Under a certain prior structure – and to provide more intuition – this boils down to evaluating the models based on the Bayesian information criterion (BIC). The recorded BIC values are then normalized to yield weights (posterior model probabilities, PMPs) that sum up to one.[13] Second, we follow Eklund and Karlsson (2007) and Feldkircher (2012) and use the predictive likelihood instead of the marginal likelihood to gauge the performance of the different candidate models.[14] For that purpose, we have to split our data into an estimation and an evaluation (holdout) sample. It can be shown that it is important to reserve a large portion of the dataset for the holdout rather than the estimation window (Feldkircher, 2012; Laud and Ibrahim, 1995). Accordingly, we reserve 50% of our data for the estimation part and 50% for the evaluation part. Note that the predictive likelihood boils down to a single number when evaluated with realized data. The posterior inclusion probability (PIP) attached to a particular variable is simply the sum of the weights (weights based either on marginal likelihood or on predictive likelihood) of the models that contain the variable of interest.

To specify a bridge equation based on the BMA exercise, we follow Barbieri and Berger (2004) and select variables that have PIPs ≥ 0.5. These form the so-called "median" model, which can be shown to possess excellent forecasting properties (Barbieri and Berger, 2004, Feldkircher, 2012)15. The results for both BMA variants (based on marginal and predictive likelihood) are summarized in Table 1, which reports the top five regressors per country under both BMA variants and their respective PIPs in parentheses.

The BMA exercises yielded very parsimonious models throughout the region. All models consist of only one to a maximum of three variables that have PIPs ≥ 0.5. Thus, the BMA framework yielded very decisive inference for a small set of variables, with the PIPs of the remaining variables being close to zero. In most countries, there is evidence of measures of industrial production or manufacturing turnover as good leading indicators. Also, for some countries – such as Czech Republic, Slovakia, Slovenia and Romania – euro area indicators appear to be the most robust leading indicators of economic activity.

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[13] Raftery (1995) provides an excellent introduction to the BMA framework, while Madigan and York (1995) offer a detailed description of the MC^3 algorithms that are needed to approximately evaluate the model space, since it is computationally not feasible to assess the full set of potential models.
[14] In addition and as a robustness check, we also used a BMA prior setup that accounts for multicollinearity of the regressors. More specifically, we used the tessellation sampler, which is of the class of "dilution" priors put forward in George (2010) and is applied to a growth dataset in Moser and Hofmarcher (2014).
[15] Alternatively, one could use the BMA-weighted coefficients to conduct the forecasts instead of singling out only the variables with PIPs ≥ 0.5. However, as shown theoretically in Barbieri and Berger (2004), the median model tends to dominate a forecast based on the full set of (weighted) coefficients.

