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Nowcasting Czech GDP in real time☆

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ABSTRACT

In this paper, we employ a Dynamic Factor Model (DFM) to nowcast Czech GDP. Using multiple vintages of historical data and taking into account the publication lags of various monthly indicators, we evaluate the real-time performance of the DFM over the 2005–2012 period. The main result of this paper is that the accuracy of model-based nowcasts is comparable to that of the nowcasts of the Czech National Bank (CNB). Moreover, combining the DFM and the CNB nowcasts results in more accurate performance than in the case of the individual nowcasts alone. Our results also suggest that foreign variables are crucial for the accuracy of the model, while omitting financial and confidence indicators does not worsen the nowcasting performance.

1. Introduction

Because of considerable publication delays in the release of GDP data, the current state of the economy is subject to sizeable uncertainty. Accurate and timely estimates of the current state of the economy are therefore especially important for policymakers, who make their decisions in real time. In the present turbulent situation, obtaining the most up-to-date forecasts of GDP, possibly after each new data announcement, is becoming even more important, for example, in the event of irregular monetary policy meetings in the midst of a crisis or other unexpected developments in the economy. Such up-to-date forecasts of Czech GDP produced in real time are the objective of this study.

Forecasters face several problems when producing predictions in real time. Macroeconomic variables are announced in a non-synchronous manner, that is, they have different publication lags. As a result, forecasters have to work with datasets that contain many missing observations towards the end of the sample (the so-called ragged end problem). Another problem forecasters typically face is the fact that data are sampled at different frequencies. Most of the traditional forecasting models — such as leading indicator models and classical vector autoregressions — cannot easily deal with these issues: they cannot utilize the most up-to-date data releases in a model-consistent fashion.

The nowcasting framework of Giannone et al. (2008) has become the workhorse model of short-term forecasters at many central banks and other institutions (for an extensive list of references see Bańbura et al., 2013). The framework is based on a dynamic factor model cast in the state-space representation and on the application of the Kalman filter to deal with mixed frequencies and unbalanced datasets.[1] The framework can accommodate a potentially large number of variables by summarizing the information with a few common factors, thus overcoming the so-called curse of dimensionality (Stock and Watson, 2002b; Bernanke and Boivin, 2003). An additional advantage of the framework is that it allows forecasters not only to predict variables of interest in real time, but also to interpret and comment on the sources of the changes in the forecasts. This provides a story-telling dimension and a deeper understanding of the forecast that is almost as important to policymakers as the accuracy of the forecast itself. This feature is missing from most of the statistical models that are currently used for near-term projections.

An additional challenge for real-time forecasters is the presence of data revisions. Typically, the forecasting exercises and model selection are performed using revised data. It is well known, however, that the revisions to macroeconomic data are frequent and large (Faust et al., 2005; Garratt and Vahey, 2006; Aruoba, 2008; Croushore, 2011; Fernandez et al., 2011). Therefore, working with the last available data may provide starkly different results than those obtained using real-time data (as documented by many studies: Robertson and Tallman, 1998; Faust et al., 2003; Orphanides, 2001; Kugler et al., 2005; Molodtsova et al., 2008; Marcellino and Musso, 2011; Ince and Papell, 2013). As for the properties of revisions to Czech GDP, in our previous research (Rusnak, 2013), we find that the revisions are relatively

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[1] Previous seminal contributions include Wallis (1986) and Evans (2005). See also Foroni and Marcellino (2013), who provide a survey of state-of-the-art mixed frequency models that can deal with ragged end problems.

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large. Performing a proper real-time forecasting exercise using Czech data therefore seems to be greatly needed.

The short-term forecasting performance of various models of Czech GDP has been assessed before by many studies (Benda and Ruzicka, 2007; Arnostova et al., 2011; Havranek et al., 2012; Horvath, 2012). Unfortunately, most of these studies do not account for publication lags and data revisions, which renders the relevance of their results to policymakers rather questionable.[2] Consider, for example, the official comments that the CNB makes after each release of GDP. Out of 32 comments published by the Czech National Bank (CNB) during the 2005–2012 period, roughly 17 of them mention revisions to the national accounts as one of the sources of the deviation of the official CNB forecasts from the announced data. Obviously, revisions must be therefore considered an important issue to policymakers. Truly real-time exercises to evaluate the performance of dynamic factor models in the presence of data revisions are still relatively scarce. The exceptions are Schumacher and Breitung (2008) for Germany, Camacho and Perez-Quiros (2010) for the euro area, and Bańbura et al. (2013) and Lahiri and Monokroussos (2013) for the US. To the best of our knowledge, we are the first to investigate the performance of forecasts of Czech GDP in a truly real-time setting that employs unrevised vintages of historical data.

In this paper, we focus on the performance of the DFM in obtaining accurate forecasts of the current quarter GDP growth (so-called nowcasts). Accurate nowcasts are important since they serve as inputs to the structural models that are used for medium to long-term prediction (the CNB uses a G3 DSGE model, see Andrle et al., 2009, for details). Furthermore, the CNB comments on the releases of the latest GDP growth figures and discusses the deviations from its official predictions. This makes the accuracy of CNB nowcasts of crucial importance.

Formal model-based forecasts are typically compared to naive benchmarks or to other competing models. Comparisons with official central bank forecasts are rare, but do exist, especially in the context of model combinations (Lees et al., 2007; Adolfson et al., 2007; Groen et al., 2009; Edge et al., 2010; McDonald and Thorsrud, 2011). A common finding of these studies is that the accuracy of model-based forecasts of GDP is comparable to that of the official forecasts of the respective central banks.[3] In this paper, we contribute to this literature by evaluating the performance of the dynamic factor model using Czech real-time data and comparing it with the accuracy of the nowcasts of the Czech National Bank.

Finally, we show how one can use the methodology of Bańbura and Modugno (2010) to decompose the updates of Czech GDP nowcasts into the contributions of the individual variables — so-called *news*. This is possible since the dynamic factor model produces forecasts for all of the variables included. One can then interpret changes in the forecasts stemming from the differences between the actual data released and their predicted values. For example, it is reasonable to assume that a higher-than-expected value of industrial production will cause the forecast to be revised upwards. The dynamic factor model can quantify such statements. Similar decompositions of forecast updates are now regularly used by many central banks (see for example ECB, 2008; Bundesbank, 2009) to enhance the understanding of their short-term forecasts.

Our results suggest that the nowcasting performance of the medium-scale DFM is comparable to the nowcasts of the Czech National Bank. In addition, we find that the simple average of the DFM and CNB nowcasts is more accurate than the nowcasts of the DFM and CNB alone. We also find that the DFM nowcasts add value to the CNB nowcasts: conditional on the CNB nowcast, on average, GDP growth turns out to be higher when the DFM nowcast is higher. Similarly to D'Agostino and Giannone (2012) we find that the relative performance of the DFM is better at times of crisis, which are characterized by large comovements of variables. We also find that the inclusion of foreign variables is crucial: if we exclude foreign variables the performance worsens significantly, while the omission of financial variables or surveys does not result in a dramatic deterioration of the forecasting accuracy.

The remainder of this paper is organized as follows. Section 2 briefly discusses the dynamic factor model, Section 3 describes our real-time dataset and provides details of the empirical exercise together with its results. Section 4 presents examples of nowcast update decompositions, while Section 5 provides further results and sensitivity checks. Section 6 concludes.

2. Dynamic factor model

Dynamic factor models aim at capturing the most important features of the data while remaining parsimoniously specified. They do so by assuming that the bulk of the comovements in macroeconomic variables are driven by just a few common factors (this seems to be the case in the US, see Giannone et al., 2005). The technology of dynamic factor models has evolved over time. The first generation consisted of small-scale models estimated by maximum likelihood and the Kalman filter (Engle and Watson, 1981; Mariano and Murasawa, 2003; Camacho and Perez-Quiros, 2010). These models were able to handle data irregularities, but were unable to utilize more than a few variables.

Forecasters and policymakers, however, monitor a large number of different time series (Bernanke and Boivin, 2003). Because the time span of most of the series is rather short — a problem of even bigger importance in economies that transformed to a market economy relatively recently — applying traditional models to a large number of variables would result in parameter proliferation and imprecise forecasts. Therefore, the second generation of factor models uses nonparametric principal component estimation of factors from large cross sections (Chamberlain and Rothschild, 1983; Forni and Reichlin, 1998; Forni et al., 2000; Stock and Watson, 2002a; Stock and Watson, 2002b). However, principal components cannot deal with ragged ends on their own.

The third generation of factor models combines the first and second generations: factors approximated by principal components are utilized within a state-space framework (Giannone et al., 2008; Rünstler et al., 2009; Bańbura and Rünstler, 2011). Thus, they constitute a model that can handle large data sets with data irregularities present in a real-time forecasting setting. The asymptotic properties of these models can be found in Doz et al. (2011).

Finally, the most recent papers use the expectation-maximization algorithm to obtain maximum likelihood estimates of large models that are able to deal with unbalanced datasets (Schumacher and Breitung, 2008; Bańbura and Modugno, 2010). On the whole, this approach consists of iterating between the two steps: estimating the parameters conditional on the factors, and estimating the factors conditional on the parameters from previous iterations. The asymptotic theory is provided in Doz et al. (2012).

An accessible survey of dynamic factor models can be found in Stock and Watson (2010), while Bai and Ng (2008) provide a more technical survey. Bańbura et al. (2010b), Bańbura et al. (2013) survey the application of factor models with a focus on nowcasting.

