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Abstract

In this paper we use a battery of various mixed-frequency data models to forecast Czech GDP. The models employed are mixed-frequency vector autoregressions, mixed-data sampling models, and the dynamic factor model. Using a dataset of historical vintages of unrevised macroeconomic and financial data, we evaluate the performance of these models over the 2005–2012 period and compare them with the Czech National Bank's macroeconomic forecasts. The results suggest that for shorter forecasting horizons the accuracy of the dynamic factor model is comparable to the CNB forecasts. At longer horizons, mixed-frequency vector autoregressions are able to perform similarly or slightly better than the CNB forecasts. Furthermore, moving away from point forecasts, we also explore the potential of density forecasts from Bayesian mixed-frequency vector autoregressions.

Abstrakt

V tomto článku pracujeme se sadou modelů využívajících data různých frekvencí a na jejich základě predikujeme HDP České republiky. Použité modely zahrnují vektorové autoregrese pro různé frekvence, modely dat různých samplovacích frekvencí a dynamický faktorový model. Za použití historických časových řad nerevidovaných makroekonomických a finančních indikátorů hodnotíme přesnost těchto modelů pro období let 2005–2012 a srovnáváme ji s makroekonomickými predikcemi České národní banky (ČNB). Výsledky naznačují, že přesnost dynamického faktorového modelu je pro kratší horizonty predikce srovnatelná s predikcemi ČNB. Na delším horizontu jsou pak modely vektorové autoregrese pro různé frekvence srovnatelné nebo dokonce nepatrně lepší než predikce ČNB. Kromě bodových predikcí také zkoumáme potenciál predikcí hustot HDP vycházejících z bayesovské vektorové autoregrese pro různé frekvence.

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Nontechnical Summary

For central banks to be able to implement monetary policy successfully, the ability to forecast the current and future macroeconomic environment is crucial. This paper looks at models that produce such forecasts and evaluates the precision of the forecasts produced in real time. Real-time forecasters need to tackle several specific issues. First, some macroeconomic indicators are published with a significant lag. For example, GDP for a particular quarter is released in the third month of the next quarter. Second, the data used for forecasting are usually available at various sampling frequencies. So, forecasters work with daily data (e.g. the exchange rate), monthly data (e.g. industrial production, unemployment), and quarterly data (e.g. GDP). Finally, real-time forecasters face the fact that macroeconomic aggregates are revised (sometimes substantially) by statistics bureaus.

In this paper, we use a battery of various models that have been developed only recently and that are able to deal with these issues. The models applied include mixed-frequency vector autoregressions (MF-VAR), mixed-data sampling models (MIDAS), and the dynamic factor model (DFM). We employ these models to produce forecasts of GDP, which is the main indicator of the state of the economy.

The main focus is on assessing the forecasting ability of the selected approaches in the case of Czech GDP. In order to facilitate comparison with the macroeconomic forecasts produced by the Czech National Bank (CNB), we collect a dataset of historical vintages of unrevised macroeconomic variables. The nature of the models used allows us to include financial indicators such as interest rates, credit growth, and stock market growth. In order to exploit timely information we also add survey indicators about industry and consumer confidence. Finally, to capture the fact that the Czech economy is a small open economy, we also make use of several foreign indicators covering macroeconomic, survey, and financial variables. Using this dataset, we evaluate the forecasting performance of these models over the 2005–2012 period.

The results suggest that for shorter forecasting horizons the accuracy of the dynamic factor model is comparable to the CNB forecasts. At longer horizons, mixed-frequency vector autoregressions are able to perform similarly or slightly better than the CNB forecasts. Regarding nowcasting it turns out that the precision of point forecasts generally increases as new information becomes available over the nowcasting period. Finally, we investigate the potential of density nowcasts from Bayesian mixed-frequency vector autoregressions. We show that the uncertainty related to GDP nowcasts decreases over the nowcasting period as additional information from the underlying indicators becomes available.

1. Introduction

Forecasting is one of the key tasks of central banks, as monetary policy decision-making draws heavily on expected future developments in the economy. The role of forecasting is especially important for inflation targeting central banks, which set their policy rates so as to guarantee that the inflation forecast is close to the target at a given monetary policy horizon. The accuracy of the inflation outlook depends on appropriation estimation of the current and future values of other macroeconomic indicators. In this respect, GDP – an indicator of the performance of the economy – is one of the most important variables.

