A simple approach to nowcasting GDP growth in CESEE economies

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Given the publication time lag inherent in national accounts data, we explore the informational content of higher-frequency indicators that become available during a quarter in nowcasting current-quarter GDP growth rates for 11 Central, Eastern and Southeastern European (CESEE) economies. Building on recent findings, we restrict our choice to three model classes: (1) principal component models, (2) bridge equations and (3) simple autoregressive (AR) models without higher-frequency variables. Moreover, we propose a variety of forecast combinations to arrive at the highest possible forecast accuracy. Our estimation sample starts in the first quarter of 2003, and our evaluation period ranges from the second quarter of 2012 to the fourth quarter of 2017. We find that higher-frequency indicators contain useful information for predicting current economic activity in most of the economies in our sample. Using forecast combinations of models with and without higher-frequency variables yields additional gains in predictive accuracy. The best performers ultimately selected vary strongly across countries: we find 10 different models for 11 countries. Eight country models produce a statistically significantly smaller forecast error than the benchmark. Calculating a CESEE-11 country aggregate based on the individual country forecasts yields a forecast performance that is highly superior to that of the benchmark.

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"It is difficult to make predictions, especially about the future." This humorous saying has been attributed to many famous people and can also be applied to economics, despite the existence of powerful techniques and sophisticated econometric models to arrive at highly probable and often rather precise statements about future economic developments. Yet economists are not just faced with the difficulty of making predictions about the future ("forecasts"), but also about the present ("nowcasts"). This is due to the long publication lag for important economic variables, such as the components of GDP. Estimates of current economic activity are an important starting point for the analysis of the business cycle and the medium-term outlook and provide a useful reference in a policy context. Over the past years, various computational techniques have been developed to fully exploit all the information available at the time of producing a forecast. These purely computational techniques are subsumed under the term "nowcasting" and in contrast to traditional forecasting techniques, they do not include expert judgment. While indicators that summarize the current state of economic activity are nothing new – for example, the €-coin indicator for economic activity in the euro area has been published since 2001, and the Federal Reserve Banks of New York and Atlanta

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regularly publish nowcasts for the U.S. economy using different methods[2] –, surprisingly few publicly and regularly available nowcasts exist for the Central, Eastern and Southeastern (CESEE) economies.

In this paper, we propose country-specific nowcasting models for the 11 EU Member States in Central, Eastern and Southeastern Europe (CESEE-11)[3]. We adopt a foreign forecaster's perspective and attempt to implement a simple and easily applicable nowcasting tool to be used in regular country monitoring at the OeNB. As we are not aware of any public source of regular nowcasts for these economies, we have developed our own tool. It strikes a balance between finding the best model for every country and keeping the operating expense manageable for this number of countries. This approach also allows us to evaluate the forecast performance of the ultimately selected country models on a regular basis. Therefore, we opt for easily tractable models and avoid overly sophisticated methods that build on big data, allow for non-linearities and represent too much of a black box. We also attempt to limit data requirements to an extent that allows monthly updates of all 11 models in a fast and mechanical way.[4]

Section 1 reviews the literature on nowcasting for the CESEE region. Section 2 presents the baseline models; it introduces the principal component (PC) model, bridge equations (BE) and pure time series models (AR models), as well as variations and forecast combinations that we consider in the analysis. Section 3 describes the indicators that are fed into the baseline models and explains the measures used to compare the forecast performance of these models and to guide our selection of a preferred model for each country. Section 4 reports the results for individual models, countries and the CESEE-11 aggregate, and section 5 concludes the study.

1 Review of existing nowcasting studies for CESEE

Apart from a few studies on Russia and models for Croatia, the Czech Republic, Slovakia and Romania, the literature on nowcasting for CESEE is rather scarce.

Arnoštová et al. (2011) compare different model classes for the Czech Republic and find that standard principal component models outperform all others. Rusnák (2016) employs a dynamic factor model for nowcasting Czech GDP in real time and obtains satisfactory estimates. He stresses the importance of foreign variables for the accuracy of the model's nowcasts. Tóth (2017) applies a small dynamic factor model (DFM) to produce GDP nowcasts for Slovakia and obtains a higher forecast accuracy compared with naive models. Armeanu et al. (2017) use a large DFM based on 86 high-frequency indicators for Romania. Extracting three components, the authors can beat traditional Stock/Watson-type models in terms of forecast accuracy. Finally, Kunovac and Špalat (2014) develop a factor model for Croatia based on a large set of 41 indicators. This model likewise produces smaller forecasting errors compared with the naive benchmark random walk model and with bridge equations (with retail trade and industrial production). The authors stress an additional gain from averaging nowcasts obtained through different factor models.

[2] *More information on the methodologies behind these indicators can be found here: for "GDPNow" by the Fed Atlanta, see Higgins (2014) and for the Fed New York's "Nowcast Report," see Banbura et al. (2013) and Giannone et al. (2008).*

[3] *The CESEE-11 aggregate comprises the following countries: Bulgaria, Croatia, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia.*

[4] *As outlined in the next section, the use of more indicators does not necessarily result in more precise nowcasts. Hence this choice does not necessarily represent a tradeoff between forecast quality and input costs.*

Recently available nowcasting models for Russia differ in terms of the methodology used. Mäkinen (2016) uses a range of small-scale models to produce estimates of Russian GDP growth for the first quarter of 2016 and finds that DFMs beat naive AR and autoregressive distributed lag models in terms of forecast accuracy. Porshakov et al. (2016) also report superior forecasting accuracy of DFMs over common alternative models for obtaining GDP nowcasts for Russia. Finally, Mikosch and Solanko (2017) adopt forecast pooling across different model classes (bridge equations, mixed data sampling and unrestricted mixed-frequency models) and report superior performance over standard benchmark models. They further find evidence that the indicators with the greatest informational content for producing the nowcasts vary over time and differentiate between economic downturns and recoveries.

Apart from these country-specific applications, the smaller CESEE economies in particular have received little attention in the nowcasting literature so far. However, we want to highlight two preceding articles that take a cross-country perspective on the CESEE region and lay the foundations for the model specifications that we propose in the present paper. According to the findings in Feldkircher et al. (2015), models that use high-frequency indicators yield more accurate forecasts than naive models such as AR(1) or random walk projections of GDP. Using both bridge equations and a small DFM, the authors can beat the naive benchmark for their sample of seven CESEE economies. In the case of Poland and Slovakia, only the DFM model outperforms the naive benchmark. Therefore, they recommend selecting a country-specific modeling approach for every CESEE economy based on out-of-sample forecasting performance.

Havrlant et al. (2016) demonstrate that principal component models work well for the CESEE-11 economies and yield on average smaller forecasting errors than DFMs. They further confirm that models with fewer indicators perform significantly better than models based on larger sample sets. This result is in line with Boivin and Ng (2006) and Bai and Ng (2005) and could be related to a violation of the weak orthogonality assumption and the relatively short time period for which high-frequency indicators are available for the sample of CESEE economies.

While the two studies focused on testing different model classes against each other, in this paper we follow the conclusions of Feldkircher at al. (2015) and try to select the best model for each country individually.

2 Description of model classes and forecast combination techniques

We intentionally restrict our modeling choice to simple and tractable models that have proven to yield reasonably accurate forecasts in the very short term (i.e. a horizon covering the past, current and next quarter). We build on the findings in Havrlant et al. (2016) and Feldkircher et al. (2015) and focus on the PC, BE and simple AR models, which were found to outperform other simple and tractable modeling approaches (such as DFMs or bridge equations with Bayesian variable selection).