In our empirical exercise we will use the latest generation dynamic factor model estimated by the expectation-maximization algorithm. We begin by specifying the model for monthly variables:

$$x_t = \Lambda f_t + \varepsilon_t \tag{1}$$

$$f_t = A_1 f_{t-1} + \cdots + A_p f_{t-p} + u_t, \tag{2}$$

where x_t is a vector of monthly variables transformed into stationary ones, f_t is a vector of r (unobserved) common factors, and u_t is a vector

[2] Arnostova et al. (2011), in their replication of Rünstler et al. (2009), account for publication lags, but their analysis is based on a revised dataset.

[3] Note that not all of these papers use unrevised data, so the comparability should be interpreted with caution.

of idiosyncratic shocks. Λ denotes a matrix of factor loadings, while $A_1, \ldots, A_p$ denote the autoregressive coefficients for the factors. Quarterly variables are modeled using the approximation of Mariano and Murasawa (2003). We adopt the convention that the quarterly GDP level, denoted by GDP_t^Q, is assigned to the third month of the quarter. The unobserved monthly counterpart of GDP is denoted by GDP_t^M.

$$GDP_t^Q = GDP_t^M + GDP_{t-1}^M + GDP_{t-2}^M \quad t = 3, 6, 9, \ldots \tag{3}$$

We further define

$$Y_t^Q = 100 * log\left(GDP^Q\right) \tag{4}$$

$$Y_t^M = 100 * log\left(GDP^M\right), \tag{5}$$

where *log* denotes natural logarithm, and assume that the monthly growth rate of GDP, $y_t = Y_t^M - Y_{t-1}^M$, admits the same factor model representation as the monthly variables:

$$y_t = \Lambda_Q f_t + \varepsilon_t^Q. \tag{6}$$

We link y_t with the observed GDP data by constructing the following partially observed monthly series:

$$y_t^Q = \begin{cases} Y_t^Q - Y_{t-3}^Q & t = 3, 6, 9, \ldots \\ \text{unobserved} & \text{otherwise} \end{cases}. \tag{7}$$

Finally, we use the approximation suggested by Mariano and Murasawa (2003):

$$\begin{aligned} y_t^Q &= Y_t^Q - Y_{t-3}^Q \approx \left(Y_t^M + Y_{t-1}^M + Y_{t-2}^M\right) - \left(Y_{t-3}^M + Y_{t-4}^M + Y_{t-5}^M\right) \\ &= y_t + 2y_{t-1} + 3y_{t-2} + 2y_{t-3} + y_{t-4}. \end{aligned}$$

Direct numerical maximization of the likelihood can be computationally challenging and inefficient if a model contains more than a few variables. Therefore, the estimation is performed using the expectation-maximization algorithm (Shumway and Stoffer, 1982; Watson and Engle, 1983; Schumacher and Breitung, 2008). We use the methodology of Bańbura and Modugno (2010), who generalize the method so that the DFM can deal with an arbitrary pattern of missing observations. In brief, the estimation can be described as consisting of iterations of two steps. In the first step, the expectation of the log-likelihood conditional on the estimates from the previous iteration is calculated. In the second step, the parameters are re-estimated using the expected likelihood from the previous step. The initial values are obtained by filling in the missing observations by draws from N(0,1) and estimating the principal components on the balanced part of the sample (similarly as in Giannone et al., 2008). For further technical details of the EM iterations we use in this application, see Bańbura and Modugno (2010).

3. Real-time nowcasting exercise

3.1. Real-time data set

We compose a real-time database of 99 monthly vintages: the first vintage is from October 2004, and the last from December 2012. We collect a panel of 28 headline macroeconomic variables that covers headline hard data, financial variables, surveys, and foreign variables. Most data start in January 2000 and span up to the latest observation available in that particular vintage. The exceptions are the government bond yield and the service confidence indicator, which start in April 2000 and May 2002, respectively. Our dataset is relatively balanced in the number of series pertaining to each group. In particular, we have nine series of hard data covering the production, labor, and trade sectors of the economy. A further seven financial series cover exchange and interest rates, stock prices, and credit aggregates, while five survey series cover confidence indicators of business and consumers. Finally, we add six series of foreign variables covering hard, financial, and survey variables. The variables are transformed to stationarity by taking log-differences (or first differences in the case of several confidence indicators).[4] Further, before estimation, the variables are standardized to have zero mean and unit variance.

For the series that are subject to frequent revisions (ten overall, most of the hard data variables) we use the OECD Real-Time Database. In addition, we collect vintages of credit from CNB Monetary Statistics Monthly Bulletin publications. Most of the financial variables (interest and exchange rates) and surveys are not revised. The exception is the euro area business climate indicator, which is revised due to changes in the composition of the euro area. Therefore, for this variable we collect vintages from press releases available on the European Commission website. Unemployment is not revised, but it is published as not seasonally adjusted. Performing seasonal adjustment on the latest available series first and then using the data sequentially would probably introduce information about trends that was not available at the time of the forecast (see also Orphanides and van Norden, 2002). Therefore, we perform seasonal adjustment sequentially, using only the information available at the time of the relevant forecast.[5]

The number of variables is relatively small compared to what is typically used in factor model applications.[6] However, Bańbura et al. (2010a) and Bańbura et al. (2010b) show that the gains from including more than 20–40 variables are rather modest and that disaggregate information does not improve the forecast accuracy. Arnostova et al. (2011) consider 98 indicators to forecast Czech GDP, but almost half of them are disaggregate information on industrial production and sales. We do not include this disaggregate information since this would probably result in contaminating the estimated common factor with idiosyncratic shocks to industrial production and sales (see also Boivin and Ng, 2006, for a more general discussion). By including only headline variables, we are, in fact, also loosely following the recommendation of Alvarez et al. (2012) to include only one reference series for each economic concept. Note also that the set of the variables we use in this exercise coincides to the large extent with the data that are typically monitored by the market participants in the Czech Republic.

Other than dismissing the disaggregate sectoral information and omitting some variables due to unavailability of real-time vintages (such as fiscal data covering monthly government spending and tax revenues), we opt not to pre-select the indicators any further. We find pre-selection of indicators rather problematic. First, the existing procedures recommended by Boivin and Ng (2006) and Bai and Ng (2008) do not take into account the presence of ragged ends and differences in the timeliness of the variables. Arnostova et al. (2011) compute bivariate correlations with GDP and exclude those with a correlation lower than 0.5. We opt not to follow this practice since it neglects the ragged ends and potential dynamic cross-correlation between different variables. Second, it is well known that the predictive content of individual variables is not stable over time (De Mol et al., 2008; Rossi and Sekhposyan, 2010; Stock and Watson, 2012; Kuzin et al., 2013) and

[4] Note that it is not clear whether one should also difference the confidence indicators: some authors prefer to keep them in levels (Camacho and Perez-Quiros, 2010), while others do difference them (Giannone et al., 2008; Bańbura et al., 2013). We followed the suggestion of a referee and also estimated the specification with surveys in levels: the results suggest that the accuracy of the model deteriorated, so we decided to keep the surveys in differences. These results are available upon request.

[5] Seasonal adjustment was performed by employing Demetra software and using the Tramo-Seats procedure. Note that the real-time vintages of construction from the OECD Real-Time Database were also only available as not seasonally adjusted. Therefore, we adjusted them as well.

[6] Note that the Monte Carlo evidence by Doz et al. (2012) suggests that sufficient EM estimation robustness can be obtained with just a handful of variables.

Table 1
Data set.

No.	Group	Variable	Revisions	Pub. lag	Unb. pat.	Source
1	Hard	Real GDP	Y	68 to 71	4,5,3–4,5,3	OECD
2	Hard	Industrial production index	Y	37 to 45	2–2	OECD
3	Hard	Construction output	Y	37 to 45	2–2	OECD
4	Hard	Retail Sales	Y	35 to 49	2–2	OECD
5	Hard	Unemployment rate	N	8 to 11	1–1	MLSA
6	Hard	CPI total	N	8 to 11	1–1	CZSO
7	Hard	Exports (current prices)	Y	35 to 39	2–2	OECD
8	Hard	Imports (current prices)	Y	35 to 39	2–2	OECD
9	Hard	Export price index	N	43 to 47	3–2	CZSO
10	Hard	Import price index	N	43 to 47	3–2	CZSO
11	Financials	CZK/EUR exchange rate	N	0	1–0	CNB
12	Financials	M2	Y	30 to 31	2–1	OECD
13	Financials	Credit	Y	30 to 31	2–1	CNB MB
14	Financials	3 M PRIBOR	N	0	1–0	CNB
15	Financials	1Y PRIBOR	N	0	1–0	CNB
16	Financials	PX-50 stock index	N	0	1–0	PSE
17	Financials	Czech government bond yield (10Y)	N	0	1–0	CNB
18	Surveys	Consumer confidence indicator	N	−7 to −2	1–0	CZSO
19	Surveys	Industry confidence indicator	N	−7 to −2	1–0	CZSO
20	Surveys	Construction confidence indicator	N	−7 to −2	1–0	CZSO
21	Surveys	Trade confidence indicator	N	−7 to −2	1–0	CZSO
22	Surveys	Services confidence indicator	N	−7 to −2	1–0	CZSO
23	Foreign	EURIBOR 3 M	N	0	1–0	ECB
24	Foreign	EURIBOR 1Y	N	0	1–0	ECB
25	Foreign	Oil price (Brent)	N	0	1–0	Data stream
26	Foreign	Ifo business climate Germany	N	−10 to −4	1–0	IFO
27	Foreign	Euro area business climate	Y	−4 to −1	1–0	EC
28	Foreign	Germany exports	Y	40	2–2	OECD