An important aspect of forecasting is that the time series used in the forecasting process are often available at various sampling frequencies. For example, GDP is published quarterly, whereas labor market data are available monthly and financial data even daily. Most of the standard forecasting models assume that the data are sampled at the same frequency. As a consequence, higher frequency data are in practice typically aggregated to a lower frequency. There are, however, costs of ignoring the availability of high frequency data in the forecasting process. First, we lose information through temporal aggregation. Second, we lose the opportunity of providing real-time forecast updates at a higher frequency (e.g. every month when forecasting a quarterly indicator). Another aspect related especially to real-time forecasting is that the datasets available at a particular point in time are unbalanced. These ragged-edge datasets are the consequence of different frequencies per se and, in addition, the result of different publication lags for particular time series.

In this paper, we evaluate the performance of commonly used mixed-frequency models when nowcasting and forecasting GDP in real-time. We consider the following mixed-frequency data models recently proposed in the forecasting literature: mixed-data sampling (MIDAS), mixed-frequency vector autoregression (MF-VAR), and the dynamic factor model (DFM). MIDAS is a univariate approach that uses distributed lag polynomials, thus yielding a parsimonious specification suitable for forecasting. MF-VAR is a multivariate system that is set up as if all the data were available at the highest frequency in the dataset regardless of whether or not all the data points are observable. Finally, the DFM exploits comovements among macroeconomic variables by assuming that they are driven by a small number of unobserved factors.[1]

Our evaluation focuses on the nowcasting and forecasting of Czech GDP. In order to assess the value of these models for practical use within the forecasting process in the central bank, we design our forecasting exercises so that the accuracy of the models can be compared with the macroeconomic forecasts of the Czech National Bank (CNB). In other words, we use vintages of unrevised real-time data in order to facilitate comparison with the forecasts of the CNB, so that neither the model-based forecasts nor the CNB's forecasts have a significant information advantage stemming from different datasets.

The presented econometric analysis extends two recent studies by Arnoštová et al. (2010) and Rusnák (2013a). Arnoštová et al. (2010) explore several single-frequency models to forecast

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[1] Recently developed time-series models employing mixed-frequency data also include factor-MIDAS (Marcellino and Schumacher, 2010) and mixed sampling frequency VAR models (Ghysels, 2012). For a recent overview of methods that deal with mixed-frequency data see Foroni and Marcellino (2013).

quarterly GDP using monthly indicators.[2] Rusnák (2013a) deals with a dynamic factor model that, similarly to MIDAS and MF-VAR, combines data of different frequencies directly. The results from the two above-mentioned studies are discussed to complete our discussion of the performance of mixed-frequency data models.

In addition to point nowcasts and forecasts, density nowcasts are touched upon. For that purpose, a variant of MF-VAR is estimated by Bayesian techniques (MF-BVAR). This exercise allows, among other things, for a discussion of the uncertainty related to point nowcasts and its change with the arrival of new information.

The results based on the 2005–2012 evaluation period suggest that all of the models considered are able to beat a naïve benchmark (a random walk forecast). Over the nowcasting period a striking increase in the precision of the nowcasts in the third month of the nowcasted quarter coincides with the release of GDP data for the previous quarter. For nowcasting horizons, only the dynamic factor model is able to compete with the CNB nowcasts. Regarding forecasting, at longer horizons mixed-frequency VAR and the dynamic factor model deliver forecasts that are comparable to or better than the CNB forecasts. At shorter horizons, the CNB forecasts perform best.

Even though the examination of density forecasts is largely intended to illustrate the use of this tool for the Czech case, some results are worth emphasizing. It turns out that the size of the uncertainty decreases with the arrival of new information over the nowcasting period. Moreover, the estimates obtained later during the nowcasting period, which are surrounded by less uncertainty, are no worse than the less precise estimates at the beginning of the nowcasting period.

The rest of the paper is organized as follows. Section 2 presents the mixed-frequency data models used in the analysis and discusses their estimation. The dataset is introduced in Section 3. In Section 4 the results of the nowcasting and forecasting exercises are presented. Section 5 provides several notes on the uncertainty related to nowcasts based on the MF-BVAR model. Finally, Section 6 concludes. Some additional results related to robustness issues are included in appendices.

2. Models and Estimation

The motivation to examine all the currently used mixed-frequency data models – MIDAS, MF-VAR, and the DFM – stems from the fact that there is no theoretical preference a priori between the model approaches. As argued by Kuzin et al. (2011), MIDAS regression is a parsimoniously parameterized single-equation model but does not account for dynamic interrelations among the variables. On the other hand, while MF-VAR might be able to better capture the dynamics of the variables, it is more vulnerable to the curse of dimensionality, since one needs to specify a

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[2] Arnoštová et al. (2010) consider a naïve MA(4) model of GDP, the model based on prediction of the expenditure components of GDP used in the CNB for near-term output forecasting, a simple bivariate VAR model of quarterly GDP and an aggregated monthly indicator, and a bridge equations model that starts with forecasting of monthly indicators, which are then combined with the GDP series in a VAR model for quarterly data. Apart from these four models, Arnoštová et al. (2010) also examine several factor models based on static principal components and dynamic factors.

dynamic model for all variables.[3] The DFM also tries to exploit the dynamics of the variables, but attempts to turn the curse of dimensionality into a blessing by exploiting the comovements of the variables using a small number of common factors.