Table 1 – Posterior Inclusion Probabilities of top 5 regressors

	marginal likelihood Indicator	PIP	predictive likelihood Indicator	PIP
Bulgaria	Production in total industry	0.65	Factors limit. build. act. - insuff. demand	0.94
	EA - Turnover in manuf., non-dom. mark.	0.28	Compet. posit. on for. EU markets, past 3m	0.62
	Unemployment rate	0.26	EA - New orders in rec. months	0.57
	Production in manufacturing	0.05	Turnover in manufacturing, dom. mark.	0.47
	Factors limit. build. act. - Insuff. demand	0.03	Export expectations for the months ahead	0.42
Czech Republic	EA - Unemployment rate	0.89	EA - Turnover in manufact., non-dom. mark.	0.67
	EA - Gross wages and salaries in industry	0.66	EA - Production in manufacturing	0.32
	EA - Production in mining and quarrying	0.15	EA - Duration of product., curr. order-books	0.20
	Real GDP	0.09	EA - Production in total industry	0.13
	EA - Turnover in manufact., non-dom. mark.	0.08	EA - Current level of capacity utilization (%)	0.11
Hungary	Production in total industry	0.99	Production in total industry	0.97
	Real GDP	0.84	Employment expectations over the next 3m	0.66
	Turnover in retail t., excl. motor v. & motorc.	0.08	Factors limit. build. act. - shortage of labour	0.16
	Assessm. of the current stocks of fin. prod.	0.01	Real GDP	0.14
	Production in manufacturing	0.01	Factors limit. build. act. - weather conditions	0.12
Poland	Turnover in manufacturing, domestic market	0.57	Factors limit. build. act. - weather conditions	0.39
	Production in total industry	0.17	Turnover in manufacturing, domestic market	0.38
	Turnover in manufacturing	0.03	Production in total industry	0.33
	Unemployment rate	0.02	Turnover in manufacturing	0.21
	Production in manufacturing	0.01	Intention to buy a car within the next 12 m	0.20
Romania	EA - Turnover in manufact., non-dom. mark.	0.53	EA - Turnover in manufact., non-dom. mark.	0.48
	Price expect. over the next 3 m, construct.	0.52	HICP	0.32
	EA - Production in manufacturing	0.43	EA - Production in manufacturing	0.31
	Employm. exp. over the next 3 m, construct.	0.20	Consumers' financ. sit. over the last 12 m	0.27
	Build. act. development over the past 3 m	0.15	EA - Turn. in mining and q., non-dom. mark.	0.24
Slovenia	EA - Unemployment rate	0.94	EA - Unemployment rate	0.87
	Unit labor costs, whole economy	0.76	Production in manufacturing	0.50
	Production in manufacturing	0.68	Turnover in retail t., excl. motor v. & motorc.	0.26
	Households' unempl. exp. over the next 12m	0.10	EA - Production in manufacturing	0.26
	Turnover in manufacturing	0.09	Assessm. of current prod. capacity in indust.	0.24
Slovakia	EA - Turnover in manufact., non-dom. mark.	0.35	EA - Turnover in manufact., non-dom. mark.	0.79
	Turnover in retail t., excl. motor v. & motorc.	0.25	ECB Commodity Price index	0.51
	EA - Production in manufacturing	0.15	Intention to buy a car within the next 12 m	0.27
	EA - Turn. in retail t., excl motor v. & mot.c.	0.11	Real GDP	0.23
	ECB Commodity Price index	0.08	IFO Assessment of business situation	0.18

Source: Authors' calculations.

The empirical model specification for each CESEE country from this exercise can be read from Table 1.[16] In what follows, we use the indicators identified by the BMA variant using the predictive likelihood, since these results are more robust against structural breaks and overfitting and this variant is explicitly designed for the purpose of forecasting (Eklund and Karlsson, 2007). With one exception, we used only indicators that reached PIPs ≥ 0.5 under predictive likelihood. Hence, the model for Bulgaria contains three indicators that are all measured by Eurostat's business and consumer surveys and released in the last week of the month or quarter: Insufficient demand as a limiting factor to building activity (monthly frequency), competitive position on foreign markets inside the EU over the past three months (quarterly frequency), and euro area new orders in recent months (quarterly frequency). The model for the Czech Republic contains only one monthly indicator: euro area manufacturing turnover in the nondomestic market (six-week publication lag). The Hungarian bridge equation contains the monthly IP index (six-week publication lag) and monthly employment expectations over the next three months from business and consumer surveys (released in the last week of the month). For Poland, the highest PIP was 0.39. Therefore, we lowered the cutoff level to 0.3 for Poland and included manufacturing turnover in the domestic market (six-week publication lag), weather conditions as a limiting factor to building activity (released in the last week of the month), and the IP index. The Slovenian bridge equation uses the monthly unemployment rate of the euro area (five-week publication lag) and the IP index as explanatory variables. To nowcast Slovak real GDP growth, the BMA routine identified euro area manufacturing turnover in the nondomestic market and the ECB Commodity Price Index (one-week publication lag) as relevant monthly indicators. Finally, euro area manufacturing turnover in the nondomestic market is identified as the exogenous predictor in the bridge equation for Romanian real GDP growth.

[16] For both BMA variants, we employ a BMA setup similar in spirit to Fernández et al. (2001) which implies setting the hyperparameter g=K^2, with K denoting the total number of variables in our dataset. The prior on the model space follows a binomial beta distribution, implying a prior inclusion probability of ½ per regressor (Ley and Steel, 2009). All results are based on 1 million posterior draws. Moreover, note that the BMA exercise was based on just one horizon (a nowcast in the third month of a quarter). However, our forecasting results below suggest that the choice of horizon matters only marginally for predictive accuracy, whereas model performance differs rather strongly between countries.