In the following, we describe these three model classes and the variations within them to arrive at the best-performing nowcasting model for each country. In addition to exploring the forecasting performance of individual models from these model classes, we also test various forecast combinations, as described in section 2.4.

2.1 Spanning the range of principal component models

Our starting point is a principal component model as in Havrlant et al. (2016). The model is described by the following equations:

$$x_{it}^{Q} = \lambda_i PC_t^{Q} + \omega_{it} \tag{1}$$

$$y_t^{Q} = \Phi_h PC_{t-1}^{Q} + \psi_t \tag{2}$$

where x_{it}^{Q} is the quarterly aggregate of monthly indicator i and transformed to be stationary, with zero mean and unit variance. y_t^{Q} is the quarterly growth rate of real GDP. The terms ω_{it} and ψ_t are idiosyncratic shocks, which may be serially correlated. Shifting the x_{it} series appropriately resolves the issue of uneven endpoints of series due to differences in publication lags. Hence, the panel of indicators is rebalanced so that the last observations of x_{it}^{Q} and y_t^{Q} correspond. Vector PC_t^{Q} contains J common factors estimated by principal component analysis, and λ_i is a vector of J factor loadings specific to each indicator i. Note that the principal components are estimated at quarterly frequency. Once the PC_t^{Q} series has been estimated, equation (2) is fitted by OLS to obtain the vector of J coefficients Φ_h. As we work with a static model here, we need to lag PC_t^{Q} in equation (2) by one period to forecast GDP growth one quarter ahead.

We vary the principal component model along the following dimensions:

- The number of principal components pc (i.e. common factors) J can vary between one and four: pc$J$
- Equation (2) can be augmented by lagged GDP (y_{t-1}^{Q}), which yields a specification without or with lagged dependent variable (abbreviated here as g): pc$J$ versus gpc$J$
- Alternatively, lagged GDP (y_{t-1}^{Q}) can be included in the list of indicators when it is not included in the main equation (2)[5]: pcg$J$
- To remove noise arising from the deep reaction in most CESEE countries to the global financial crisis, we can include a crisis dummy c which takes the value 1 for the first quarter of 2009 and 0 otherwise: pcJc

Considering all possible combinations of the above alterations, we arrive at 24 different model specifications (*pc1, pc2, pc3, pc4, gpc1, gpc2, gpc3, gpc4, pcg1, pcg2, pcg3, pcg4, pc1c, pc2c, pc3c, pc4c, gpc1c, gpc2c, gpc3c, gpc4c, pcg1c, pcg2c, pcg3c, pcg4c*).

2.2 Variants of bridge equations

Bridge equations combine the information inherent in short-term indicators and the time series properties of the quarterly GDP series to arrive at a good estimate of current-quarter (and sometimes next-quarter) GDP (see Baffigi et al., 2004, for a good overview). We adopt a simple form of a bridge equation based on Gajewski (2014), who nowcasts GDP growth in the euro area using individual sentiment indicators only (such as ESI, PMI, €-coin) and without extrapolating monthly indicators over the quarter.[6] More precisely, he shows for the four largest euro area

[5] *Hence, the list of indicators used to estimate the factors includes both x_{it}^{Q} and y_{t-1}^{Q}, i.e. the GDP growth rate is used together with the quarterly aggregates of the monthly indicators to extract the principal components.*

[6] *In his framework, the quarterly aggregate of the monthly indicator is equal to the indicator value in the first month of a quarter. In the second month, Gajewski (2014) uses the simple average of the first- and second- month value and, similarly, in the third month, a three-month average is used. Of course, we will stick to our aggregation rules as set out in table A1 and use either averages, sums or the last observation according to the indicator.*

countries that considering one sentiment indicator leads to a significantly higher forecast performance compared with an AR(1) model. Hence, we will estimate several model specifications where we use single indicators only, i.e. without extracting any components. In contrast to Gajewski (2014), we do not restrict the choice of indicators to sentiment indicators only but make use of the pool of our 21 indicators.[7] We will proceed in the following way.

First, we must select the indicator(s) that we want to use. A common approach is to choose the indicator that exhibits the highest correlation coefficients with quarterly GDP growth. However, table A2 – where we present correlation coefficients of all indicators in all countries – shows that there is no one indicator that stands out in terms of its correlation to GDP growth. As there are several indicators showing a roughly equally high correlation coefficient with GDP growth, we choose three indicators in each country, i.e. the ones with the highest values.

Then, based on the selection of indicators x_t^Q we will estimate 14 different specifications that vary with respect to (1) the number of indicators and (2) the lag structure of the indicators. The basic model is based on quarterly data and is defined as follows:

$$y_t^Q = \alpha y_{t-1}^Q + \beta_1 x_t^Q + \beta_2 x_{t-1}^Q + \gamma crisis + \varepsilon_t, \tag{3}$$

where *crisis* is a dummy variable taking the value 1 in the first quarter of 2009. Table A1 in the annex indicates the operation by which each monthly indicator is transformed to quarterly frequency. Again, we arrive at different specifications here which arise from the following variations. First, each of the three indicators is added separately to the basic model, which results in three specifications, henceforth referred to as *be1*, *be2*, *be3*. The number stands for the respective indicator, starting with the one exhibiting the highest correlation coefficient. Hence, in the case of Poland, for example, *be1* represents a model that considers industry production (highest value), while *be2* includes turnover in the manufacturing sector (second-highest value) and so forth (see table A2). Second, we add two indicators to the baseline model, which again results in three specifications (*be12, be13, be23*). Furthermore, we also allow for a model where all indicators are included (*be123*). Finally, we consider lagged values of indicators by additionally adding them to each of the seven models specified so far. This yields seven additional specifications, which we indicate with the letter *L* (i.e. *be1L*, *be2L*, *be3L*, *be12L*, *be13L*, *be23L*, *be123L*). Hence, we are left with 14 bridge equation models overall.

2.3 Pure time series models

An even simpler approach to estimating concurrent GDP is to use the time series properties of the GDP series itself without relying on additional up-to-date information provided by monthly indicators. As it is often difficult to beat the AR(1) model in terms of forecast accuracy, we also consider this model class a fully valid alternative to our simple models. Equation 4 describes the baseline AR model:

$$y_t^Q = \alpha + \beta y_{t-1}^Q + \gamma crisis + \varepsilon_t \tag{4}$$

[7] *This approach is similar to but somewhat more general than the "bridge equations with the usual suspects" which are tested in Feldkircher et al. (2015).*

We work with quarterly data; therefore, we include up to four lags in different model specifications, and we vary these simple AR models by including and excluding the crisis dummy. The models are estimated using maximum likelihood techniques[8] to predict GDP growth rates. In total, we add 8 AR model specifications to our set of model candidates (i.e. *ar1*, *ar2*, *ar3*, *ar4*, *ar1c*, *ar2c*, *ar3c*, *ar4c*).

2.4 Forecast combinations

The literature often refers to improvements in forecast performance from pooling forecasts that are produced using different models (e.g. Kuzin et al., 2013). We also explore this technique, using the following forecast combinations.