Notes: Pub. Lag stands for publication lag and indicates the typical publication delay of a variable in days (based on 2005–2012 publication calendars), and Unb. Pat. stands for unbalancedness patterns and indicates the number of missing observations for the middle of the month and the end of the month, respectively; for GDP (because it is released quarterly) the numbers correspond to the first, second, and third month of each quarter. CZSO denotes the Czech Statistical Office, CNB denotes the Czech National Bank's ARAD Database, CNB MB denotes the Czech National Bank's Monetary Statistics Monthly Bulletin, PSE denotes the Prague Stock Exchange, ECB denotes the European Central Bank's Statistical Data Warehouse, MLSA denotes the Ministry of Labor and Social Affairs, OECD denotes the OECD Real-time Database, and EC denotes the European Commission. All indicators except for GDP are at monthly frequency. All of the variables are in logarithms and differenced, except for the industry, construction, trade, and services confidence indicators, which are differenced only.

therefore pre-selecting the indicators might not be the optimal strategy. Third, a model that includes all of the key variables might be of greater interest to policymakers than a model with pre-selected indicators only, since policymakers might want to comment on various headline data releases. Fourth, pre-selecting indicators using data from tranquil periods might have a negative effect on the accuracy of forecasts during crisis periods. Finally, we believe that by not including too many variables (over)representing the same concept, the dynamic factor model will assign the correct weights to the variables included (see Bańbura et al., 2013, for more details).

GDP data are released approximately ten weeks after the end of the reference quarter (in the first half of the third month of the subsequent quarter). Most of the hard data are published with varying delays ranging from one to seven weeks. On the other hand, with the exception of money and credit aggregates the financial variables are available with no lag. The surveys are, in fact, published several days before the end of the reference month. Details about the variables used, including their publication lags and sources, are summarized in Table 1.

3.2. Design of the nowcasting exercise

Our nowcasting exercise is designed as follows. We perform 31 nowcasting rounds, starting with 2005Q1. For each quarter we perform 14 forecast updates, which reflect the arrival of new information over time. Throughout the text we will refer to forecast origins during the preceding quarter (Q(−1)) as forecasting, those during the current quarter (Q(0)) as nowcasting, and those during the following quarter (Q(+1)) as backcasting. The first forecast is performed in the middle of the first month of the preceding quarter (Q(−1)M1 mid). We update the forecasts in the middle and at the end of each month. The last forecast update is performed at the end of the first month of the following quarter (Q(+1)M1 end). We do not perform any additional update, as the preliminary (flash) estimate of GDP is released in the first half of the second month of the following quarter.[7] Since at the time of writing this paper (December 2012), only 2012Q3 GDP growth is available for evaluation, the last nowcasting round we perform is for 2012Q3.

We could, in principle, perform more updates during a month, i.e., after each publication release. However, in practice trade, industry, construction, unemployment, and the CPI are released early at the beginning of the month — although the relative ordering of publication changes from month to month. Consequently, we prefer to model this as a simultaneous release, since we believe it is closer to reflecting the real-time situation.

As for the evaluation of forecasts, we use both the first release and the latest vintage available (December 2012). The argument for using the former is that the Czech National Bank officially discusses every first release value of GDP and explains the reasons behind the deviations from its nowcast. Therefore, the accuracy of the model with respect to this first release is of importance to the CNB. On the other hand, the latest vintage data are arguably closest to reflecting the “true” value of GDP growth. As a result, we opt for using both series to evaluate the accuracy of the nowcasts.

Given that our time series dimension is rather short (beginning in Jan 2000) we opt for a parsimonious specification with regard to the number of factors and lags. We model comovements with one factor and the dynamics of the factor with two lags. While specifications with one or three lags give virtually same results, increasing the number of factors results in deterioration of the forecasting accuracy (see subsection A.3 for more details).

[7] The correlation between the preliminary and first releases and the preliminary and final releases of GDP over the 2007Q4–2012Q2 period is 0.95 and 0.84, respectively.

3.3. In-sample properties

Before presenting the results of the out-of-sample exercise, we describe here several properties of the DFM estimated with the data available in September 2012, which corresponds to Q(0) M3 end of our last nowcasting round.

Fig. 1 presents the estimated factor, which reflects the common element that drives the comovements of the variables included in our model. We compare the factor to the leading indicator produced by the OECD, which is designed to predict turning points in the Czech business cycle relative to the trend.[8] Overall, the factor and the OECD leading indicator are very similar and it seems that both track the business cycle dynamics in Czech Republic quite well.

Next, to get more insight into the forces driving the DFM nowcasts we report the estimated loadings in Fig. 2. Note that the loadings reflect mostly contemporaneous correlations, and we make no attempt to establish the causality. The loadings indicate that most of the series are procyclical, while unemployment, the exchange rate, export and import prices, and the government bond yield seem countercyclical. Except perhaps for the exchange rate, the loadings are in line with what one might expect a priori about the contemporaneous correlations with the business cycle.[9] As for the relative magnitudes, the foreign variables have the largest loadings. Notably, the trade variables along with interest rates also have high magnitudes. On the other hand, construction, M2, and government bond yields possess rather small loadings, but we prefer to keep them in the model since we do not want to select variables based on in-sample measures.

3.4. Nowcasting performance

Fig. 3 reports the results from our real-time nowcasting exercise. For each forecasting round, i.e.,for each of the 14 different forecast origins starting from the middle of the first month of the preceding quarter until the end of the first month of the following quarter, we plot the corresponding root mean square error (RMSE). The RMSE gives us an idea of the out-of-sample forecast uncertainty that is tied to a given forecast origin.

First, we consider several naive benchmarks: a model where the last available growth is a new forecast (random walk (RW)), an autoregressive model of order two (AR(2)), and a moving average of the last four available quarters (MA(4)). We observe that the DFM performs better than any of the naive benchmarks. On the whole, it seems that with the arrival of new information the forecasting errors seem to decrease, although not always. This fact was also shown succinctly by Lahiri and Monokroussos (2013).

We also compare the performance of the DFM to so-called bridge-equation models, which are the tools traditionally used in central banks (Kitchen and Monaco, 2003; Baffigi et al., 2004).[10] In Fig. 3, we present the RMSE of the mean of the individual bridge equation forecasts. We observe that the bridge equations become more precise with more information, but cannot really compete with the DFM. They are able to beat the naive benchmarks, except for the forecast origins at the end of the current quarter and the beginning of the next quarter, where they seem to perform worse than the RW and MA(4) benchmarks. The relatively worse performance of bridge equation models is worth noting. This result might be the consequence of the fact that we only use bivariate specification, where in each model only one indicator and GDP growth is estimated and the models are equally weighted. This suggests that a more complicated model (such as DFM) that is able to capture the dynamic cross-correlations of the data might be needed to improve predictability of Czech GDP. See also Brunhes-Lesage and Darné (2012) for a comparison of forecasts from bridge and factor models.

In Fig. 3, we also plot the RMSE of the CNB nowcasts. The CNB nowcasts are taken from the final forecast books that are prepared regularly by the Monetary Policy Department for the quarterly Situation Report. The CNB produces its GDP nowcast at the end of the last month of the reference quarter (Q(0)M3 end). The CNB nowcast is produced by a model that consists of a set of equations of expenditure components, estimated at quarterly frequency. The CNB nowcasts are adjusted by expert judgment, typically reflecting the latest developments of leading indicators or other subjective evaluation (see Arnostova et al., 2011, for more details). We also compare the accuracy of the one-quarter-ahead forecasts (Q(−1)M3 end). Overall, the performance of the model-based DFM nowcasts is comparable to that of the nowcasts of the CNB, while at the one-quarter-ahead horizon the DFM seems to fare rather worse than the CNB. While the CNB nowcasts are a result of a model and expert judgment, the nowcasts produced by the DFM are entirely model-based without imposing subjective judgment. The comparative performance is therefore good news, since the DFM nowcast might serve as a good cross-check of the nowcast.

Fig. 4 presents the nowcasts made by the CNB and the DFM over the 2005–2012 period (nowcasts from Q(0)M3 end forecast origins). The first release GDP growth and the growth as of the latest available vintage are also plotted. The figure suggests that the nowcasts by the CNB and the DFM are very similar in the first half of the evaluation sample, while in the second half they often seem to point in different directions. This is likely the consequence of the increased overall uncertainty in the period after the global financial crisis.

Table 2 reports the performance of the DFM and the CNB over the whole sample and two subsamples: a pre-crisis subsample covering the 2005Q1–2008Q2 period and a crisis subsample covering 2008Q3–2012Q3.[11] We present the performance relative to the random walk. The performance of the three naive models is very similar, but we choose the random walk as the benchmark since it has the best performance for the horizon when the CNB nowcasts are produced (Q(0)M3 end).

The average forecasting error of the naive random walk model is 0.93 for the nowcast and almost 1.3 for the one-quarter-ahead horizon. The DFM and CNB are able to reduce the average forecast errors by 30 to 50% relative to the naive RW model. The results also suggest that indirect pooling of information as represented by the bridge equations is not as successful as direct pooling within a single dynamic factor model: the gains in the forecasting accuracy of the bridge equations relative to the naive model are small.