3.3 INDICATOR SELECTION FOR THE SMALL DYNAMIC FACTOR MODEL

In selecting the number of indicators for the small DFM, all available monthly indicators were first transformed to quarterly frequency and their correlation with quarterly real GDP growth rates was calculated. In line with Camacho and Perez-Quiros (2010, 2011), we set the target number of indicators to below 10. We first reduced the full set of available indicators to about 20 based on the following considerations: Our goal was to include variables that central banks generally follow and comment in connection with real activity. This meant including both hard and soft indicators, as the latter have shorter publication lags. As most of the studied CESEE countries are small and open economies with strong trade links to the euro area and in particular to Germany, it seems natural to consider the euro area or German indicators in addition to domestic ones. Among the domestic indicators, industrial production indices, exports, retail sales, the unemployment rate and economic sentiment indicators showed the highest correlation with real GDP growth.

A class of variables that was a priori excluded from the preselection was price data, as the structure of the DFM is too simple for it to differentiate between supply and demand shocks. We also disregarded financial variables for the DFM, such as exchange rates, interest rates or stock prices. The main reason was that these variables display increased volatility; moreover, their correlation with real activity in the CESEE economies is very limited.

The final set of variables for each country model is reported in Table 2. The number of selected indicators ranged from six to eight for each country, depending on correlations (both contemporaneous and with leads) with GDP growth and the quality of the model's estimates on the full sample. Correlation analysis helped to choose between indicators of similar types, e.g. sales in industry versus sales in manufacturing, industry sales versus industry turnover, euro area PMI versus euro area ESI, or German industry turnover versus euro area industry turnover. To determine the quality of the estimates, we checked whether the coefficients in (3) were positive and below one and whether they were statistically significant. If these criteria did not give satisfactory answers, we excluded the variable from the model.

Table 2 – Correlations of monthly indicators and GDP growth

Indicator	Bulgaria	Czech Republic	Hungary	Poland	Romania	Slovenia	Slovakia
Economic Sentiment Indic.	**0.54**	**0.55**	0.38	**0.42**	**0.44**	**0.58**	**0.36**
Unemployment rate	-0.44	**-0.59**	-0.45	-0.48	-0.27	**-0.56**	-0.45
Industrial proudction	**0.69**	**0.70**	**0.79**	0.54	0.46	**0.83**	0.67
Manufacturing product.	0.66	0.67	0.78	**0.56**	0.45	0.82	0.61
Turnover in industry	0.63	0.69	0.78	0.59	**0.59**	0.74	**0.71**
Turnover in manufact.	0.63	0.68	0.78	0.58	0.59	0.74	0.71
Retail sales	**0.67**	**0.56**	**0.60**	**0.55**	**0.61**	**0.68**	**0.63**
Export	**0.30**	**0.67**	**0.74**	**0.41**	**0.50**	**0.75**	**0.58**
EA industrial proudction	0.63	0.75	**0.69**	0.41	0.64	**0.78**	0.70
EA manufact. production	0.61	**0.73**	0.69	0.42	0.62	0.78	0.68
EA inustrial turnover	**0.68**	0.77	0.68	0.43	**0.65**	0.78	0.73
EA manufacturing turnover	0.68	0.76	0.68	0.43	0.65	0.78	**0.74**
EA Economic Sentim. Ind.	0.58	0.76	0.61	**0.62**	0.56	0.80	0.49
Purchasing managers ind.	**0.57**	**0.77**	**0.62**	**0.56**	**0.53**	**0.79**	0.51
IFO exp. German exports	**0.63**	**0.79**	**0.68**	**0.45**	**0.62**	**0.81**	**0.59**

Note: figures in bold indicate the inclusion of the indicator in the DFM.
Source: Authors' calculations.