A simple averaging of results from pooling across all model variations. We also check whether pooling across variations within each of the three model classes separately yields superior results. Since a simple average gives equal weight to extremely bad and extremely precise forecasts, we also experiment with a weighted average. Here we must distinguish between an ideal weighting scheme and one that is feasible in a real-time forecasting setting. The weights are defined in a dynamic way based on the performance of each model specification. An ideal weighting scheme gives maximum weight to the output of the best-performing model and minimum weight to the most imprecise forecast. However, forecast performance is not known ex ante, hence this weighting scheme is not feasible in real time. A feasible weighted average constructs weights based on previous forecast performance, i.e. the weights are selected based on best forecast performance in the previous period. For our dynamic forecast combination, we use the inverse of the mean average error for constructing the weights (see next section for a presentation of forecast accuracy measures used in the evaluation of forecast performance).

Finally, we also explore a more specific method of averaging selected specifications based on their static forecast performance. In this static forecast combination approach, we exploit both time series properties of the GDP series and more readily available information from monthly indicators by calculating the pairwise average between each AR model and each principal component model as well as between each AR model and each bridge equation.[9] This pairwise averaging results in 304 (8*24 + 8*14) forecast averages, from which we choose the most accurate.

In sum, adding pure model and pooled estimates together, we arrive at 356 possible nowcasts for each country (24 PC forecasts, 14 BE forecasts, 8 AR forecasts, simple average, ideal weighted average, feasible weighted average, average of all PC forecasts, average of all BE forecasts, average of all AR forecasts and 304 pairwise averages). We will compare these model estimates with a simple benchmark to assess their relative forecast performance. In the literature, the prime candidates for such a benchmark are either an AR(1) model or a random walk model. Since we include AR(1) models in our set of candidates, we benchmark the results against the random walk (RW).

[8] *More specifically, we use Stata's arima command. The default setting chosen uses a combination of the Berndt-Hall-Hall-Hausman and the Broyden-Fletcher-Goldfarb-Shanno algorithm to find an optimum. Note that our results do not change if we estimate these models with simple OLS.*

[9] *Note that the nowcasts from the AR(p) models do not vary within one quarter, i.e. the monthly nowcast of quarterly GDP growth rates is the same for all three months within a quarter. Variation within the quarter stems solely from the PC and BE forecasts.*

3 Data and forecast performance measures

As mentioned in the introduction, nowcasting refers to forecasting the present using an automated routine which extracts information from currently available data. In our case, we use a rather small set of only 21 monthly indicators to produce a purely model-based estimate of current-quarter GDP. The set of indicators is described in subsection 3.1 below. As we start from a total of 356 model-based estimates, we also need a clear criterion to select the best model, i.e. the one yielding the smallest forecast error for each country. We explain the measure of forecast accuracy on which we base our selection in subsection 3.2 below.

3.1 Description of monthly indicators

The selection of indicators to be included in the principal component models was guided by the findings in Havrlant et al. (2016) relating to the consistently better forecasting performance of small-scale models in the context of CESEE economies. More specifically, we select 21 monthly indicators from different economic categories, and within each category, we choose an indicator according to its correlation with GDP.

From Eurostat we take monthly series for industrial production, manufacturing turnover, production in construction, retail trade, the economic sentiment indicator (ESI), unemployment rate, imports and exports, and from the ECB we obtain passenger car registrations. In addition, we include industrial production in the euro area and in the three most important trading partners (from Eurostat) and the HWWI indices of world market prices and crude oil. Further, we use the Markit Manufacturing Purchasing Managers Index (PMI®) for the euro area, the €-coin indicator[10] and the CESifo index of export expectations. To capture the influence of financial markets on real activity, we also include market interest rates (the 3-month and 12-month EURIBOR provided by Macrobond). Table A1 in the annex lists all indicators in detail and provides more information, e.g. on frequency transformation and publication lags. Recall that we transform monthly indicators to quarterly frequency (either by averaging, summing or using the last observation) before extracting common factors.

Publication lags range from none for ESI (released on the last day of each month), euro area PMI and export expectations (as we extract the data and compute our nowcasts on the day of release) to seven weeks for production in construction[11]. For most indicators, the publication lag is five to six weeks.

Note that not all indicators are available for all countries and years. Our sample starts in January 2003, yet the ESI for Croatia starts only in January 2008. Further, production in construction does not exist for Croatia, Estonia, Latvia and Lithuania. Car registrations are not available for Croatia, and the time series starts only in 2006 in Bulgaria and Romania. Therefore, we do not include this series in the models for these two countries, either.

The database is updated on the 20th of each month. Apart from the ESI and unemployment, all indicators have been released by this day. We calculate three nowcasts

[10] *The €-coin indicator is itself a real-time monthly estimate of euro area-wide GDP growth, computed each month by the staff of the Banca d'Italia. See https://eurocoin.cepr.org/ for more information or Altissimo et al. (2010) for a technical description of this indicator.*

[11] *However, in contrast to GDP, which is published with the same time lag, the frequency of production in construction is monthly, hence we obtain two updates on this indicator during a quarter before the next GDP figure is released.*

for each quarter. The nowcast calculated in month t is based on data referring to month *t-1*; therefore, in January, we estimate a nowcast for the fourth quarter, using data up until December. In February, when data for January become available, our nowcast relates to the first quarter and we update the nowcast for the first quarter by April. In May, we move to estimating second quarter GDP and so on.

3.2 Measures of forecast accuracy

We perform quasi-out-of-sample forecasts for the period ranging from the second quarter of 2012 to the fourth quarter of 2017. In total, our evaluation sample covers almost 6 years, which yields 69 observations (i.e. months).[12] From these estimates, we calculate several measures of forecast performance.[13] Unfortunately, real-time GDP data series are not available for all the countries in our sample. We must rely on recently published GDP growth figures in our calculation of forecast errors (hence "quasi-out-of-sample") with the well-known caveat that we ignore the effect of different data vintages on the results.[14]

Our model selection criterion is the mean absolute error, $MAE = \frac{\sum_{n=1}^{N=69} |y_n - \hat{y}_n|}{N}$, where $\hat{y}$ denotes realized quarterly GDP growth and refers to our GDP nowcast. We choose this indicator because it reflects the absolute size of the forecast error. In our case, it can be interpreted by means of percentage points of GDP growth rates. The model with the lowest MAE will be selected as the optimal model – this is done for each country individually.

In addition, we test whether the MAE of the optimal model is statistically smaller than the MAE of the benchmark model (i.e. RW model) by means of a Diebold-Mariano statistic. This test (Diebold and Mariano, 1995) is based on the null hypothesis that the forecasting ability of two models is equal. A rejection of the null hypothesis is evidence of better forecast accuracy of the nowcast model.

Furthermore, we will present the following indicators:[15]

1 Mean forecast error: $MFE = \frac{\sum_{n=1}^{N=69} (y_n - \hat{y}_n)}{N}$, whereby a negative sign implies an over-prediction of GDP growth. The MFE is an indication of forecast bias.

2 Root mean square error: $RMSE = \sqrt{\frac{\sum_{n=1}^{N=69} (y_n - \hat{y}_n)^2}{N}}$, whereby a smaller RMSE indicates higher forecast accuracy.

Direction of change – percentage of cases in which the forecast movement direction of GDP growth relative to its previous level coincides with the direction of change of realized GDP growth. In other words, it gives the percentage of cases where the model correctly predicts the sign of the growth rate: $DOC = 1$ *if* $\{(y_{t+1} - y_t) > 0$ *and* $(\hat{y}_{t+1} - y_t) > 0\}$ *or if* $\{(y_{t+1} - y_t) < 0$ *and* $(\hat{y}_{t+1} - y_t) < 0\}$ and 0 otherwise.