The forecasting improvements seem to come mainly from the crisis period, while the improvements in the pre-crisis period are more modest. This is in line with (D'Agostino and Giannone, 2012), who show that the performance of more complex models relative to simple benchmarks is better during more volatile periods characterized by large comovements. Kuzin et al. (2013) note that the forecasting errors of many models are larger in absolute terms during crises and that the improvements in relative performance stem from the fact that the naive

[8] The components of the OECD leading indicators are: the balance of payments, demand and production evolution surveys, the CPI, consumer confidence, exports, and share prices. For more details see http://stats.oecd.org/mei/default.asp?lang=e&subject=5&country=CZEhttp://stats.oecd.org/mei/default.asp?lang=e&subject=5&country=CZE. We present the vintage of the leading indicator as of September 2012. To facilitate comparison, we present the monthly growth rates of the indicator scaled by the mean and standard deviation of the factor estimated by the DFM.

[9] The exchange rate is defined as the Czech koruna against the euro, hence an increase corresponds to a depreciation of the currency. Since there might be delays between the time of the exchange rate shock and the effect on trade or the economy as a whole, the negative contemporaneous correlation might be plausible. Alternatively, the loading might be a consequence of the fact that the Czech currency typically depreciates when investors are expecting an overall deterioration in economic activity in the region.

[10] More information about the specification of the bridge equations is provided in the Appendix A.

[11] The subsample split also approximately corresponds to the date of change of the core forecasting model used by the CNB. In 2008, the CNB switched from a quarterly projection model to the G3 DSGE model. For more details, see Andrle et al. (2009).

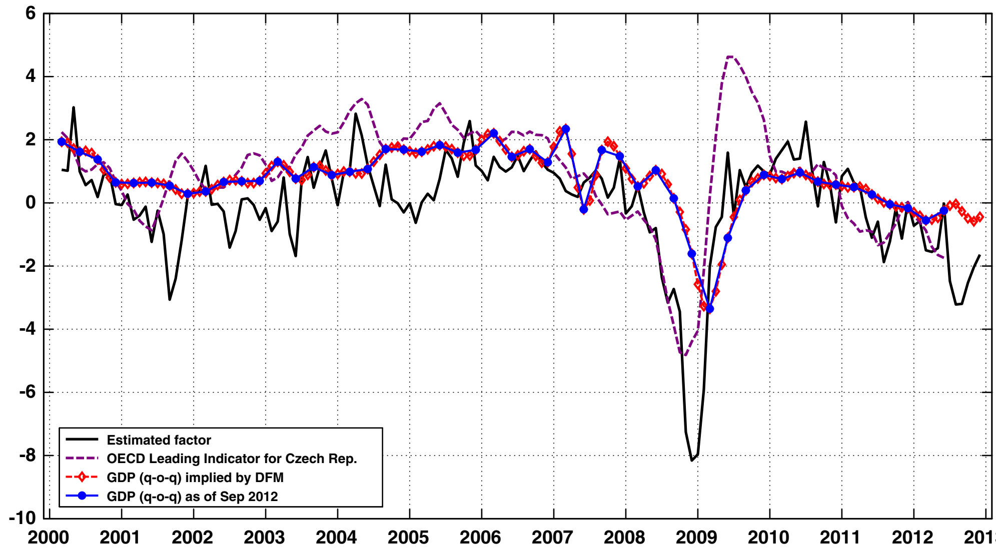

Fig. 1. Factor estimated in Sep 2012.

benchmarks performed worse. This is also our case: the forecast errors of the naive models are approximately three times higher during crisis periods than in pre-crisis times. More evidence about the pre- and post-crises performance of factor models can be found in Dias et al. (2015).

We also report the performance of the combination of the CNB and DFM nowcasts, which is obtained as the simple mean of the two nowcasts. This combination of nowcasts might serve as insurance against uncertain instabilities, an issue even more important during times of crisis (Clark and McCracken, 2010), (Aiolfi et al., forthcoming). The results suggest that the combination performs better than the CNB or DFM nowcast alone. The gains are highest during the crisis period. This can be due to fact that forecast errors show different degree of correlation within the two subsamples. While in the pre-crisis period the forecast errors seem to be rather correlated, in the crisis period they are frequently going in different directions. This might be the consequence of the increased overall uncertainty in the period following the global financial crisis.

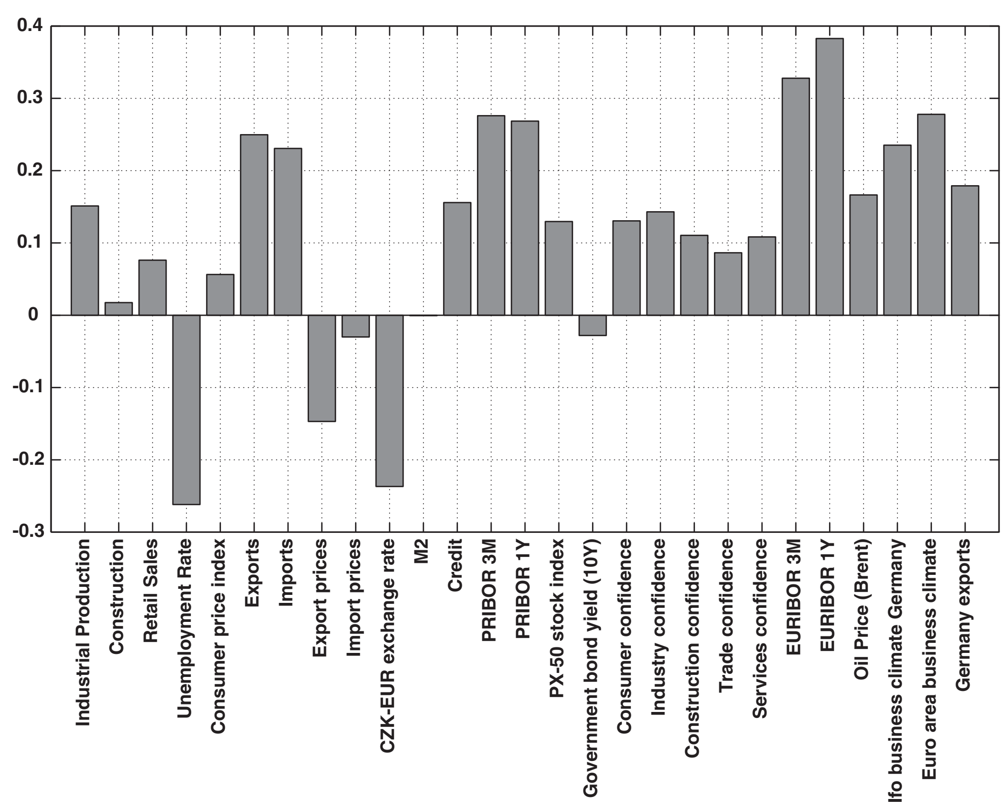

Fig. 2. Loadings estimated in Sep. 2012.

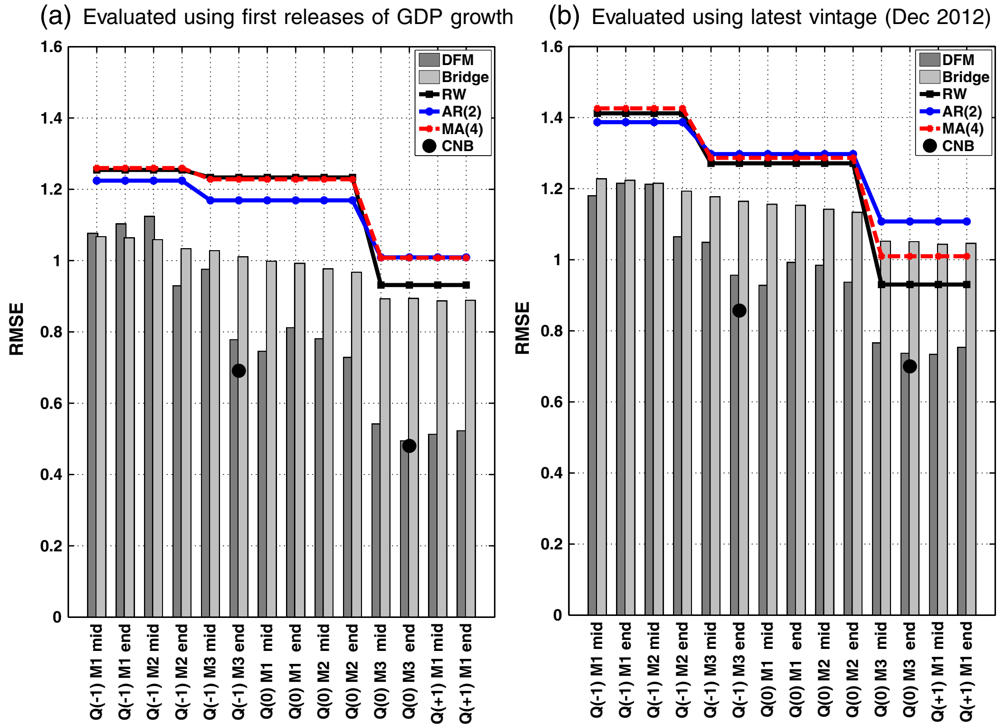

Fig. 3. Root mean square errors of different forecasts.