4. RESULTS: FORECAST ACCURACY

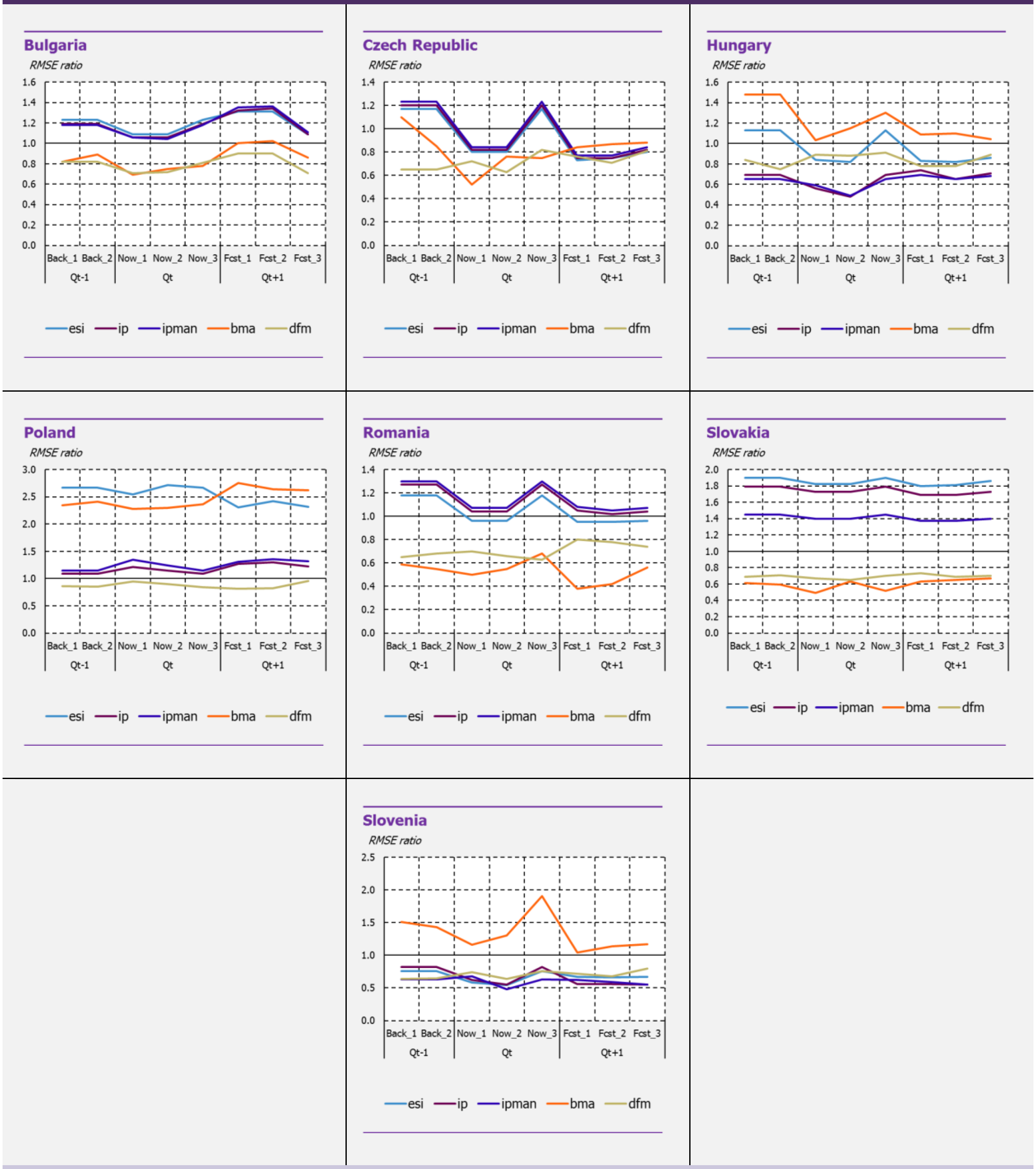
In this section, we present the results of five competing nowcasting models for CESEE countries. We estimate three forecast horizons, i.e. one backcast (previous quarter real GDP growth), one nowcast[17] (current quarter real GDP growth) and one forecast (next quarter real GDP growth) and produce three monthly forecasts per horizon. We drop the backcast in the third month, as previous-quarter real GDP growth has already been released at this time.

All models are estimated for the period from the first quarter of 2000 to the second quarter of 2008. Our evaluation period ranges from the third quarter of 2008 to the third quarter of 2014, covering the period since the Great Recession. Out-of-sample forecasting accuracy is measured by the root mean squared error (RMSE). Given the lack of real-time GDP data series for some of the countries in our sample, we follow the usual practice and use the latest available GDP growth figures to calculate forecasting errors (i.e. we simulate so-called "quasi out-of-sample" forecasts). Hence, we ignore the impact of different data vintages on the results.