[12] *To be precise, GDP figures for Croatia, Slovenia and Estonia become available somewhat later than those of other countries, which implies that we lose one-third of the observations in the evaluation for these three countries.*

[13] *We focus here on point estimates in our assessment of forecast accuracy in order to maintain comparability with most of the existing literature. In particular, we want to compare our results with the two preceding papers by Feldkircher et al. (2015) and Havrlant et al. (2016). These studies serve as a starting point for deriving a nowcasting procedure that will be applied regularly for our sample of 11 CESEE countries.*

[14] *While it would be possible to reconstruct vintages for the GDP and industry production series for most of these countries (albeit in a rather time-consuming way), such vintage data are unfortunately not available for the remaining monthly indicators.*

[15] *See for example Slacik et al. (2014) for a more detailed description of these forecasting accuracy measures.*

4 Results – selecting the models with the smallest forecast error

We first assess the forecasting performance of individual models, distinguishing between nowcasts based on PC, BE and AR models. We then present the results from averaging nowcasts. In the next step, we explore the gain from using a different model or model average in each of the three months within a quarter.[16] Finally, we present our preferred model for each country and a regional average. We calculate the forecast performance indicators described above based on 69 monthly observations in our evaluation period. The model with the smallest MAE among all country-specific models is classified as the best performer.[17] We compare the MAEs as well as the other performance measures introduced in the preceding section with the ones obtained from estimates of a simple RW model which uses neither additional, high-frequency information nor the time series properties inherent in the GDP series. The RW model serves as our benchmark.

4.1 Best performers among the country-specific models

The results from the 46 "pure" models are summarized in table 3A in the annex. In table 1, we report the forecast measures for the best-performing model according to the MAE. Three findings stand out.

First, except for Slovakia, the best-performing country models always exhibit a smaller MAE than the RW model. This is also true of the RMSE. In terms of the MFE, the RW model consistently underpredicts GDP in all countries, while the bias differs by country based on informed nowcasts using the selected best-performing model. However, the absolute value of the MFE using our selected models is lower only in 3 of 11 countries (and not different from the MFE of the RW model in a further three countries). This suggests on average a smaller, yet more consistent bias of the RW model. Finally, the direction of change (DOC) indicator is always well above 50 for both the selected model-based nowcast and the benchmark. This indicates that all models are likely to predict turning points correctly. The selected model outperforms the RW model on this criterion in six countries.

Second, 7 of 11 country models significantly outperform the benchmark model as indicated by the Diebold-Mariano test. Although the models exhibit a smaller MAE, the nowcast models for the Czech Republic, Slovakia, Lithuania and Latvia do not show a significantly better forecast performance than the RW model in a strictly statistical sense.

Third, we confirm the finding in Feldkircher et al. (2015) that there is no one model that is equally suitable for all countries. In fact, we find ten different "best" model specifications from all model classes and variations for 11 countries. An AR(4) model including a crisis dummy emerges as the best performer only for two countries, Bulgaria and Slovakia, yet only in the case of Bulgaria does this model also significantly outperform the RW benchmark as indicated by the Diebold-Mariano test. In all other countries, the specifications differ widely. More specifically, we identify four variants of AR models, four variants of BE models and three different PC specifications as the best-performing models.

[16] *We thank the anonymous referee for this suggestion.*

[17] *MAEs for all 46 models and 11 countries are available from the authors upon request.*

Table 1

The best performers among 46 "pure" models

	Best-performing model					Random walk (benchmark)				Diebold-Mariano	
	Model type	MAE	RMSE	MFE	DOC	MAE	RMSE	MFE	DOC	ΔMAE	Statistic
CZ	be23	0.47	0.56	0.00	0.77	0.53	0.71	0.03	0.82	0.06	0.89
BG	ar4c	0.23	0.27	–0.03	0.81	0.32	0.37	0.02	0.55	0.09***	3.79
HU	be123	0.38	0.45	0.20	0.69	0.60	0.79	0.15	0.73	0.23*	1.79
PL	be13L	0.34	0.43	–0.12	0.77	0.58	0.68	0.04	0.60	0.24***	4.45
RO	pcg2c	0.73	0.86	0.17	0.67	1.03	1.30	0.01	0.68	0.30***	7.63
SI	gpc2c	0.34	0.47	0.06	0.81	0.52	0.61	0.10	0.67	0.18***	3.00
SK	ar4c	0.23	0.34	–0.19	0.63	0.11	0.14	0.03	0.74	–0.12	–1.45
HR	ar3c	0.41	0.51	0.07	0.64	0.62	0.75	0.08	0.59	0.21***	2.58
EE	pc1	0.48	0.58	–0.10	0.80	1.01	1.23	0.03	0.61	0.52***	2.94
LT	ar1	0.42	0.57	–0.05	0.83	0.52	0.75	0.03	0.77	0.10	1.64
LV	be2L	0.46	0.58	0.22	0.71	0.58	0.76	–0.00	0.73	0.11	1.48

Source: Authors' estimations.

*Note: MAE = mean average error, RMSE = root mean square error, MFE = mean forecast error, DOC = direction of change (see section 3.2 for a description of the indicators). The Diebold-Mariano test is based on the null hypothesis: difference in MAE is zero, two-tailed significance levels: * p<0.10, ** p<0.05, *** p<0.01.*

Overall, short-term macroeconomic indicators make a valuable contribution to obtaining reliable information on current-quarter GDP growth in CESEE economies, but there is still room for improvement in terms of forecast accuracy.

4.2 Pooling of forecasts

Rather surprisingly, forecast pooling does not yield large gains in forecast accuracy. Table 2 summarizes the MAEs of all forecast averages. When we look at the results for simple forecast averages (i.e. pooling across all possible specifications or within model classes), we find improvements only for Slovenia (using the average across all PC models), Estonia (average across all models) and Romania (average across all BE models). However, these small improvements are not statistically significant. What is worse, we cannot observe an improvement for countries where we were not able to beat the random walk with any of the single-model specifications.

A dynamic forecast combination would clearly allow us to obtain more precise nowcasts, yet only if we knew the best-performing models ex ante. However, such a procedure is not feasible in real time. Using lagged weights does not yield any improvement except for Slovenia.

Finally, we look at the results from pairwise forecast combinations shown in the last two columns of table 2 (indicating which specification or combination is used and the corresponding MAE). For 6 of the 11 countries, such a pairwise combination reduces the MAE, while choosing a single model remains the best option in 5 countries. More precisely, in Hungary, Romania, Croatia and the Baltic states, a combination of either a PC or a BE model with an AR model leads to more accurate nowcasts. However, only in Latvia is the improvement sufficiently strong to render the nowcast significantly better than an RW estimate according to the Diebold-Mariano test.