The three model classes are described in the following sub-sections. The rest of the models used for forecasting performance analysis are then discussed. Our set of models will be compared with a naïve (random walk) forecast and a CNB macroeconomic forecast.

We estimate the MIDAS and MF-VAR models using only GDP and one indicator variable at a time, while the dynamic factor model is estimated using all of the indicators jointly. We prefer this approach for the MIDAS and MF-VAR models since these models – unlike the DFM – are not equipped to deal with the curse of dimensionality that arises when one considers all of the indicators. Kuzin et al. (2011) follow a similar strategy.

2.1 Mixed-data Sampling (MIDAS)

The MIDAS approach was first applied in volatility forecasting (Ghysels et al., 2004), but since then a vast literature has accumulated documenting the gains from using higher frequency information in forecasting real activity in the U.S. and the euro area (see, for example, Clements and Galvão, 2008, Kuzin et al., 2011, and the survey by Andreou et al., 2011, for additional references). In addition, Clements and Galvão (2009) and Armesto et al. (2010) corroborate these findings using real-time vintages. See Ghysels et al. (2007) and Andreou et al. (2011) for comprehensive surveys on MIDAS.

We are interested in forecasting quarterly GDP growth $y_{t_q+h}^Q$ (h quarters ahead) using a monthly indicator for the i-th month in quarter t_q, X_{i,t_q}^M. In our baseline application we use an unrestricted MIDAS (U-MIDAS) specification:

$$y_{t_q+h}^Q = \mu + \delta y_{t_q}^Q + \sum_{j=0}^{p^Q} \sum_{i=0}^{N_M-1} \beta_{N_M-i+j*N_M} X_{N_M-i,t_q-j}^M + u_{t_q+h}, \tag{1}$$

where N_M denotes the number of months in a quarter. The advantage of the unrestricted specification is that it can easily be estimated by OLS. We use U-MIDAS as our baseline MIDAS model, but we also investigate the robustness of our results to different polynomial schemes for coefficients β in Appendix C. The results in Appendix C show that the forecasting performance of U-MIDAS is similar to that of other MIDAS specifications. This is in line with Foroni et al. (2014), who show in a Monte Carlo experiment that when the difference between frequencies is small (e.g. monthly vs. quarterly in our case) one might not need to employ more complex polynomial schemes such as Almon or beta lag polynomials, and that U-MIDAS generally performs well.

In our baseline estimations, we use the last six available observations of the monthly indicator (lags and leads depending on the forecast horizon). Since GDP growth tends to be rather persistent, we also include a lag of GDP growth to improve the forecasting accuracy. Note that

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[3] Regarding the relative forecasting performance of MIDAS and MF-VAR in output forecasting, Kuzin et al. (2011) show that in the case of nowcasting and forecasting of euro area GDP, MF-VAR performs better for longer horizons (5 to 9 months) while MIDAS outperforms MF-VAR at shorter horizons (1 to 4 months).

MIDAS is a single equation model which does not model the dynamics of the indicators on the right-hand side. Therefore, MIDAS can only provide direct forecasts, which results in a need to re-estimate the model for each forecasting horizon.

2.2 Mixed-frequency VAR (MF-VAR)

Mariano and Murasawa (2003, 2010) applied methods dealing with different sample frequencies to the quarterly time series of output and a monthly indicator within an MF-VAR framework. Recent contributions to this stream of literature can be divided according to whether the estimation of the system of equations is based on maximum likelihood (Kuzin et al., 2011) or Bayesian methods (Marcellino et al., 2012; Schorfheide and Song, 2011; Chiu et al., 2011).

MF-VARs are multivariate models able to account for endogenous variables of different sampling frequencies. The model is set up to produce forecasts of the highest sampling frequency of the time series entering the analysis. The following specification is formulated for the quarterly series of GDP and a monthly indicator (e.g. industrial production in a sector, a business climate index, etc.).