The success of the combination suggests that the purely model-based DFM might add value to the CNB nowcasts in the sense that it contains useful information missing from the CNB nowcasts. We further investigate this issue formally by running the following regression:

$$y_t = \alpha + \beta_1 \hat{y}_t^{CNB} + \beta_2 \hat{y}_t^{DFM} + \varepsilon_t, \tag{8}$$

where $\hat{y}_t^{CNB}$ denotes the CNB forecast and $\hat{y}_t^{DFM}$ denotes the model-based DFM forecast. Similar regressions are typically employed in the literature (Romer and Romer, 2000; Bjornland et al., 2012).

The results in Table 3 suggest that the DFM could possibly have added value to the CNB nowcasts: conditional on the CNB's forecasts GDP growth turns out to be higher when the DFM nowcast is higher. The subsample results, however, suggest that this result was limited to the crisis period.

Finally, we look at the role of financials, surveys, and foreign variables for the performance of the DFM. Fig. 5 presents the out-of-sample RMSE for models that exclude different groups of variables. Looking at the figure, several observations stand out. First, excluding surveys leaves the accuracy of the model intact, except perhaps for the early forecast origins. Second, the role of the financial variables is ambiguous. Finally, the foreign variables seem to be crucial for the performance of the model, since their exclusion from the model results in larger errors, consistently so across different forecasting origins. Our results are robust with regard to the actual series used for evaluating the forecasts. Our results corroborate the findings of Liu et al. (2012) who

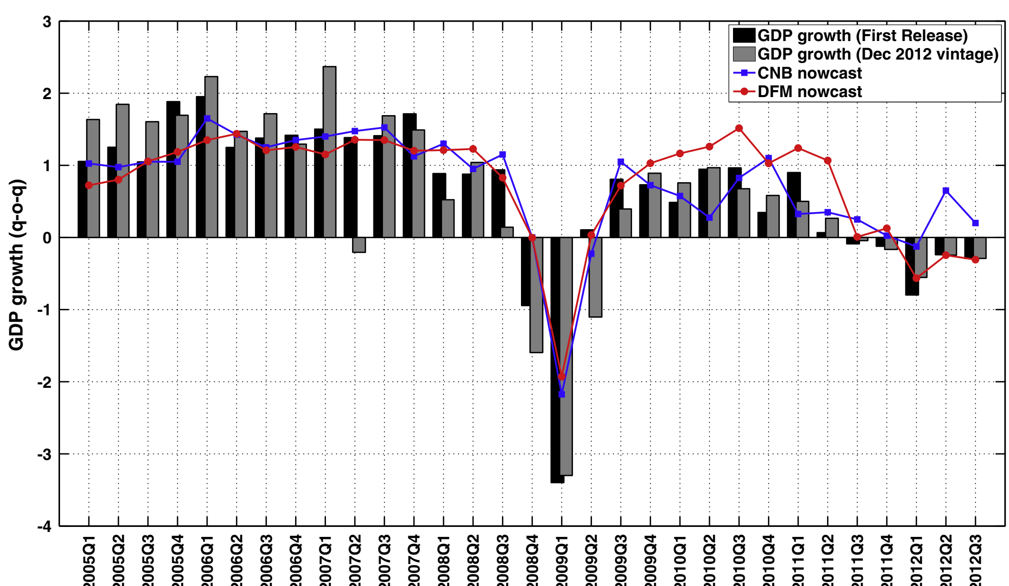

Fig. 4. Quarterly GDP growth and its nowcasts as of Q(0)M3 end.

Table 2
Root mean square errors.

	Full sample		Pre-crisis		Crisis	
	(2005Q1–2012Q3)		(2005Q1–2008Q2)		(2008Q3–2012Q3)	
	Q(−1)M3 end	Q(0)M3 end	Q(−1)M3 end	Q(0)M3 end	Q(−1)M3 end	Q(0)M3 end
Evaluated using first releases of GDP growth						
Random Walk (absolute RMSE)	1.23	0.93	0.48	0.39	1.61	1.21
RMSE relative to RW						
Bridge	0.82	0.96	1.07	1.22	0.80	0.93
DFM	0.63	0.53	1.01	0.94	0.59	0.48
CNB	0.56	0.52	0.94	0.84	0.52	0.48
Combination CNB & DFM	0.54	0.47	0.91	0.86	0.51	0.42
Evaluated using GDP growth in December 2012 vintage						
Random Walk (absolute RMSE)	1.27	0.93	0.78	0.74	1.56	1.06
RMSE relative to RW						
Bridge	0.92	1.13	1.08	1.12	0.88	1.13
DFM	0.75	0.79	1.05	1.04	0.68	0.67
CNB	0.67	0.74	1.02	0.96	0.58	0.65
Combination CNB & DFM	0.68	0.74	1.01	0.99	0.58	0.61

Notes: Bridge stands for the nowcast obtained as the average of the nowcasts from the individual bridge equations. DFM stands for the nowcast obtained from the dynamic factor model. CNB stands for the official nowcast of the Czech National Bank. Combination CNB & DFM stands for the nowcast obtained as the simple mean of the CNB and DFM nowcasts.

Table 3
Does the DFM add value to the CNB's GDP nowcasts?

	$y_t = \alpha + \beta_1 \hat{y}_t^{CNB} + \beta_2 \hat{y}_t^{DFM} + \varepsilon_t$					
	Full sample		Pre-crisis		Crisis	
	(2005Q1–2012Q3)		(2005Q1–2008Q2)		(2008Q3–2012Q3)	
	Q(−1)M3 end	Q(0)M3 end	Q(−1)M3 end	Q(0)M3 end	Q(−1)M3 end	Q(0)M3 end
Dependent variable: first releases of GDP growth						
α	−0.46*	−0.39***	1.14*	0.57**	−0.58*	−0.43***
	(0.27)	(0.06)	(0.57)	(0.22)	(0.28)	(0.07)
	0.84***	0.72***	0.41	0.53	0.58*	0.61***
	(0.21)	(0.08)	(0.37)	(0.39)	(0.29)	(0.15)
β_2	0.71***	0.64***	−0.21	0.11	0.78***	0.68***
	(0.17)	(0.06)	(0.45)	(0.41)	(0.24)	(0.09)
R^2	0.67	0.90	0.13	0.17	0.57	0.90
Dependent variable: GDP growth in December 2012 vintage						
α	−0.53	−0.46***	2.48***	2.12**	−0.73*	−0.57***
	(0.36)	(0.14)	(0.30)	(0.79)	(0.39)	(0.19)
β_1	0.92***	0.86***	0.06	0.94	0.53**	0.57***
	(0.29)	(0.19)	(0.41)	(0.55)	(0.23)	(0.18)
β_2	0.69***	0.56***	−1.01**	−1.56**	0.81**	0.69***
	(0.24)	(0.16)	(0.36)	(0.69)	(0.28)	(0.22)
R^2	0.57	0.74	0.11	0.12	0.55	0.85

Notes: Autocorrelation and heteroskedasticity robust standard errors (Newey and West, 1987) are in parenthesis.

also find that foreign indicators are useful in improving forecast accuracy.

Note also that the role of the various groups of variables is different for different forecast origins, i.e., the timeliness of the variables matters. In our case, there is some role for surveys at the beginning of the nowcasted quarter (Q(0)M1), when little data for that quarter is actually available. In the case of financial variables, excluding them seems to actually decrease the forecast errors during forecasting (Q(−1)). See also Ferrara et al. (2014), who study the role of financial variables for the growth forecasts in more detail. On the other hand, they seem to be important during nowcasting (Q(0)) and backcasting (Q(+1)). The role of timeliness was also clearly demonstrated by Lahiri and Monokroussos (2013).

The importance of foreign variables is not surprising, as the Czech Republic is a small open economy (the share of exports and imports in GDP was roughly 146% in 2011).[12] Previous studies employing dynamic factor models seem to suggest that in different countries the inclusion of different blocks of variables is crucial for the accuracy of the DFM. Bańbura et al. (2013) and Bańbura and Rünstler (2011) show that the role of surveys is crucial using US and euro area data, respectively. (Aastveit and Trovik, 2012) find that the inclusion of foreign variables has a negative impact on the performance of the model using Norwegian data, while financial variables seem to be key to the accuracy of their model. (Matheson, 2010) finds that excluding surveys worsens the nowcasting performance of the DFM in New Zealand, while Yiu and Chow (2011) find that excluding interest rates increases the forecast errors of the DFM for China. Note, however, that none of the above-mentioned countries is as open as the Czech Republic. The share of exports and imports in GDP for Norway, the most open of these countries, is approximately 70% in 2011, barely half of the Czech Republic's figure. So, it is quite plausible that the shocks hitting the export-dependent Czech economy are different in nature and magnitude from those hitting more closed economies (e.g., terms of trade shocks).

Note that we also performed Diebold-Mariano tests to evaluate the statistical significance of the differences in the predictive abilities of

[12] See OECD Factbook 2013, available at http://dx.doi.org/10.1787/factbook-2013-enhttp://dx.doi.org/10.1787/factbook-2013-en.