Table 2

Forecast combinations

Country	Best single model		Simple forecast averages				Dynamic forecast combination		Pairwise forecast combination[2]	
	(memo item)		all models	PC models	BE models	AR models	current weights[1]	lagged weights		
CZ	be23	0.47	0.50	0.50	0.50	0.54	0.38	0.50	be23	0.47
BG	ar4c	0.23	0.33	0.36	0.38	0.26	0.22	0.29	ar4c	0.23
HU	be123	0.38	0.39	0.39	0.37	0.48	0.25	0.40	ar4c/be123	0.36
PL	be13L	0.34	0.38	0.38	0.37	0.43	0.29	0.36	be13L	0.34
RO	pcg2c	0.73	0.77	0.78	0.73	0.77	0.62	0.72	ar2c/be123L	0.71
SI	gpc2c	0.34	0.34	0.32	0.35	0.49	0.24	0.31	gpc2c	0.34
SK	ar4c	0.23	0.33	0.34	0.37	0.33	0.15	0.30	ar4c	0.23
HR	ar3c	0.41	0.40	0.41	0.43	0.43	0.26	0.45	ar3c/gpc2c	0.37
EE	pc1	0.48	0.47	0.52	0.58	0.53	0.18	0.43	ar4c/be1	0.38
LT	ar1	0.42	0.47	0.50	0.47	0.45	0.29	0.47	ar3/pc1c	0.41
LV	be2L	0.46	0.49	0.50	0.50	0.50	0.27	0.52	ar3c/be12	0.46

Source: Authors' estimations.

[1] *Note that this estimator is unfeasible.*

[2] *This selection is based on all single models (N:46) plus all pairwise averaged models (= unweighted mean of each PC and BE model with each AR model, N:38x8=304).*

Note: PC, BE and AR refer to principal component, bridge equation and autoregressive time series models.

4.3 Differentiating by forecast month

Clearly, new information about economic activity continuously becomes available over the three months within a quarter. Therefore, the best nowcasting model may vary across the first, second, and third month within a quarter. We explore possible gains from selecting a different model specification for each month, following the constant pattern of data releases.

Table 3 displays the MAEs of the best-performing models when we distinguish by forecast month. The first two columns repeat the best model among single models and pairwise forecast combinations while ignoring the variation across individual months. The next six columns report the best model and the corresponding MAE for each month. The last column shows the MAE that is obtained when we vary the underlying model specification across the three months.

Looking first at the changes in model selection over time, we observe that the number of pure AR models or models with AR combinations declines from the first to the third month within a quarter. This is an expected outcome, which confirms that the monthly indicators become more informative over time. In the first month of a quarter, an AR model or a combination of an AR model with a model based on monthly indicators emerges as the best performer in eight countries. In the third month, this number is reduced to five. Pure BE models often perform best in the second month, while in the third month PC models gain ground.

Comparing the MAE from the memo item with the last column, we observe a minor improvement in the accuracy of the nowcast for Hungary, Poland, Romania and Lithuania. However, in all four cases, the Diebold-Mariano test still does not indicate a statistically significantly better forecasting performance than the RW model (not reported, but available upon request). Hence, while this routine would clearly complicate regular monthly updates, the gains in forecast accuracy appear to be minor.

Table 3

Best model by forecast month

Country	Best single and combined models (memo item)		Best model in month 1		Best model in month 2		Best model in month 3		Combining best models for months 1 to 3
	Model type	MAE	Model type	MAE	Model type	MAE	Model type	MAE	
CZ	be23	0.47	ar1c/pc3	0.47	be23	0.46	be23	0.48	0.47
BG	ar4c	0.23	ar4c	0.23	ar4c	0.23	ar4c	0.23	0.23
HU	ar4c/be123	0.36	ar4c/be123	0.34	ar3c/be123L	0.34	pc3c	0.32	0.33
PL	be13L	0.34	be3	0.35	be13L	0.32	be13L	0.32	0.33
RO	ar2c/be123L	0.71	be13L	0.67	be13L	0.67	pc3	0.69	0.68
SI	gpc2c	0.34	pc3c	0.39	be1	0.34	gpc2c	0.29	0.34
SK	ar4c	0.23	ar4/pcg1	0.22	ar4c	0.23	ar4c	0.23	0.23
HR	ar3c/gpc2c	0.37	ar1c/pc4c	0.37	ar4c/gpc4c	0.37	ar3c/gpc2	0.37	0.37
EE	ar4c/be1	0.38	ar4	0.48	ar4c/be12	0.38	ar3c/gpc1c	0.36	0.40
LT	ar3/pc1c	0.41	ar1	0.42	ar1/pcg3	0.39	ar3/pc1c	0.39	0.40
LV	ar3c/be12	0.46	ar3/be2L	0.46	ar3c/pcg4c	0.44	be2	0.41	0.44

Source: Authors' estmations.

Note: MAE = mean average error. For Slovenia, Croatia and Estonia, estimates for month 1 are available for a restricted set of models (PC and AR models).

4.4 Preferred model choice

When we consider all the variations and combinations of models and model specifications that we explored and their relative forecasting performance, we arrive at the following preferred modeling choice: we choose from pure models from all three model classes and pairwise combinations of pure AR models with either BE or PC models without varying our models across months within a quarter. The preferred model specifications and their forecasting performance are summarized in table 4. For 8 of the 11 countries, our models produce a more accurate nowcast than an RW model according to the Diebold-Mariano test. For the Czech Republic, Slovakia and Lithuania, we were not able to find any variation or modification of

Table 4

Preferred nowcast specification by country and CESEE aggregate

Country	Best-performing model					Random walk (benchmark)				Diebold-Mariano	
	Model type	MAE	RMSE	MFE	DOC	MAE	RMSE	MFE	DOC	ΔMAE	Statistic
CZ	be23	0.47	0.56	0.00	0.77	0.53	0.71	0.03	0.82	0.06	0.89
BG	ar4c	0.23	0.27	–0.03	0.81	0.32	0.37	0.02	0.55	0.09***	3.79
HU	ar4c/be123	0.36	0.44	0.22	0.70	0.60	0.79	0.15	0.73	0.24**	2.04
PL	be13L	0.34	0.43	–0.12	0.77	0.58	0.68	0.04	0.60	0.24***	4.45
RO	ar2c/be123L	0.71	0.88	0.07	0.67	1.03	1.30	0.01	0.68	0.32***	3.22
SI	gpc2c	0.34	0.47	0.06	0.81	0.52	0.61	0.10	0.67	0.18***	3.00
SK	ar4c	0.23	0.34	–0.19	0.63	0.11	0.14	0.03	0.74	–0.12	–1.45
HR	ar3c/gpc2c	0.37	0.47	–0.06	0.68	0.62	0.75	0.08	0.59	0.24**	2.33
EE	ar4c/be1	0.38	0.48	–0.06	0.89	1.01	1.23	0.03	0.61	0.63***	3.21
LT	ar3/pc1c	0.41	0.56	–0.14	0.79	0.52	0.75	0.03	0.77	0.11	1.24
LV	ar3c/be12	0.46	0.61	–0.13	0.77	0.58	0.76	–0.00	0.73	0.12**	2.29
CESEE-11	weighted av.	0.23	0.29	–0.02	0.69	0.32	0.41	0.05	0.74	0.09**	2.05