Following Mariano and Murasawa (2003) we assume that the observed quarterly level of GDP, $Y_{t_q}^Q$, relates to the unobserved monthly levels of GDP in the relevant quarter, $\widetilde{Y}_{t_m}^M$, as their geometric mean:

$$\log Y_{t_q}^Q = \frac{1}{3}\left(\log \widetilde{Y}_{t_m}^M + \log \widetilde{Y}_{t_m-1}^M + \log \widetilde{Y}_{t_m-2}^M\right), \tag{2}$$

where the time index t_m denotes months. Subtracting from equation (2) the same equation lagged by three months provides an equation in observed q-o-q growth rates, $y_{t_q}^Q$, and unobserved m-o-m growth rates, $\widetilde{y}_{t_m}^M$:

$$y_{t_q}^Q = \frac{1}{3}\widetilde{y}_{t_m}^M + \frac{2}{3}\widetilde{y}_{t_m-1}^M + \widetilde{y}_{t_m-2}^M + \frac{2}{3}\widetilde{y}_{t_m-3}^M + \frac{1}{3}\widetilde{y}_{t_m-4}^M. \tag{3}$$

Combining unobserved monthly observations of the GDP growth rate with a monthly indicator $X_{t_m}^M$ into the VAR model structure yields:

$$z_{t_m} = \sum_{j=1}^{p^M} \beta_j z_{t_m-j} + u_{t_m}, \tag{4}$$

where $z_{t_m} = \begin{pmatrix} \widetilde{y}_{t_m}^M - \widetilde{\mu}_y^M \\ X_{t_m}^M - \mu_X \end{pmatrix}$ and $u_{t_m} \sim N(0, \Sigma)$.

Equation (3) relates observed and unobserved variables and together with equation (4) can easily be rewritten into a linear state space form (for $p^M \leq 5$):

$$s_{t_m+1} = A s_{t_m} + B v_{t_m}$$
$$\begin{pmatrix} \widetilde{y}_{t_m}^Q - \mu_y^Q \\ X_{t_m}^M - \mu_X \end{pmatrix} = C s_{t_m} \qquad s_{t_m} = \begin{pmatrix} z_{t_m} \\ \vdots \\ z_{t_m-4} \end{pmatrix}, \qquad (5)$$

where $v_{t_m} \sim N(0, I_2)$. The specification of matrices A, B, and C together with equation (5) for $p^M > 5$ can be found in Mariano and Murasawa (2010).

System (5) is estimated by the EM algorithm and is then used to forecast output by the Kalman smoother procedure. As is usual in this context the observed data are demeaned prior to the estimation to reduce the size of the parameter set. The mean is then added to the forecasted values. The one-step-ahead forecasts are then iterated to obtain forecasts for longer horizons. The number of lags, p^M, is determined using the Bayesian Information Criterion for each estimated model separately. The maximum lag considered is six months.

The bivariate system (5) is estimated for all monthly indicators, and the individual forecasts are then combined into a simple mean. As a robustness check, the weighting scheme based on the previous forecasting performance of a particular bivariate VAR is employed. More specifically, the weights are computed as the inverse of the mean squared errors over the previous four quarters.[4] The weights of the bivariate models are then normalized to unity and used to calculate the resulting forecast. The results are largely unaffected by the choice of alternative weighting scheme and are presented in Appendix A.

2.3 Mixed-frequency Bayesian VAR (MF-BVAR)

The MF-VAR model is estimated by the EM algorithm, which allows us to deal with missing values of GDP growth. Another possible approach to the estimation of MF-VAR draws on Bayesian techniques. More precisely, we employ the Gibbs sampler as in Chiu et al. (2012). The sampler draws subsequently from the conditional posteriors of the model parameters and from the assumed distribution of the missing values. For each draw of model parameters and missing values a forecast is computed. The median of the simulated distribution of the forecasts for each forecasting horizon is then taken.

Note that the point forecasts produced by MF-VAR estimated by Bayesian techniques (MF-BVAR) can provide results different from the MF-VAR model, as the Bayesian approach allows one to incorporate additional information in the form of priors on top of the information provided by the data.

We follow Chiu et al. (2012) and define:

$$w_{t_m} = \begin{pmatrix} \widetilde{y}_{t_m}^Q \\ X_{t_m}^M \end{pmatrix}, \qquad (6)$$

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[4] Since nowcasts are computed for several points in a quarter only, the MSE is computed at the same point in the previous four quarters.

where again $\widetilde{y}_{t_m}^Q$ is quarterly growth of GDP with missing values for the second and third month of the quarter, and $X_{t_m}^M$ denotes a fully observable monthly indicator. The model is formulated as a VAR-type model:

$$w_{t_m} = A + \sum_{j=1}^{p^M} B_j w_{t_m-j} + u_{t_m},\tag{7}$$

where $u_{t_m} \sim N(0, \Sigma)$. The Gibbs sampler is described in Appendix A of Chiu et al. (2012). As an alternative, the Gibbs sampler discussed in Schorfheide and Song (2013) can be used. These two samplers differ in the way the missing values are treated.