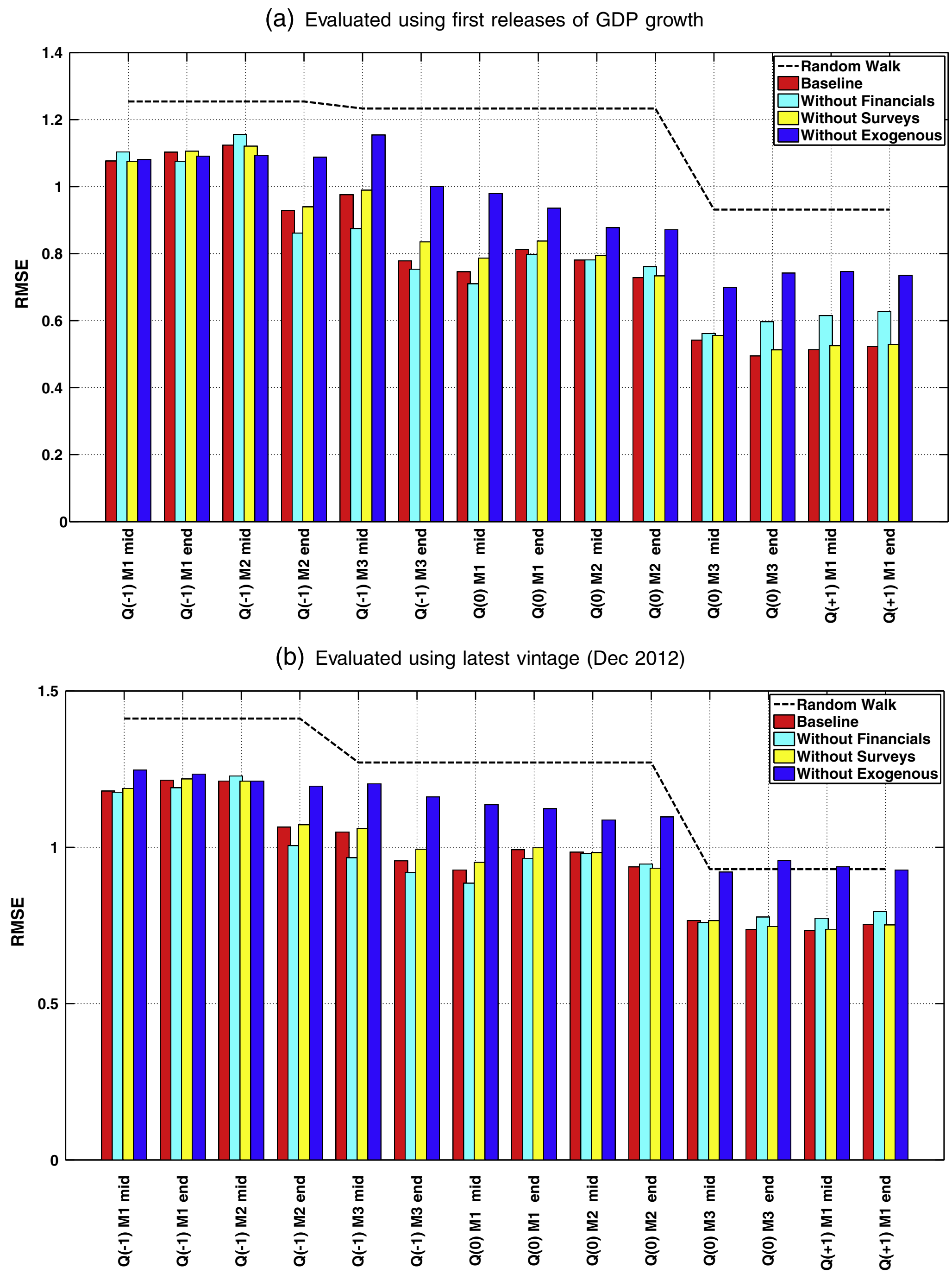

Fig. 5. Performance of the model when excluding various groups of data.

the DFM and CNB nowcasts (Diebold and Mariano, 1995).[13] However, the test results pointed in almost all cases to statistically insignificant (at the 5% level) differences between the competing models. This is not surprising given the small evaluation sample of only 31 observations.[14]

[13] We used the (Newey and West, 1987) estimator of the long-run variance of the difference between the squared prediction errors.

[14] See also Ashley (2003), who points out that typically more than 100 observations are needed to establish statistically significant differences in forecasting ability across models.

4. Interpreting new data releases through the lens of the DFM

In this section, we use the methodology of Bańbura and Modugno (2010) to show how the nowcasting framework can be used to read the flow of data releases through lens of the dynamic factor model. It is of interest to know the sources of changes in the nowcast that occur after new data are released. For example, when newly released data about the euro area business situation are worse than expected, the model-based nowcast of the GDP will be revised down. Because the DFM produces forecasts for all variables, we can precisely decompose the changes in the nowcasts. Similar decompositions are regularly used in central banks (ECB, 2008; Bundesbank, 2009) to complement their real-time nowcasting exercises with story-telling. In fact, the CNB performs similar decompositions for the interest rate within the core model (Andrle et al., 2009). But the core model is geared towards producing medium to long-term predictions, so it cannot be used directly to decompose the changes in the GDP nowcasts as a result of newly published data.

We denote Ω_v as the information set at the release v and $\mathbb{D}$ as the set of parameters estimated on the information set Ω_v. Further, we denote $\tilde{\Omega}_{v+1}$ as the information set with the same unbalancedness pattern as Ω_v, but using the latest data vintage.

We can then decompose the change of the nowcast into three parts: the effect of re-estimation, the effect of data revisions, and the effect of *news*.

1. The effect of re-estimation is computed as the difference between the nowcast obtained using the old information set Ω_v using the new parameters $\mathbb{D}_{v+1}$ and the nowcast obtained using the old information set Ω_v and the old parameters $\mathbb{D}_v$:

$$\mathbb{E}[y|\Omega_v, \mathbb{D}_{v+1}] - \mathbb{E}[y|\Omega_v, \mathbb{D}_v].$$

2. The effect of data revisions is computed as the difference between the nowcast obtained using the new information set with the same unbalancedness pattern as the old one $\tilde{\Omega}_{v+1}$ and the new parameters $\mathbb{D}_{v+1}$ and the nowcast obtained using the old information set Ω_v and the new parameters $\mathbb{D}_{v+1}$:

$$\mathbb{E}\left[y|\tilde{\Omega}_{v+1}, \mathbb{D}_{v+1}\right] - \mathbb{E}[y|\Omega_v, \mathbb{D}_{v+1}].$$

3. The effect of *news* (the unexpected component of the released data):

$$\mathbb{E}[y|\Omega_{v+1}, \mathbb{D}_{v+1}] - \mathbb{E}\left[y|\tilde{\Omega}_{v+1}, \mathbb{D}_{v+1}\right].$$

In computing the effect of *news* we follow Bańbura and Modugno (2010). They show that one can find coefficients $\delta_{j,v+1}$ such that:

$$\mathbb{E}[y|\Omega_{v+1}, \mathbb{D}_{v+1}] - \mathbb{E}\left[y|\tilde{\Omega}_{v+1}, \mathbb{D}_{v+1}\right] = \sum_j \delta_{j,v+1}\left(x_{j,T_{j,v+1}} - \mathbb{E}\left[x_{j,T_{j,v+1}}|\tilde{\Omega}_{v+1}, \mathbb{D}_{v+1}\right]\right). \tag{9}$$

The nowcast revision is a weighted average of the *news*. The resulting revision stemming from a release of new data depends on the size as well as the weight of the given variable.

With Eq. (9) at hand, we are now able to use the lens of the dynamic factor model to interpret the information from the new data releases. Fig. 6 presents the evolution of the nowcast as the new information arrives. At each nowcast update, we decompose the size of the update into the contributions of re-estimation, revision, and *news* from the respective variables. To keep the exposition clear, we group the news from individual variables into groups.

We illustrate the contribution of news to the nowcast updates on the example of 2011Q3 Czech GDP growth. We choose this example because the second quarter of 2011 marked the peak of the recovery from the 2009 recession. At the beginning of the preceding quarter the nowcast for 2011Q3 is still rather optimistic, probably reflecting the lack of data corresponding to the 2011Q3 period. The first sizeable downward update of the nowcast is caused by the release of data at the end of May 2011: all of the new data point to a worsening of economic activity. This probably stems from the sharp rises in bond yields. This negative news is corroborated by further data releases pointing to a larger deterioration in expected growth. Following additional negative news coming mostly from the foreign indicators in August and from the hard data in September, the nowcast at the end of the quarter points to zero quarterly growth. The flash estimate released in the middle of November confirms the stall of the economy, while the first release of the national accounts even points to negative quarterly growth.

5. Further results

5.1. Nowcasting the expenditure components of the national accounts

Dynamic factor models can be useful in nowcasting other policy-relevant quarterly variables, for example, the expenditure components of GDP. Indeed, several papers have employed dynamic factor models to successfully nowcast the components of GDP (Angelini et al., 2010; Godbout and Lombardi, 2012; Lahiri et al., forthcoming).