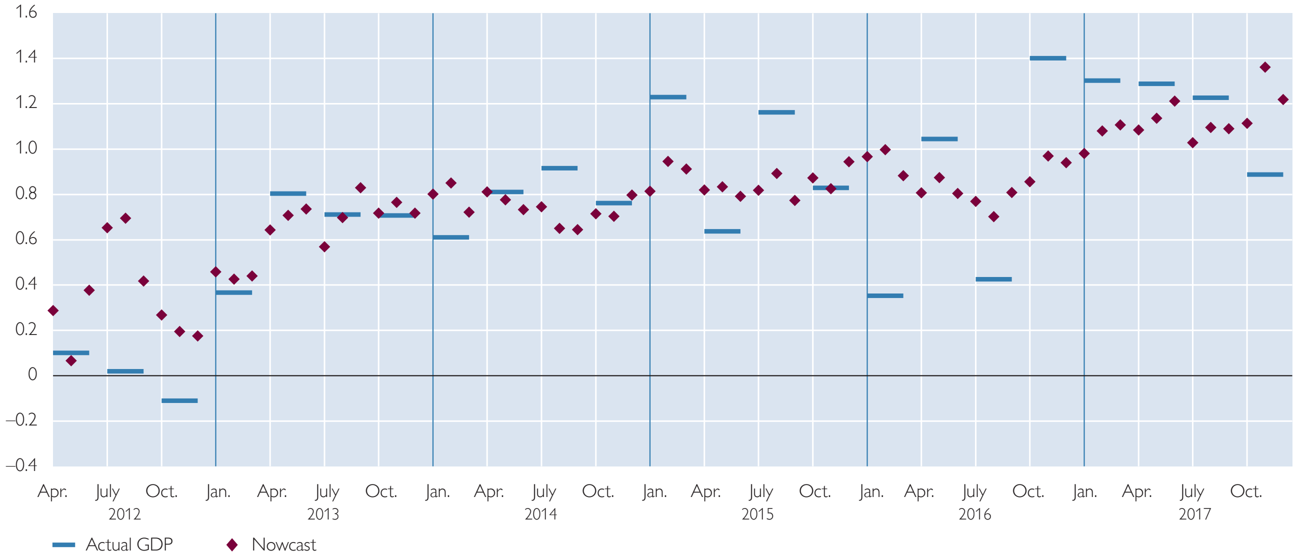
Source: Authors' estimations.

*Note: MAE = mean average error, RMSE = root mean square error, MFE = mean forecast error, DOC = direction of change (see section 3.2 for an explanation of the indicators); Diebold-Mariano test is based on the null hypothesis: difference in MAE is zero, two-tailed significance levels: * p<0.10, ** p<0.05, *** p<0.01.*

Chart 1

Out-of-sample nowcast and real GDP growth in CESEE-11

Quarter on quarter in %



Source: Eurostat, authors' calculations.

our baseline models that would be able to beat the benchmark. However, for the Czech Republic and Lithuania, we can produce a smaller MAE than the benchmark, even if the difference is not statistically significant. Overall, we consider the results to be satisfactory, with a rather high hit rate when it comes to correctly predicting the direction of change in GDP and producing on average a low and variable bias across countries. Especially with respect to the direction of change criterion, we were able to improve the forecasting performance considerably compared with the results for the pure models presented in table 1.

Table 4 also reports a regional aggregate for all 11 countries. To calculate the CESEE-11 aggregate, we weight the nowcasts of individual countries by using the GDP values (in PPP) of the countries observed in 2014. The MAE of the CESEE-11 nowcast amounts to 0.23 percentage points of GDP growth. This is quite low compared with the relatively high and highly variable growth rates in this region over the last five years. Chart 1 illustrates GDP developments and how our pooled nowcast, based on country-specific model specifications, tracks economic activity in the CESEE-11 region over the evaluation period.

5 Summary and conclusions

National accounts data are released with a seven-week lag. This first release includes headline GDP and its components and is thus particularly relevant for policy-makers. To be able to better assess the current level of economic activity between the quarterly releases of GDP in the 11 CESEE countries examined, we propose a computational approach that makes use of the information inherent in higher-frequency indicators which are published during each month of a quarter. We build on previous studies (Feldkircher et al., 2015, and Havrlant et al., 2016) and employ principal component models and bridge equations using a rather small set of carefully selected monthly indicators as well as time-series models as our baseline model setting.

More specifically, we extract principal components from a set of 21 monthly indicators covering both country-specific and international developments. This serves as a basis for specifying a selection of 24 models that vary along several dimensions (e.g. number of extracted components, lag structure, inclusion of crisis dummy and treatment of lagged dependent variable). We then add to this pool of principal component models a pool of bridge equations, adding another 14 specifications to draw from, as well as eight pure AR models. Finally, we propose several forecast combination techniques to arrive at 356 possible nowcasts for each country.

Based on out-of-sample forecasts, we choose the model with the smallest mean absolute error for each country and compare its performance to a random walk model. Our estimation sample starts in the first quarter of 2003, our evaluation period ranges from the second quarter of 2012 to the fourth quarter of 2017.

Our findings can be summarized as follows: First, we find clear evidence that high-frequency indicators can be used to improve short-term forecasts, as they yield rather accurate estimates of current GDP growth. Calculating quasi-out-of-sample forecasts based on these models, we can always find a principal component model, a bridge equation, a variation of such a model or a combination with an AR model that outperforms the RW benchmark in terms of the mean absolute error (except in the case of Slovakia). More importantly, in 8 of 11 CESEE countries, we were able to find a model specification with a statistically significantly smaller forecast error than the benchmark according to the Diebold-Mariano test.

The results are similar for other forecast accuracy measures: In most cases, our nowcast models result in a lower root mean square error than the naive benchmark, and we also beat the benchmark in terms of getting the direction of change right (apart from the Czech Republic, Hungary and Slovakia).

Second, we confirm the finding by Feldkircher et al. (2015) that the optimal model varies strongly across countries: For 11 countries, we find 10 different best-performing models. There are only two countries for which the same time series model specification yields the highest forecast accuracy, namely Bulgaria and Slovakia.

Third, we see a gain in careful forecast pooling, both across models and across countries. For six countries, we can obtain more accurate nowcasts when we average model estimates with estimates from a pure AR model (using up to four lags of GDP). Interestingly, we do not observe much gain in pooling across all available forecasts, as this mixes both highly accurate and very imprecise forecasts. Since there is no feasible way of attaching higher weights to the best-performing forecasts in a dynamic setting, we opted for a static selection of best-performing forecasts from both model classes – PC and BE models based on monthly indicators and AR models using only time series information. The pairwise combination of these models yielded a notable gain in the accuracy of the nowcasts. We also explored further gains from using different models in each month, as new information builds up over the three months of a quarter. Yet, while we clearly find fewer AR-based and more BE and PC models among the best performers in the second and third month of a quarter – indicating the growing importance of additional information from monthly indicators as the quarter evolves –, we were not able to produce a worthwhile improvement in the forecast accuracy measures. Hence, for the sake of simplicity and efficiency in daily routine, we opted against this additional differentiation. Finally, we calculated a weighted average of the individual country estimates to obtain a nowcast for the CESEE-11 country aggregate. This nowcast is highly superior to the benchmark and produces statistically significantly smaller forecast errors and notably a smaller forecast bias.