Regarding the prior assumed for the model parameters, we employ the independent normal inverse-Wishart prior. Since the data are transformed to be stationary prior to estimation, the prior mean for the AR parameters is set to zero. The prior variance of the AR parameters is set in line with the Minnesota-style prior with the standard hyperparameter values as in Canova (2007). The inverse-Wishart distribution for the prior on the covariance matrix of the error term is assumed to have an identity matrix as a scale matrix and three degrees of freedom.

Note that in contrast to the MF-VAR model, the series entering the analysis are not demeaned, as the uncertainty of the intercept is of interest as well as the uncertainty related to the other model parameters. To simulate the posterior distributions, 6,000 draws from the Gibbs sampler are generated. The first 5,000 draws are discarded to minimize the effect of the initial values of the sampler, and the last 1,000 draws are used for inference. In model (7), we assume six lags ($p^M = 6$).

Similarly to MF-VAR and MIDAS, the bivariate models based on a particular monthly indicator (7) are combined such that the median nowcast of a particular model enters the combination procedure. The simple mean of the medians is presented. The weighted mean – using the inverses of the MSE over the last four quarters as weights – is presented in Appendix A.

2.4 Dynamic Factor Model (DFM)

One of the most heavily used mixed-frequency data models is the dynamic factor model (Giannone et al., 2008; Camacho and Perez-Quiros, 2010; Banbura and Modugno, 2014). Therefore, we also compare the MIDAS and MF-VAR models with the DFM. Similarly to MF-VAR, the DFM is a multivariate approach that uses monthly indicators to predict quarterly GDP. The model is cast into state space representation and is estimated by the EM algorithm. By using the Kalman filter and smoother, the model is able to handle missing observations and unbalanced datasets as well as mixed frequencies.

The dynamic factor model is specified as follows:

$$x_t = \Lambda f_t + \varepsilon_t,\tag{8}$$

$$f_t = A f_{t-1} + u_t,\tag{9}$$

where x_t is a vector of monthly indicators and quarterly GDP, Λ is a matrix of factor loadings, f_t stands for an unobserved common factor, while A captures the dynamics of the factor. Shocks ε_t and u_t are assumed to be mutually uncorrelated. We use one factor to capture the comovements across variables and two lags to describe the autoregressive dynamics of the factor. Further details about the model and the specification we use can be found in Rusnák (2013a), who also evaluates the performance of the DFM for forecasting Czech GDP under various specifications. Further, technical details of the estimation using the EM algorithm can be found in Banbura and Modugno (2014).

Note that the difference between the DFM and MIDAS and MFVAR lies in how the models aggregate the information coming from the different indicators. While the DFM weights the different indicators endogenously within the estimation procedure, the individual MFVAR and MIDAS forecasts are weighted out of the model using a specific weighting scheme (simple and MSE-weighted means).

2.5 The CNB's Macroeconomic Forecasts

We compare the forecasts from the three models with the CNB's macroeconomic forecasts. Currently, GDP forecasting up to one quarter ahead (referred to as near-term forecasting at the CNB) is based on a set of linear regressions, which capture the dynamics of single expenditure components. Additional information stemming from monthly indicators is incorporated in the form of expert judgment. Subsequently, the predicted expenditure components are aggregated, and further expert judgment is applied in order to obtain a sufficiently smooth trajectory of overall GDP.

For forecasting horizons longer than one quarter ahead, the CNB's GDP forecast is based on the structural core model of the CNB. A small open-economy gap model – QPM (Coats et al., 2003) – was used until 2008, and a standard DSGE model – g3 (Andrle et al., 2009) – has been applied since then. Again, expert judgments are often incorporated into the forecast during the forecasting process (Brůha et al., 2013).

3. Data

There is a range of variables of monthly frequency that might provide information useful for the forecasting of GDP. Our approach in selecting the indicators is to focus on the so-called headline macro aggregates and not to consider disaggregated information (due to the unavailability of real-time data and the possible over-representation of one variable or sector in the dataset). Our dataset thus comprises real GDP growth and 27 indicators covering hard data and financial, survey, and foreign variables.

Hard data indicators are included because of their natural connection with the production side (e.g. industrial production, construction) and the expenditure side (e.g. sales, unemployment rate) of the economy. Financial variables are considered since there is some evidence of the importance of these variables for Czech GDP (Havranek et al., 2012). Furthermore, survey variables have been shown to be crucial for precise and timely nowcasting in the U.S. and some other countries (Giannone et al., 2008). Finally, the rationale for including data capturing foreign developments is

straightforward: the Czech economy is a small open economy and is therefore strongly affected by foreign variables.