All bridge equations are specified with an autoregressive term for real GDP growth. We estimate three bridge equations with a single indicator (our "usual suspects" models) and one bridge equation in which the number and choice of indicators is determined by the BMA results using the predictive likelihood criterion. In the first three bridge equations, the selection of lags for the dependent variables (i.e. GDP growth) and independent variables (i.e. short-term indicators) was based on the goodness-of-fit and in-sample forecasting ability. In the fourth bridge equation, the BMA results determined the lag structure for the independent variables. For each model and each forecast horizon, we calculate the respective RMSE and compare it with the RMSE of our preferred benchmark model. The latter is a simple first-order autoregressive model, an AR(1) model, for quarterly real GDP growth.[18]

[17] Please note that in this section we define "nowcast" very strictly: In general, short-term forecasts encompassing model-based estimates of GDP for a horizon that ranges one quarter back and up to two quarters ahead are denoted as "nowcasts" in the literature. In this section, we use "nowcast" to define very precisely the model-based estimate of current quarter GDP growth (as opposed to an estimate of the previous or next quarter).
[18] The quality of the results is unchanged when we use a naive benchmark (i.e. a random walk model). These results are available on request.

Figure 1 – Predictive accuracy of the models relative to the AR(1) - benchmark



Source: Authors' calculations.

Figure 1 shows the ratio of the RMSE of our five models to the benchmark. For all countries and all horizons, we can identify at least one model with a lower RMSE than the benchmark. However, the type of model that outperforms the benchmark differs across countries. In other words, model performance is strongly dependent on the economy. In two countries – Hungary and Slovenia – our preferred model is a bridge equation based on the "usual suspects." More specifically, in those two countries, bridge equations based on industrial production – both for total industry and for manufacturing only – yield superior forecast accuracy compared to all other models, while the ESI-based bridge equation tops these two models only in one instance (first-month nowcast in Slovenia).

In Bulgaria and Romania, we observe a neck-and-neck race between the BMA-based bridge equation and the small DFM. Bulgaria is the only country where all models perform better than the benchmark, yet the BMA and small DFM are by far the most successful models. In particular, their performance is about equal for all three nowcasts. The DFM yields a slightly smaller forecasting error than the BMA for backcasts and forecasts. By contrast, in Romania, the BMA-based model clearly outperforms the small DFM except at one horizon (third-month nowcast). This model also shows the best forecasting performance at all horizons in Slovakia.

Poland is the only country where most models fail to yield more accurate forecasts than the benchmark. In fact, the small DFM is the only model that shows a slightly better forecasting performance than the AR(1) model, while the BMA-based and ESI-based bridge equations lead to a considerably worse forecasting performance. Their respective RMSEs are almost three times as large as the benchmark RMSE. This poor forecasting performance was to be expected for the BMA model; recall that Poland is the only country where none of the indicators attained a PIP ≥ 0.5 based on predictive likelihood and that we had to lower the threshold for inclusion to 0.3.[19]

The results for the Czech Republic are most difficult to classify. All five models can at least match or beat the benchmark; however, relative model performance varies strongly across forecast horizons. The small DFM model shows the best performance for backcasts as well as for all predictions made in the second month of a quarter. The BMA-based model outperforms all other models for first-month and third-month nowcasts and the ESI-based bridge model for same-month forecasts. However, the differences of RMSEs for forecasts between the "usual suspects" bridge equations and the small DFM are almost negligible.

[19] Alternatively, we could have included indicators in the BMA-based bridge equation based on marginal likelihood. The resulting bridge equation for Poland would include turnover in manufacturing in the domestic market as the only high-frequency indicator and would thus be almost equal in terms of forecasting performance to the "usual suspects" bridge equation using manufacturing IP. While this bridge equation is considerably better than the predictive likelihood BMA-based bridge model, its forecasting performance is still lower than the benchmark.

It is interesting to note that relative model performance is not strongly driven by the forecast horizon – except in the Czech Republic. This is indicated by the rather constant ranking of models in terms of their relative RMSE. Table 3 lists the RMSEs of the best-performing models for each country. Absolute RMSEs are also rather constant across forecast horizons, in particular for the univariate bridge equations based on the "usual suspects." These forecasts are predominantly determined by the autoregressive term, which might explain the low variability of forecasts across different horizons.