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Annex

Table A1

List of indicators

Label	Indicator	Seasonal adjustment	Source	Publication lag (weeks)	Frequency transformation
ip	Production in industry, total	SCA	Eurostat	6	average
turnover	Manufacturing turnover	SCA	Eurostat	6	average
constr	Production in construction	SCA	Eurostat	7	average
retail	Retail trade, excluding motor vehicles and motorcycles	SCA	Eurostat	5	average
esi	Economic Sentiment Indicator	SA	Eurostat	0	last observation
car	Passenger car registrations	SCA	ACEA	2	sum
unempl	Unemployment rate	SA	Eurostat	5	last observation
imp	Imports	NA	Eurostat	6	sum
exp	Exports	NA	Eurostat	6	sum
HWWI	HWWI index of world market prices	NA	HWWI	1	average
HWWI, oil	HWWI index of world market prices, crude oil	NA	HWWI	1	average
EA ip	Production in industry, euro area	SCA	Eurostat	6	average
EA pmi	Markit Eurozone Manufacturing Purchasing Managers Index (PMI®)	SA	Markit	0	last observation
EA IFO	ifo Export Expectations for German industry	SA	CESifo	0	last observation
EA €-coin	€-coin indicator	NA	Banca d'Italia / CEPR	0	last observation
EUR3	EURIBOR 3 months	NA	Macrobond	0	average
EUR12	EURIBOR 12 months	NA	Macrobond	0	average
IP_xx	Production in industry of the three most important trading partners	SCA	Eurostat	6	average
gdp	Real GDP (quarterly)	SCA	Eurostat	7	-

Source: Authors' compilations.

Note: Seasonal as well as seasonal and calendar-day adjustment of indicators is undertaken by national statistical institutes. SCA = seasonally and calender-day adjusted, SA = seasonally adjusted, NA = non-adjusted times series.

Table A2

Pairwise correlation coefficients of GDP growth and indicators (quarterly, quarter on quarter)

	CZ	BG	HU	PL	RO	SI	SK	HR	EE	LT	LV
unempl	–0.559	–0.445	–0.346	–0.319	–0.207	–0.356	–0.388	–0.462	–0.370	–0.575	–0.611
turnover	0.411	0.368	0.684	0.487	0.513	0.607	0.477	0.061	0.390	0.367	0.549
retail	0.620	0.628	0.614	0.252	0.452	0.521	0.434	0.554	0.499	0.729	0.766
pmi	0.776	–	–	0.363	–	–	–	–	–	–	–
ip	0.674	0.627	0.743	0.494	0.568	0.769	0.432	0.585	0.541	0.197	0.546
car	0.311	–	0.298	0.164	–	0.350	0.111	–	–	–	–
imp	0.337	0.413	0.346	0.054	0.444	0.285	0.430	0.316	0.115	0.505	0.426
exp	0.305	0.287	0.311	0.028	0.410	0.239	0.412	0.193	0.116	0.449	0.190
esi	0.775	0.588	0.624	0.231	0.561	0.811	0.544	–	0.728	0.672	0.811
constr	0.113	0.506	0.236	0.338	0.219	0.382	0.350	–	–	–	–
HWWI, oil	0.245	0.192	0.315	0.036	0.187	0.360	0.218	0.187	0.374	0.289	0.051
HWWI	0.272	0.226	0.364	0.090	0.248	0.411	0.223	0.246	0.416	0.314	0.081
TP1 ip[1]	0.662	0.558	0.598	0.239	0.591	0.707	0.643	0.646	0.460	0.497	0.174
TP2 ip[1]	0.513	0.474	0.502	0.098	0.495	0.795	0.501	0.682	0.381	0.599	0.223
TP3 ip[1]	0.504	0.349	0.456	0.329	0.535	0.685	0.328	0.548	0.460	0.491	0.484
EA pmi	0.762	0.580	0.647	0.270	0.480	0.855	0.484	0.580	0.584	0.618	0.536
EA ip	0.727	0.576	0.662	0.269	0.580	0.776	0.623	0.622	0.531	0.775	0.460
EA €-coin	0.787	0.600	0.596	0.374	0.473	0.839	0.541	0.640	0.600	0.620	0.614
EA IFO	0.770	0.593	0.688	0.216	0.516	0.845	0.533	0.584	0.658	0.687	0.574
euribor, 3-m	0.742	0.707	0.666	0.132	0.633	0.785	0.762	0.593	0.542	0.825	0.517
euribor, 12-m	0.738	0.695	0.675	0.136	0.611	0.803	0.700	0.593	0.544	0.789	0.462

Source: Authors' estimations.

[1] *TP denotes the trading partner of the respective country. TP1 is the main trading partner in terms of exports, TP2 is the trading partner receiving the second highest amount of exports of the respective country, and so forth.*

Table A3

Mean absolute error (MAE) of 46 models and random walk (benchmark) model

	RW	ar1	ar1c	ar2	ar2c	ar3	ar3c	ar4	ar4c	pcg1	pcg1c	pcg2	pcg2c
CZ	0.53	0.52	0.51	0.53	0.54	0.54	0.55	0.55	0.58	0.50	0.52	0.52	0.53
BG	0.32	0.31	0.32	0.27	0.24	0.25	0.23	0.26	0.23	0.38	0.38	0.35	0.35
HU	0.60	0.51	0.49	0.52	0.45	0.51	0.43	0.50	0.43	0.38	0.40	0.42	0.40
PL	0.58	0.47	0.47	0.47	0.47	0.45	0.45	0.45	0.45	0.40	0.40	0.41	0.41
RO	1.03	0.78	0.73	0.78	0.74	0.79	0.75	0.86	0.76	0.78	0.75	0.78	0.73
SI	0.52	0.48	0.47	0.52	0.46	0.52	0.46	0.52	0.47	0.36	0.35	0.36	0.36
SK	0.11	0.34	0.55	0.32	0.40	0.31	0.29	0.24	0.23	0.34	0.32	0.49	0.32
HR	0.62	0.43	0.42	0.44	0.43	0.45	0.41	0.45	0.45	0.43	0.43	0.45	0.44
EE	1.01	0.67	0.61	0.52	0.51	0.51	0.51	0.50	0.51	0.50	0.51	0.56	0.56
LT	0.52	0.42	0.47	0.44	0.49	0.42	0.48	0.43	0.54	0.60	0.47	0.61	0.53
LV	0.58	0.51	0.52	0.50	0.50	0.48	0.48	0.52	0.52	0.51	0.58	0.65	0.62

	RW	pcg3	pcg3c	pcg4	pcg4c	pc1	pc1c	pc2	pc2c	pc3	pc3c	pc4	pc4c
CZ	0.53	0.51	0.52	0.51	0.51	0.51	0.53	0.53	0.54	0.52	0.53	0.52	0.52
BG	0.32	0.39	0.34	0.40	0.40	0.39	0.39	0.37	0.37	0.40	0.35	0.40	0.36
HU	0.60	0.43	0.42	0.49	0.49	0.39	0.40	0.43	0.41	0.43	0.41	0.50	0.47
PL	0.58	0.39	0.39	0.39	0.39	0.39	0.39	0.40	0.40	0.39	0.39	0.38	0.38
RO	1.03	0.86	0.82	0.95	0.95	0.77	0.74	0.78	0.74	0.85	0.81	0.93	0.87
SI	0.52	0.34	0.34	0.34	0.34	0.37	0.35	0.35	0.34	0.34	0.34	0.34	0.34
SK	0.11	0.57	0.34	0.54	0.54	0.35	0.32	0.50	0.33	0.54	0.33	0.53	0.34
HR	0.62	0.47	0.45	0.47	0.47	0.43	0.43	0.43	0.42	0.49	0.47	0.49	0.46
EE	1.01	0.72	0.70	0.78	0.78	0.48	0.50	0.54	0.54	0.69	0.68	0.74	0.76
LT	0.52	0.66	0.54	0.68	0.68	0.62	0.48	0.63	0.54	0.65	0.56	0.66	0.55
LV	0.58	0.69	0.66	0.61	0.61	0.51	0.58	0.64	0.66	0.76	0.71	0.78	0.73