In our forecasting performance exercise we will attempt to match the dataset to the information set that is available to forecasters when they are preparing their regular forecasts. This amounts to using vintages of unrevised macroeconomic data and taking into account publication lags of macroeconomic variables (for example, GDP is released with a considerable lag, approximately 70 days after the end of the reference quarter).

Using unrevised data might be important since there is evidence that revisions to Czech GDP are of considerable magnitude (Rusnák, 2013b). The use of revised data for the out-of-sample exercise may overestimate the predictive power of the indicators and understate the forecasting errors that would have been made when forecasting using only the information available in real time. If the revisions are weakly correlated one might expect them to tend to average out when using real-time data (Giannone et al., 2008), but this is ultimately an empirical matter that we are not able to rule out beforehand. We provide the results using only the last available vintage in Appendix B.

Table 1 summarizes our dataset. We use ten series that are subject to frequent revisions, so for those series we use historical vintages obtained from the OECD real-time database. A further look at Table 1 reveals considerable variation in the publication delays for the variables. For the purposes of our forecasting exercise we map these publication delays into unbalancedness patterns observed in the middle of the month and at the end of the month. Besides the OECD real-time database, the data sources are the Czech Ministry of Labor and Social Affairs (MLSA), the Czech National Bank ARAD database (CNB), the Prague Stock Exchange (PSE), the Czech Statistical Office (CZSO), the Ifo Institute for Economic Research (IFO), and Eurostat.

Table 1: List of Variables Used in Forecasting Exercises

	Variable	Rev.	Pub. lag	Unb. Pat	Source
1	Real GDP	Y	68 to 71	4,5,3-4,5,3	OECD
2	Industrial production index	Y	37 to 45	2-2	OECD
3	Construction output	Y	37 to 45	2-2	OECD
4	Retail sales	Y	35 to 49	2-2	OECD
5	Unemployment rate	N	8 to 11	1-1	MLSA
6	CPI total	N	8 to 11	1-1	CZSO
7	Exports (current prices)	Y	35 to 39	2-2	OECD
8	Imports (current prices)	Y	35 to 39	2-2	OECD
9	Export price index	N	43 to 47	3-2	CZSO
10	Import price index	N	43 to 47	3-2	CZSO
11	CZK/EUR exchange rate	N	0	1-0	CNB
12	M2	Y	30 to 31	2-1	CNB
13	Credit	Y	30 to 31	2-1	CNB
14	3M PRIBOR	N	0	1-0	CNB
15	1Y PRIBOR	N	0	1-0	CNB
16	PX-50 stock index	N	0	1-0	PSE
17	Czech government bond yield (10Y)	N	0	1-0	CNB
18	Consumer confidence indicator	N	-7 to -2	1-0	CZSO
19	Industry confidence indicator	N	-7 to -2	1-0	OECD
20	Construction confidence indicator	N	-7 to -2	1-0	OECD
21	Trade confidence indicator	N	-7 to -2	1-0	OECD
22	Services confidence indicator	N	-7 to -2	1-0	OECD
23	3M EURIBOR	N	0	1-0	CNB
24	1Y EURIBOR	N	0	1-0	CNB
25	Oil price (Brent)	N	0	1-0	Datastream
26	Ifo Business Climate for Germany	N	-10 to -4	1-0	IFO
27	Euro area Business Climate Indicator	N	-4 to -1	1-0	Eurostat
28	German exports	Y	40	2.2	OECD

Notes: Rev. indicates whether the data used are revised or not. Pub. Lag indicates the typical publication delay of the variable in days (average during 2005–2012 period). Unb. Pat. stands for Unbalancedness Pattern and indicates the number of missing observations in the middle of the month and at the end of the month, respectively. 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.

We use a real-time database of 99 monthly vintages: the first vintage is from October 2004 and the last from December 2012. Most of the variables start from 2000M1. Note that the monthly data on the Czech government bond yield (10Y) and the services confidence indicator exhibit a few missing values at the beginning of 2000. Since MIDAS and MF-VAR assume fully observable monthly indicators, the two indicators are excluded from the estimation and forecasting for the two model classes.