To investigate the performance in the Czech case, we add five expenditure components of GDP to our baseline model: consumption, gross fixed capital formation, government consumption, exports, and imports

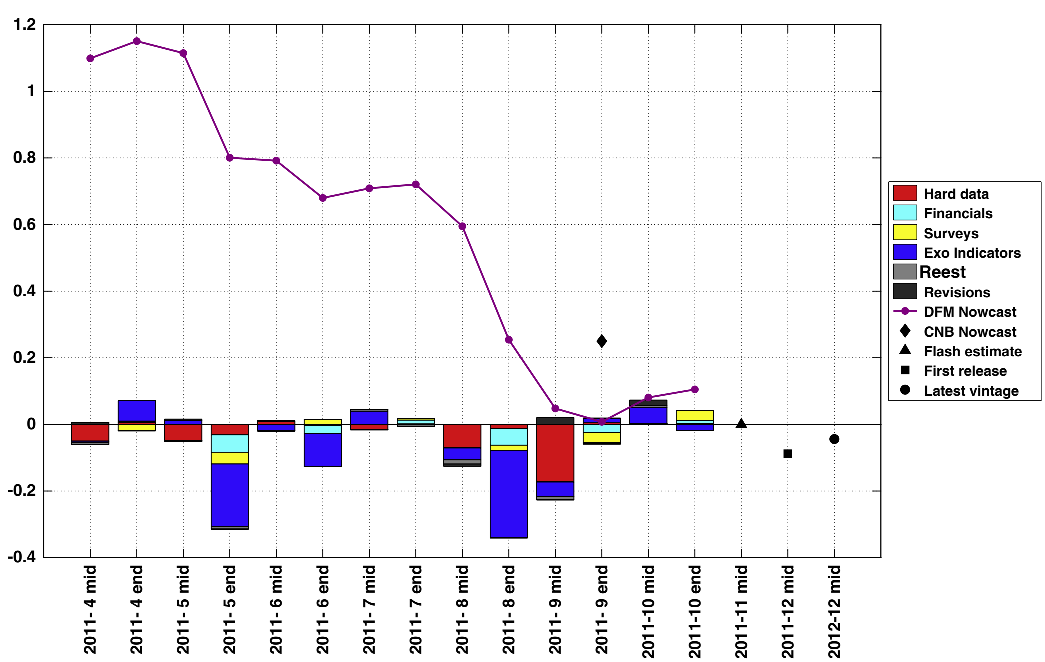

Fig. 6. Contribution of news to nowcast updates for 2011Q3 Czech GDP growth (q-o-q).

Table 4
RMSE, Forecasting GDP components at Q(−1)M3 end, 2009Q1–2012Q3.

	GDP	Consumption	GFCF	Gov. Cons.	Exports	Imports
Evaluated using first releases of GDP growth						
Random walk (absolute RMSE)	1.65	1.26	4.84	2.09	5.19	5.32
RMSE relative to RW						
DFM	0.53	1.02	0.80	0.99	0.75	0.82
CNB	0.50	0.95	0.69	0.90	0.87	0.96
Combination CNB & DFM	0.46	0.94	0.72	0.78	0.79	0.88
Evaluated using GDP growth in December 2012 vintage						
Random walk (absolute RMSE)	1.52	1.49	5.08	1.88	4.09	3.85
RMSE relative to RW						
DFM	0.56	0.97	0.61	1.11	0.73	0.75
CNB	0.53	0.86	0.50	0.93	0.84	0.94
Combination CNB & DFM	0.49	0.90	0.52	0.84	0.74	0.82

Notes: DFM stands for the nowcast obtained from the dynamic factor model, and CNB stands for the official nowcast of the Czech National Bank. Combination CNB & DFM stands for the nowcast obtained as the simple mean of the CNB and DFM nowcasts.

Table 5
RMSE, nowcasting GDP components at Q(0)M3 end, 2009Q1–2012Q3.

	GDP	Consumption	GFCF	Gov. cons.	Exports	Imports
Evaluated using first releases of GDP growth						
Random walk (absolute RMSE)	1.19	1.01	6.12	2.07	4.86	5.15
RMSE relative to RW						
DFM	0.48	1.14	0.75	0.75	0.96	1.05
CNB	0.47	1.28	0.68	0.85	0.80	0.91
Combination CNB & DFM	0.42	1.10	0.68	0.66	0.75	0.83
Evaluated using GDP growth in December 2012 vintage						
Random walk (absolute RMSE)	0.90	1.64	5.57	1.84	3.96	3.70
RMSE relative to RW						
DFM	0.69	0.78	0.74	0.86	0.90	1.12
CNB	0.62	0.80	0.63	0.95	0.89	1.04
Combination CNB & DFM	0.58	0.73	0.64	0.75	0.67	0.80

Notes: DFM stands for the nowcast obtained from the dynamic factor model, and CNB stands for the official nowcast of the Czech National Bank. Combination CNB & DFM stands for the nowcast obtained as the simple mean of the CNB and DFM nowcasts.

(all at constant prices).[15] The source of the real-time data is again the OECD Real-Time Database. The CNB forecasts/nowcasts for the expenditure components are again taken from the forecast books prepared for the regular quarterly CNB Situation Reports. The forecasts for the components are available in the forecast books only from 2009Q1, so we confine ourselves to presenting the results for this period only.

Looking at the results, several observations emerge. The accuracy of the GDP forecasts is not worsened by adding additional variables. Table 4 presents the results when forecasting one quarter ahead (forecast origin Q(−1)M3 end). The DFM forecasts seem to perform worse than the CNB forecasts for Consumption, GFCF, and Gov. Cons. But the DFM still seems to add value, as suggested by the fact that the forecast combination improves the accuracy of the forecasts. The DFM seems to dominate the CNB when forecasting Exports and Imports.

Table 6
Root mean square errors for longer horizons — 2005Q1–2012Q3.

	Forecast				
	2Q ahead	3Q ahead	4Q ahead	5Q ahead	6Q ahead
Evaluated using first releases of GDP growth					
Random walk (absolute RMSE)	1.29	1.38	1.52	1.56	1.52
RMSE relative to RW					
DFM	0.85	0.85	0.78	0.75	0.79
CNB	0.75	0.77	0.76	0.78	0.84
Combination CNB & DFM	0.77	0.79	0.76	0.75	0.81
Evaluated using GDP growth in December 2012 vintage					
Random walk (absolute RMSE)	1.44	1.53	1.67	1.70	1.67
RMSE relative to RW					
DFM	0.83	0.85	0.80	0.78	0.80
CNB	0.74	0.78	0.79	0.81	0.86
Combination CNB & DFM	0.76	0.80	0.79	0.79	0.83

Notes: The forecasts are produced at the forecast origin Q(0)M3 end. The first forecast is produced in March 2005 and the last forecast in September 2012. DFM stands for the forecast obtained from the dynamic factor model, and CNB stands for the official forecast of the Czech National Bank. Combination CNB & DFM stands for the nowcast obtained as the simple mean of the CNB and DFM nowcasts.

Table 5 reports the results for nowcasting the current quarter, i.e., forecast origin (Q(−1)M3 end). On the whole, the DFM seems to nowcast better for Consumption and Government Consumption. Note that in the case of exports and imports the dynamic factor model fares worse, but still seems to add value, as combining the DFM and CNB nowcasts decreases the nowcast errors.

Note that one could also perform the *news* exercise with components similar to those presented in the previous section.

5.2. Forecasting the performance of the DFM at longer horizons

While the DFM is geared towards nowcasting, it might be of interest to evaluate the accuracy at longer horizons as well. Because the variables are transformed to stationarity, the forecast of the DFM at longer horizons will converge to the steady states (historical means). As for the CNB forecasts, these are also converging to the steady states implied by the DSGE model, but they are conditional on expected shocks (largely coming from external developments).

In Table 6 we report the average accuracy of the RW, DFM, and CNB forecasts at horizons two to six quarters ahead. These forecasts are produced at the forecast origin (Q(0)M3 end). The gains relative to the naive random walk forecasts are smaller than for nowcasting and one-quarter-ahead forecasting. Furthermore, the results suggest that the accuracy of the forecasts is comparable, with the CNB slightly dominating at the two to three-quarter horizon, while the DFM seems to be slightly more accurate at longer horizons.[16] Combining the forecasts does not result in any apparent improvements. Again, the Diebold–Mariano test of differences in the accuracy of the forecasts indicates no statistical differences between the CNB and DFM forecasts. Since the CNB's monetary policy horizon is four to six quarters ahead, it might be of interest to use forecasts from the DFM as a cross-check even at forecasting horizons beyond the current quarter.

6. Concluding remarks

In this paper, we evaluate the real-time accuracy of the nowcasts produced by the dynamic factor model over the 2005–2012 period. We find that the accuracy of the model-based nowcasts is

[15] We could also impose a restriction that would reflect the national account identities. However, Angelini et al. (2010) find, using the euro area data, that the improvements from imposing this constraint are rather modest.

[16] We also tried a specification that includes outlooks for foreign demand, the foreign PPI, and EURIBOR. There were no improvements in the accuracy of the forecasts. These results are available upon request.

comparable to the nowcasts of the Czech National Bank. The accuracy improves if the two nowcasts are combined. Furthermore, we find that the role of foreign variables is crucial for the performance of the DFM: excluding them results in larger forecast errors. We also show how one can interpret the changes in the nowcasts as news contributions from new data releases. The framework might be useful in nowcasting other variables as well. We demonstrated good performance for nowcasting of the expenditure components of Czech GDP. Finally, the forecasting abilities of the DFM even at longer horizons (up to six quarters ahead) are also competitive with the CNB's forecasts.

Our results are in line with the anecdotal evidence provided by Sims (2002), who documents that the advantage of judgmental forecasts probably stems mainly from their ability to utilize disparate sources of data in real time and is largely limited to the current and one-quarter-ahead horizon. Our results suggest that, indeed, because of the ability of the dynamic factor model to exploit the latest releases of new data, it is able to compete successfully with the CNB forecasts.