Taking a closer look at the definition of "horizon," we have to differentiate between two conceptually different horizons: The first horizon refers to whether we are looking at a backcast, nowcast or forecast; the second horizon depends on the month within a quarter in which the forecast is made. We would expect higher RMSEs for estimates produced in the first month and for forecasts. While we observe higher RMSEs for forecasts, the differences in RMSEs are rather small. More precisely, forecasts produce higher RMSEs for Hungary (all models), the benchmark model in the Czech Republic, Romania and Slovenia, for the BMA-based model in the Czech Republic and Slovakia and for the small DFM in Romania and Slovenia. Furthermore, differentiating between forecasts produced in individual months within a quarter yields even smaller differences in RMSEs. While the pure time series-based benchmark model tends to perform better in the third month when the information set is larger, this is not always true for the alternative models. We interpret this as the better ability of the alternative models to exploit information from high-frequency indicators early on, indicating a clear gain from the use of nowcasting models.

Table 3 – RMSE of best-performing models by country, 2008Q3-2014Q3

	Backcast		Nowcast			Forecast		
	Month 1	Month 2	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3
Bulgaria								
BMA bridge	1.55	1.67	1.46	1.58	1.47	1.76	1.81	1.83
small DFM	1.54	1.55	1.50	1.53	1.53	1.59	1.59	1.50
AR (1)	2.39	2.39	3.52	3.52	2.39	4.48	4.48	3.52
Czech Republic								
ESI bridge	1.08	1.08	1.08	1.08	1.08	1.08	1.11	1.08
BMA bridge	1.02	0.78	0.70	1.03	0.70	1.24	1.29	1.18
small DFM	0.60	0.60	0.97	0.84	0.75	1.12	1.06	1.09
AR (1)	1.09	1.09	1.68	1.68	1.09	1.94	1.94	1.68
Hungary								
IP bridge	0.65	0.65	0.72	0.62	0.65	0.99	0.88	0.90
IP-manuf. bridge	0.61	0.61	0.76	0.62	0.61	0.93	0.87	0.87
AR (1)	1.02	1.02	1.33	1.33	1.02	1.27	1.27	1.33
Poland								
DFM	0.56	0.55	0.58	0.55	0.54	0.47	0.48	0.59
AR (1)	0.59	0.59	0.62	0.62	0.59	0.56	0.56	0.62
Romania								
BMA bridge	1.08	1.00	1.12	1.23	1.25	0.88	0.96	1.26
DFM	1.19	1.25	1.56	1.49	1.16	1.81	1.77	1.65
AR (1)	2.02	2.02	2.55	2.55	2.02	2.64	2.64	2.55
Slovenia								
IP bridge	1.03	1.03	1.13	1.01	1.03	1.08	1.07	1.00
IP-manuf. bridge	0.79	0.79	1.24	0.88	0.79	1.18	1.13	1.00
ESI bridge	0.96	0.96	1.06	0.99	0.96	1.29	1.26	1.23
AR (1)	1.43	1.43	1.84	1.84	1.43	1.64	1.64	1.84
Slovakia								
BMA	1.74	1.70	1.46	1.86	1.48	1.92	1.97	1.98
AR (1)	2.43	2.43	2.32	2.32	2.43	2.30	2.30	2.32

Source: Authors' calculations.

5. Conclusions

Obtaining an accurate picture of the current stance of economic activity remains at the center of conjunctural analysis, as timely information is a prerequisite for sound economic policy decisions. Given long publication lags for national accounts data, a multitude of statistical methods and models has been developed to fill this information gap.

In this article, we compare the forecasting accuracy of two such model classes: bridge equations and small DFMs. We estimate four variants of bridge equations. The first three bridge equations are univariate models, including one prominent short-term indicator (ESI, IP and IP in manufacturing) at the time. Alternatively, we also specify a multivariate bridge equation where short-term indicators are included based on their predictive likelihood as derived from a BMA analysis. For the DFM estimates, we select indicators using correlation analysis.