We do not preselect the variables from our dataset any further. Models using variables selected based on some in-sample criteria might be subject to structural breaks and their out-of-sample

performance might not be satisfactory. On the other hand, choosing variables based on some out-of-sample training sample might not be a good strategy for the Czech Republic, since variables preselected using the pre-crisis period might lose their predictive power in the crisis period. Therefore, we use all of the variables in our dataset to produce the forecasts. The DFM should be able to arrive at proper weights for the indicators provided that the variables are not over-represented in the dataset to confuse idiosyncratic shocks with the estimated factors. For the MIDAS and MFVAR models we combine the forecasts from the individual bivariate models using simple averages or weights based on past forecast errors.

4. Results

The assessment of the out-of-sample forecasting precision is based on the root-mean-square error (RMSE), which is computed over the evaluation period. The evaluation sample covers the period 2005Q1–2012Q3. We use two measures of the observed GDP growth rate: the first release of GDP growth, and the growth rate as reported in our last available vintage, i.e., the December 2012 vintage. While the first releases might be closer to the forecasters' loss function and might be important from the communication point of view (e.g. the CNB's comments on the first data releases), the last available vintage growth rates are arguably closer to the true values, as they are based on all the available information and the latest methodology.

In what follows, we denote nowcasts as forecasts for a given quarter which are conducted during the previous quarter, during the given quarter, and in the first month of the next quarter. More precisely, the nowcasting period refers to all the middles and ends of the months of the previous quarter: *Q(-1) M1 mid, Q(-1) M1 end, …, Q(-1) M3 end*, to the same periods in the current quarter *Q(0) M1 mid, Q(0) M1 end, …, Q(0) M3 end*, and to the middle and end of the first month of the quarter following the quarter the nowcast is done for: *Q(1) M1 mid and Q(1) M1 end.* Forecasts are considered for the current quarter (nowcasts) and up to six quarters ahead.

4.1 Nowcasting

Nowcasts of GDP are used as inputs into the core CNB forecasting model, so models that are able to provide precise nowcasts are of great relevance for the CNB. Figure 1 presents the results of our mixed-frequency data models and compares the predictive accuracy with the CNB nowcasts.

The results show that the performance of the DFM is superior to all other mixed-frequency model forecasts. Moreover, the nowcasting accuracy of the DFM is comparable to the nowcasts historically produced by the CNB. MF-VAR and MF-BVAR outperform the DFM for forecasts carried out at the beginning of the previous quarter for a horizon of a quarter.

Figure 1: Root Mean Square Errors at Different Nowcast Origins

RMSE evaluated using first releases of GDP

RMSE evaluated using Dec 2012 vintage of GDP
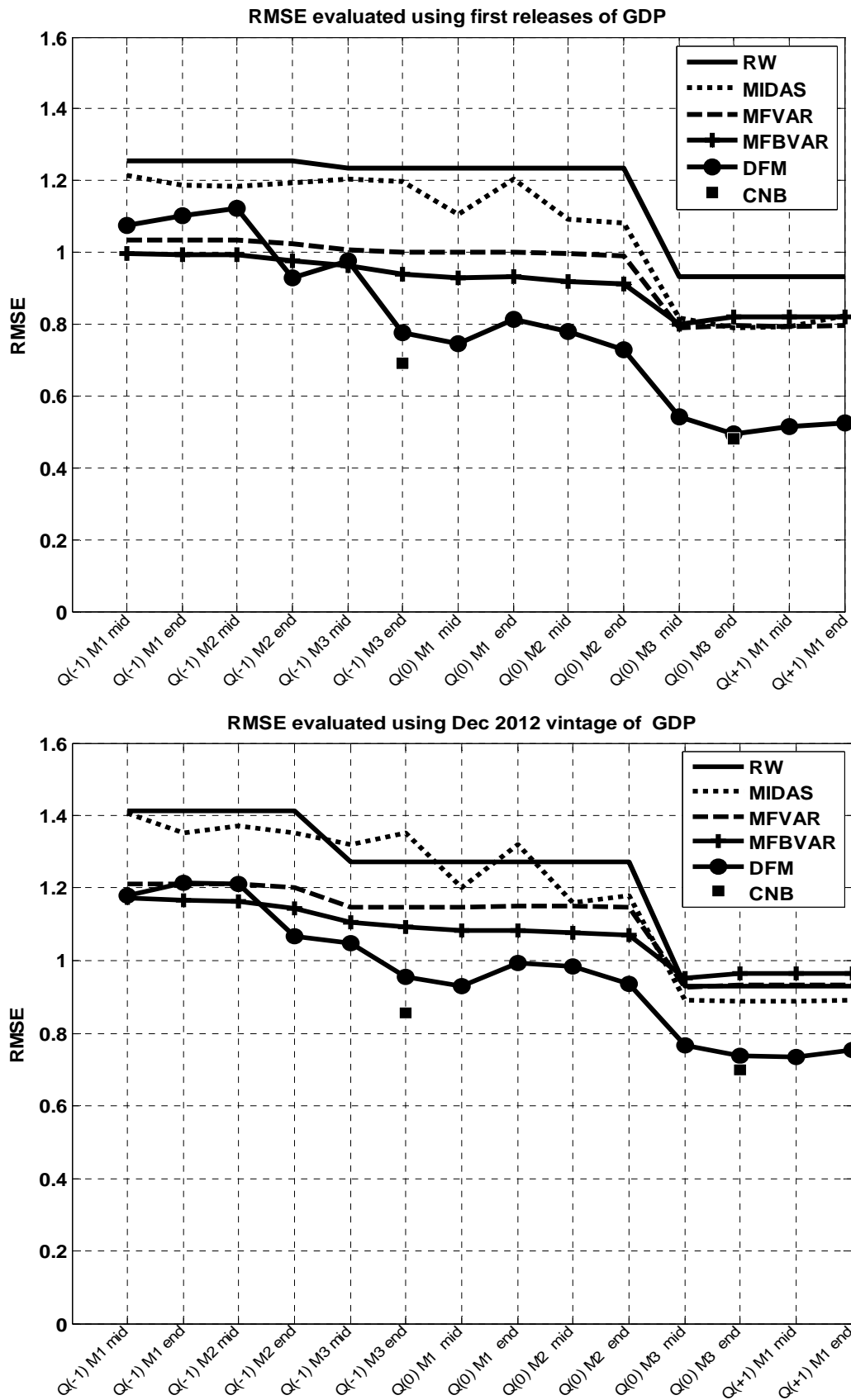
On the whole, all of the models tend to be more precise with the arrival of new information, as documented by the decreasing root mean square error. The decrease is not monotonous though, and the biggest decrease seems to come in the middle of the third month of the nowcasted quarter. This is most likely due to the release of the GDP data for the previous quarter and probably reflects additional information about GDP that is not present in the monthly indicators.