Further research could focus on comparing the accuracy of the DFM with other recently developed mixed-frequency models, such as MIDAS (Andreou et al., 2012; Kuzin et al., 2011) or Mixed Frequency Bayesian VARs (Schorfheide and Song, 2012). Moreover, with regard to the current period of increased uncertainty, accounting for stochastic volatility might bring further forecasting improvements (Marcellino et al., 2013; Carriero et al., 2012).

Finally, note that our analysis focused on the accuracy of point forecasts only. By focusing on the root mean square forecast errors, we assumed that the loss function of policymakers is quadratic or that the world is linear. Therefore, in future research, it might be of interest to focus on characterizing the uncertainty surrounding the nowcasts in a fashion similar to Aastveit et al. (2011).

Appendix A

A.1. Description of benchmark models

We denote quarterly GDP growth as y_t. In all cases only the data available at the time of the forecast are used. Therefore, in the following equations, $k = 1$ for forecast origins from $Q(0)M3$ *mid* to $Q(+1)M1$ *end*, $k = 2$ for forecast origins from $Q(-1)M3$ *mid* to $Q(0)M2$ *end*, and $k = 3$ for forecast origins from $Q(-1)M1$ *mid* to $Q(-1)M2$ *end*. The lag for AR process was selected so as to strike balance between adding enough lags to capture important business cycle properties and possible overparametrization. Additionally, selecting other lags does not change the performance substantially.

Random walk (RW)

$$y_t = y_{t-k} + \varepsilon_t.$$

Autoregressive model (AR(2))

$$y_t = \rho_0 + \rho_1 y_{t-k} + \rho_2 y_{t-k-1} + \varepsilon_t.$$

Moving average (MA(4))

$$y_t = \frac{1}{4}(y_{t-k} + y_{t-k-1} + y_{t-k-2} + y_{t-k-3}) + \varepsilon_t.$$

Bridge equations

Forecasting with bridge equations is performed in two steps:

1. First step: Forecasting of monthly indicators to get rid of ragged ends, using an AR process, where the lag is chosen using the AIC.
2. Second step: The monthly predictors are averaged to quarterly frequency and the following equation is estimated:

$$y_t = \alpha + \sum_{i=1}^{k} \beta_i^j(L) x_{it}^j + \varepsilon_t.$$

The lag is chosen using the AIC.

A.2. State-space representation of the DFM model

Our dynamic factor model can be then cast in a state-space form:

$$\begin{pmatrix} x_t \\ y_t^Q \end{pmatrix} = \begin{pmatrix} \Lambda & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \Lambda_Q & 2\Lambda_Q & 3\Lambda_Q & 2\Lambda_Q & \Lambda_Q & 1 & 2 & 3 & 2 & 1 \end{pmatrix} \begin{pmatrix} f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ \varepsilon_t^Q \\ \varepsilon_{t-1}^Q \\ \varepsilon_{t-2}^Q \\ \varepsilon_{t-3}^Q \\ \varepsilon_{t-4}^Q \end{pmatrix} + \begin{pmatrix} \varepsilon_t \\ \xi_t^Q \end{pmatrix}.$$

$$\begin{pmatrix} f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ \varepsilon_t^Q \\ \varepsilon_{t-1}^Q \\ \varepsilon_{t-2}^Q \\ \varepsilon_{t-3}^Q \\ \varepsilon_{t-4}^Q \end{pmatrix} = \begin{pmatrix} A_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ f_{t-5} \\ \varepsilon_{t-1}^Q \\ \varepsilon_{t-2}^Q \\ \varepsilon_{t-3}^Q \\ \varepsilon_{t-4}^Q \\ \varepsilon_{t-5}^Q \end{pmatrix} + \begin{pmatrix} u_t \\ 0 \\ 0 \\ 0 \\ 0 \\ \varepsilon_t^Q \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

A.3. Performance of the DFM under different specifications

Motivated by the short sample available for the Czech Republic, we largely opted for the simple parsimonious specification of our dynamic factor model. While the results of our baseline model seem to be satisfactory and comparable to the CNB nowcasts, it might be of interest to investigate the sensitivity of the results to the specification of the number of factors or the number of lags. Furthermore, we also consider several extensions, such as modeling the dynamics of the idiosyncratic component or restricting the factors to a domestic and a foreign one.

In Fig. A1, we present the results for several variations of the baseline model. First, we consider the possibility that Czech GDP is driven by two distinct factors: a factor extracted from domestic variables (Hard data, Financials, Surveys) and a factor extracted from foreign variables. This specification is labeled *Two restricted factors*. The restrictions are imposed as zeros in the loadings matrix. Next, we consider two factors, but both of them are extracted from all of the monthly indicators. This specification is labeled *Two unrestricted factors*. As an additional extension, we consider modeling the idiosyncratic shock ε_t as an autoregressive process of order one, to capture possible persistence in these shocks. This specification is labeled *AR idio*. Finally, we consider two variations of the modeling of the factor dynamics: *One lag* and *Three lags* denote the specification where the factor follows an autoregressive process of order one and three, respectively.

The results suggest that the results of various specifications are comparable with the baseline model. Specifications with two factors seem to perform slightly worse, while modeling the dynamics of factors and idiosyncratic components matters only marginally.

It is also worth checking how does the baseline model performs when we use last available data as opposed to the real-time vintages. Table A1 shows that the forecasting performance is not significantly better when one uses the last vintage data instead of real-time

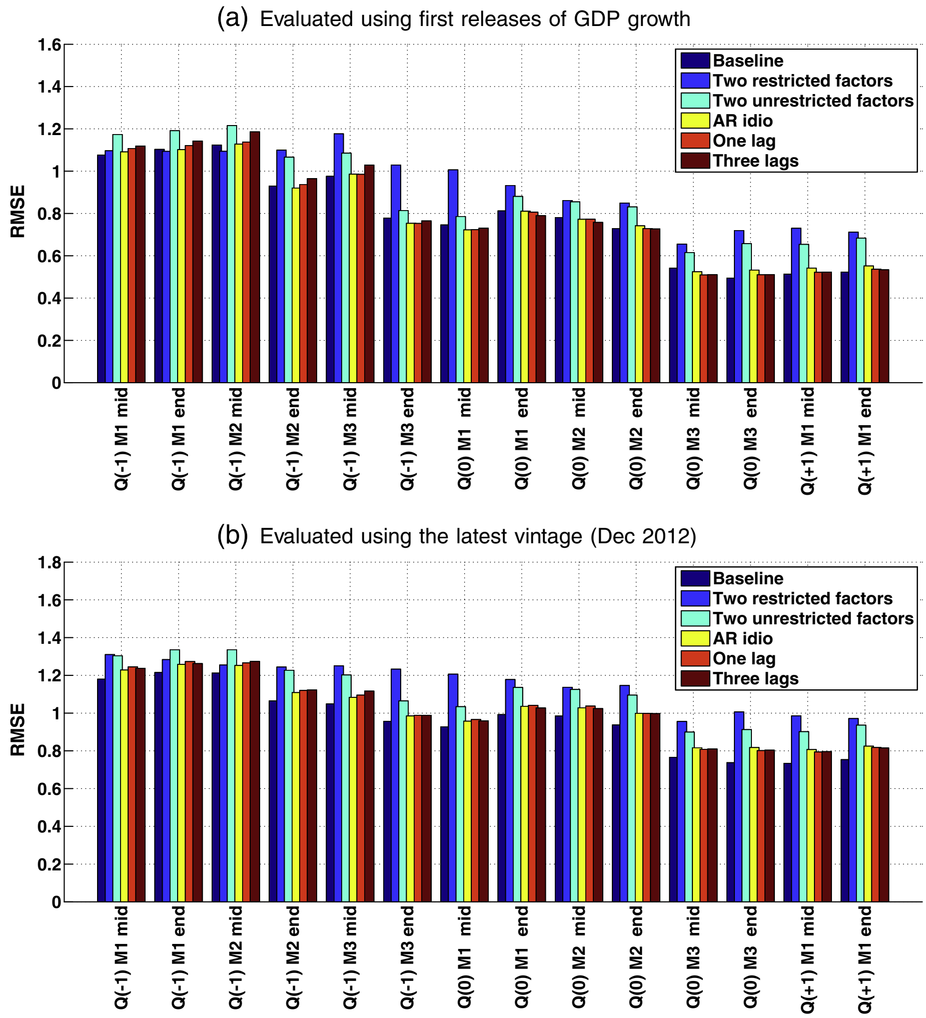

Fig. A1. Performance of the DFM model under various specifications.

Table A1
RMSE (last-vintage data vs. real-time data).

RMSE	Q(−1)	Q(−1)	Q(−1)	Q(−1)	Q(−1)	Q(−1)	Q(0)	Q(0)	Q(0)	Q(0)	Q(0)	Q(0)	Q(+1)	Q(+1)
	M1	M1	M2	M2	M3	M3	M1	M1	M2	M2	M3	M3	M1	M1
	Mid	End	Mid	End	Mid	End	Mid	End	Mid	End	Mid	End	Mid	End
Real-time	1.18	1.22	1.21	1.07	1.05	0.96	0.93	0.99	0.98	0.94	0.77	0.74	0.73	0.75
Last-vintage	1.17	1.21	1.21	1.07	1.04	0.96	0.93	1.00	0.99	0.95	0.75	0.73	0.73	0.76
Rel. RMSE	0.99	1.00	1.00	1.01	0.99	1.00	1.01	1.00	1.01	1.01	0.99	1.00	1.00	1.00

vintages, which suggests that the model is robust to the revisions (Giannone et al., 2008, find similar results).

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