	RW	gpc1	gpc1c	gpc2	gpc2c	gpc3	gpc3c	gpc4	gpc4c	be1	be12	be123	be13
CZ	0.53	0.48	0.50	0.50	0.52	0.49	0.50	0.49	0.50	0.53	0.51	0.51	0.53
BG	0.32	0.39	0.34	0.46	0.41	0.48	0.40	0.49	0.40	0.34	0.32	0.49	0.50
HU	0.60	0.39	0.40	0.43	0.41	0.44	0.42	0.51	0.49	0.43	0.38	0.38	0.41
PL	0.58	0.40	0.40	0.40	0.40	0.40	0.40	0.37	0.37	0.44	0.44	0.36	0.35
RO	1.03	0.78	0.75	0.79	0.75	0.85	0.81	0.92	0.87	0.74	0.74	0.75	0.75
SI	0.52	0.37	0.36	0.35	0.34	0.35	0.36	0.36	0.37	0.34	0.35	0.36	0.35
SK	0.11	0.44	0.35	0.51	0.38	0.56	0.40	0.58	0.42	0.38	0.42	0.42	0.38
HR	0.62	0.42	0.41	0.43	0.42	0.53	0.52	0.51	0.48	0.43	0.42	0.48	0.46
EE	1.01	0.49	0.51	0.55	0.56	0.65	0.65	0.70	0.73	0.54	0.58	0.65	0.54
LT	0.52	0.69	0.47	0.79	0.56	0.80	0.57	0.80	0.60	0.46	0.47	0.48	0.47
LV	0.58	0.51	0.54	0.59	0.62	0.61	0.61	0.61	0.63	0.58	0.49	0.62	0.65

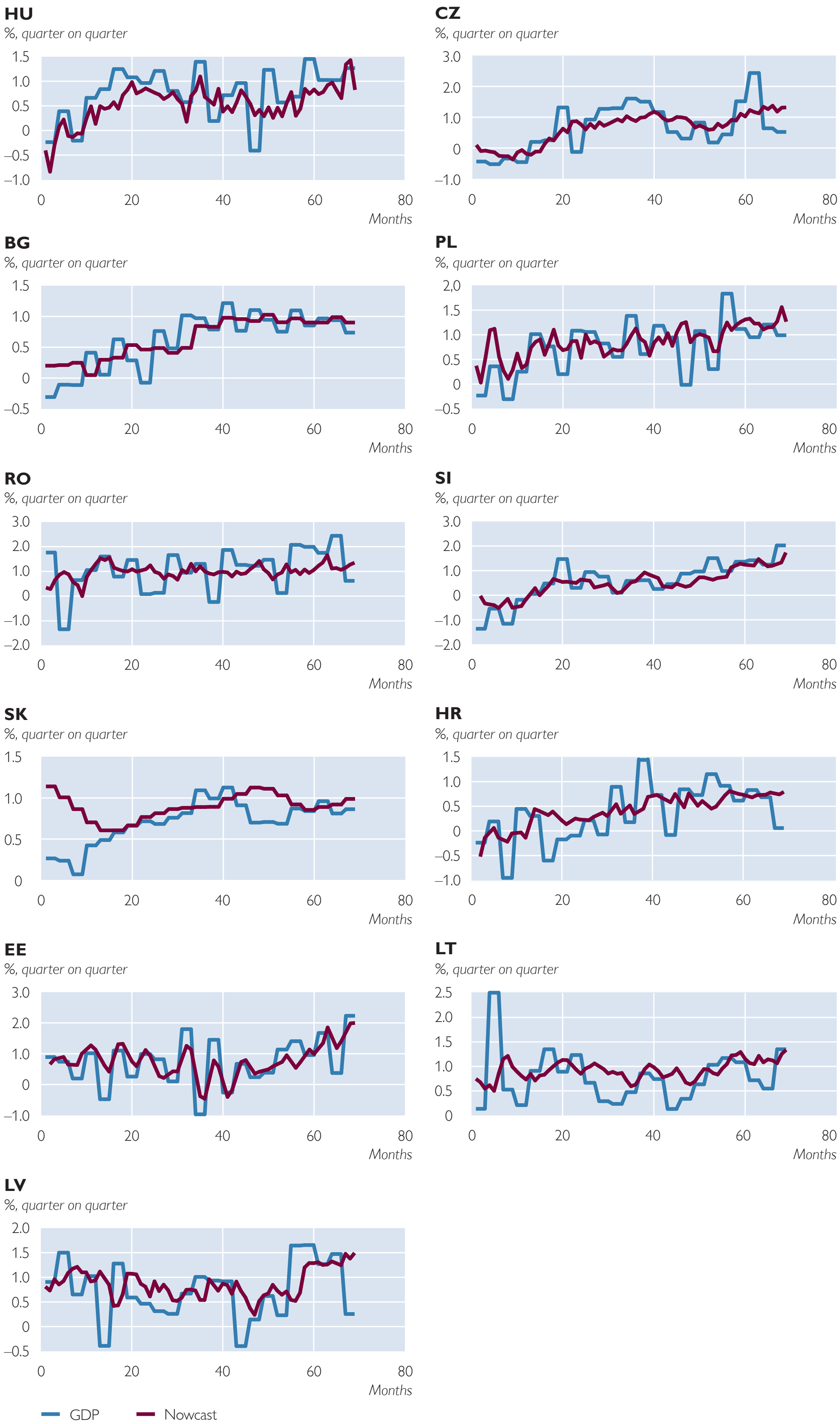
	RW	be2	be23	be3	be1L	be12L	be123L	be13L	be2L	be23L	be3L
CZ	0.53	0.48	0.47	0.52	0.53	0.53	0.51	0.52	0.50	0.51	0.50
BG	0.32	0.32	0.49	0.51	0.33	0.34	0.49	0.49	0.31	0.48	0.50
HU	0.60	0.40	0.41	0.46	0.43	0.40	0.40	0.40	0.40	0.42	0.46
PL	0.58	0.46	0.38	0.35	0.44	0.45	0.36	0.34	0.47	0.39	0.35
RO	1.03	0.74	0.75	0.74	0.75	0.77	0.76	0.73	0.75	0.74	0.74
SI	0.52	0.44	0.37	0.39	0.37	0.39	0.40	0.36	0.44	0.42	0.40
SK	0.11	0.35	0.35	0.37	0.39	0.44	0.45	0.40	0.35	0.37	0.37
HR	0.62	0.41	0.47	0.47	0.44	0.46	0.48	0.50	0.42	0.45	0.47
EE	1.01	0.79	0.81	0.89	0.62	0.65	0.76	0.64	0.79	0.84	0.90
LT	0.52	0.46	0.47	0.48	0.46	0.49	0.51	0.49	0.46	0.49	0.49
LV	0.58	0.48	0.57	0.70	0.70	0.58	0.60	0.70	0.46	0.57	0.72

Note: The figures for Estonia, Slovenia and Croatia are based on a restricted sample, as most of the models are not available in the first month of the quarter due to the longer time lag in publishing GDP data.

Source: Authors' estimations.

Chart A1

Out-of-sample nowcasts of real GDP growth for 11 CESEE countries



Source: Authors' estimations.