As a first result, we find that small-scale nowcasting models have a clear advantage over purely time-series based real GDP growth estimates for our sample of seven CESEE countries, as we are always able to beat the AR(1) forecast with such models. This is an important finding, as we are measuring forecasting performance in volatile times when the practical need for accurate estimates of the current stance of economic activity is particularly high and forecasting errors can be large. Second, we observe that model performance varies strongly across countries. For Poland, the small DFM unambiguously yields the best forecasts, while for Slovakia, the BMA-based bridge equation produces the lowest forecasting error. For all other countries, the results are not as clear-cut, but the small DFM outperforms all other models for the majority of forecast horizons in the Czech Republic and Bulgaria, the BMA-based bridge equation produces better results for Romania, and the univariate bridge equations using industrial production (or industrial production in manufacturing) show a superior forecasting ability for Hungary and Slovenia. We conclude that one model type is clearly not fit for all countries.

Third, and in contrast to Hahn and Skudelny (2008), our findings suggest that for our sample of countries, model choice is not strongly influenced by the forecast horizon. The ranking of models remains relatively unchanged for most countries, and the differences in predictive accuracy remain small overall for different forecast horizons. One notable exception is the Czech Republic, where the performance of different nowcasting models differs greatly depending on the forecast horizon.

Hence, we conclude that to maximize forecast accuracy, the choice of a nowcasting model should vary by country. At the same time, a further differentiation of nowcasting models by the forecast horizon does not seem to be warranted for the seven CESEE economies that we have examined in this paper, as the additional gains in forecast accuracy are rather small for each model across different horizons.

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ANNEX

Table A1 – List of short-term indicators

Monthly indicators

indicator	seasonal adjustment	source	publication lag (weeks)	frequency transformation
production in industry				
Industry total	swda	Eurostat	6	average
Mining and quarrying	swda	Eurostat	6	average
Manufactring	swda	Eurostat	6	average
Electricity, gas, steam and air conditioning supply	swda	Eurostat	6	average
Water collection, treatment and supply	swda	Eurostat	6	average
Turnover in industry				
Mining and quarrying	swda	Eurostat	6	average
Manufactring	swda	Eurostat	6	average
Turnover in industry; domestic market				
Mining and quarrying	swda	Eurostat	6	average
Manufactring	swda	Eurostat	6	average
Turnover in industry; non-domestic market				
Mining and quarrying	swda	Eurostat	6	average
Manufactring	swda	Eurostat	6	average
Production in construction				
Procuction in construction	swda	Eurostat	7	average
Turnover in retail trade				
Retail trade	swda	Eurostat	5	average
Retail trade, except of motor vehicles and motorcycles	swda	Eurostat	5	average
Nights spent at tourist accommodation establishments				
Nights spent at tourist accommodation establishments	swda	Eurostat	6	sum
Business and Consumer Surveys				
Consumers				
Financial situation over the last 12 months	sa	Eurostat	0	last obs.
Financial situation over the next 12 months	sa	Eurostat	0	last obs.
General economic situation over the last 12 months	sa	Eurostat	0	last obs.
General economic situation over the next 12 months	sa	Eurostat	0	last obs.
Price trends over the last 12 months	sa	Eurostat	0	last obs.
Price trends over the next 12 months	sa	Eurostat	0	last obs.
Unemployment expectations over the next 12 months	sa	Eurostat	0	last obs.
The current econ. situation is adequate to make major purchases	sa	Eurostat	0	last obs.
Major purchases over the next 12 months	sa	Eurostat	0	last obs.
The current economic situation is adequate for savings	sa	Eurostat	0	last obs.
Savings over the next 12 months	sa	Eurostat	0	last obs.
Statement on financial situation of household	sa	Eurostat	0	last obs.
Consumer confidence indicator	sa	Eurostat	0	last obs.
Industry				
Production development observed over the past 3 months	sa	Eurostat	0	last obs.
Employment expectations over the next 3 months	sa	Eurostat	0	last obs.
Assessment of order-book levels	sa	Eurostat	0	last obs.
Assessment of export order-book levels	sa	Eurostat	0	last obs.
Assessment of the current level of stocks of finished products	sa	Eurostat	0	last obs.
Production expectations over the next 3 months	sa	Eurostat	0	last obs.
Selling price expectations over the next 3 months	sa	Eurostat	0	last obs.
Industrial confidence indicator	sa	Eurostat	0	last obs.
Construction				
Building activity development over the past 3 months	sa	Eurostat	0	last obs.
Evolution of the current overall order books	sa	Eurostat	0	last obs.
Employment expectations over the next 3 months	sa	Eurostat	0	last obs.
Price expectations over the next 3 months	sa	Eurostat	0	last obs.
Construction confidence indicator	sa	Eurostat	0	last obs.
Factors limiting building activity - None	sa	Eurostat	0	last obs.
Factors limiting building activity - Insufficient demand	sa	Eurostat	0	last obs.
Factors limiting building activity - Weather conditions	sa	Eurostat	0	last obs.
Factors limiting building activity - Shortage of labour	sa	Eurostat	0	last obs.
Factors limiting building activity - Shortage of material and/or equipment	sa	Eurostat	0	last obs.
Factors limiting building activity - Other	sa	Eurostat	0	last obs.
Factors limiting building activity - Financial constraints	sa	Eurostat	0	last obs.
Retail sale				
Business activity (sales) development over the past 3 months	sa	Eurostat	0	last obs.
Volume of stocks currently hold	sa	Eurostat	0	last obs.
Expected number of orders placed with suppliers over the next 3 months	sa	Eurostat	0	last obs.
Business activity expectations over the next 3 months	sa	Eurostat	0	last obs.
Employment expectations over the next 3 months	sa	Eurostat	0	last obs.
Retail confidence indicator	sa	Eurostat	0	last obs.

Table A1 – List of short-term indicators (continued)

Monthly indicators (ctd.)

indicator	seasonal adjustment	source	publication lag (weeks)	frequency transformation
Economic sentiment indicator				
Economic sentiment indicator	sa	Eurostat	0	last obs.
Services				
Business situation development over the past 3 months	sa	Eurostat	0	last obs.
Evolution of demand over the past 3 months	sa	Eurostat	0	last obs.
Expectation of the demand over the next 3 months	sa	Eurostat	0	last obs.
Evolution of employment over the past 3 months	sa	Eurostat	0	last obs.
Expectation of the employment over the next 3 months	sa	Eurostat	0	last obs.
Services Confidence Indicator	sa	Eurostat	0	last obs.
Energy supply				
Natural gas	na	Eurostat	7	last obs.
Electricity	na	Eurostat	7	last obs.
Motor spirit	na	Eurostat	7	last obs.
Diesel oil	na	Eurostat	7	last obs.
Passenger car registrations				
Passenger car registrations	swda	ECB	2	sum
Prices				
HICP	na	Eurostat	2	average
Producer prices in industry	na	Eurostat	5	average
Labor market				
Unemployment rate	sa	Eurostat	5	last obs.
International trade				
Imports	na	Eurostat	6	sum
Exports	na	Eurostat	6	sum
Commodity prices				
ECB Commodity Price index	na	Eurostat	1	average
HWWI index of world market prices	na	HWWI	1	average
HWWI index of world market prices, crude oil	na	HWWI	1	average
IFO Business Climate Index				
IFO Business Climate	sa	CESifo	0	average
IFO Assessment of business situation	sa	CESifo	0	average
IFO Business expectations	sa	CESifo	0	average

Quarterly data

indicator	seasonal adjustment	source	publication lag (weeks)
GDP			
Real GDP	swda	Eurostat	7
Business and Consumer Surveys			
Consumers			
Intention to buy a car within the next 12 months	sa	Eurostat	0
Purchase or build a home within the next 12 months	sa	Eurostat	0
Home improvements over the next 12 months	sa	Eurostat	0
Industry			
Assessment of current production capacity	sa	Eurostat	0
Duration of production assured by current order-books	sa	Eurostat	0
New orders in recent months	sa	Eurostat	0
Export expectations for the months ahead	sa	Eurostat	0
Current level of capacity utilization (%)	sa	Eurostat	0
Competitive position over the past 3 months: domestic market	sa	Eurostat	0
Competitive position on intra-EU foreign mkts. over the past 3 m.	sa	Eurostat	0
Competitive position on extra-EU foreign mkts. over the past 3 m.	sa	Eurostat	0
Construction			
Operating time ensured by current backlog	sa	Eurostat	0
Productivity			
Employment in industry	swda	Eurostat	7
Volume of work done (hours worked) in industry	swda	Eurostat	7
Gross wages and salaries in industry	swda	Eurostat	7
Hourly labor cost index , whole economy	wa	ECB	9
Unit labor costs, whole economy	na	ECB	9
Compensation of employees	na	ECB	9

Note: Seasonal and seasonal and working day adjustment of indicators is undertaken by national statistical institutes.
Source: Authors' calculations.