The results are qualitatively similar when the forecasts are evaluated using the first releases of GDP or using the latest available vintage from December 2012. Naturally, the RMSE evaluated using the latest vintage is larger because it also reflects the presence of future revisions that are not known at the time when the forecast is made. Note that it is generally hard to predict revisions to Czech GDP out of sample (Rusnak, 2013b).

For GDP nowcasts for the euro area, Foroni and Marcellino (2014) find that the MIDAS model outperforms MF-VAR if the nowcasting period (*Q(0)* in our notation) is considered. For Czech GDP nowcasting the opposite result is found.

4.2 Forecasting

The models we consider are geared predominantly to short-term forecasting, due to their ability to work with mixed frequencies and ragged ends. Mixed-frequency models, however, might also perform well for longer-term forecasts due to their ability to provide a precise starting point. Sims (2002) provides anecdotal evidence suggesting that much of the advantage of judgmental forecasts over model-based forecasts comes from their ability to obtain more precise forecasts of the current quarter.

In this section, we therefore look at the suitability of our models for medium-term forecasting. Tables 2 and 3 present the RMSEs for forecasting horizons up to six quarters ahead. The forecast origin for these forecasts is chosen to be the end of the third month of the current quarter (*Q(0)M3 end*), since this largely corresponds to the information set available to the CNB when producing its macroeconomic forecast.

Table 2: Root Mean Square Forecast Errors (Evaluated Using First Releases)

	Nowcast	1Q-ahead	2Q-ahead	3Q-ahead	4Q-ahead	5Q-ahead	6Q-ahead
RW	0.93	1.25	1.29	1.38	1.52	1.55	1.52
DFM	0.49	0.79	1.10	1.18	1.18	1.17	1.20
MIDAS	0.79	1.14	1.27	1.28	1.29	1.34	1.37
MF-VAR	0.80	1.01	1.06	1.13	1.20	1.18	1.19
MF-BVAR	0.82	0.95	1.03	1.10	**1.15**	**1.14**	**1.15**
CNB	**0.48**	**0.70**	**0.97**	**1.06**	1.16	1.21	1.28

Note: Bold indicates the lowest value of the RMSE for a particular horizon.

Table 3: Root Mean Square Forecast Errors (Evaluated Using Dec 2012 Vintage)

	Nowcast	1Q-ahead	2Q-ahead	3Q-ahead	4Q-ahead	5Q-ahead	6Q-ahead
RW	0.93	1.28	1.44	1.53	1.67	1.70	1.67
DFM	0.74	0.96	1.20	1.31	1.34	1.33	1.34
MIDAS	0.89	1.22	1.44	1.45	1.49	1.54	1.54
MF-VAR	0.93	1.15	1.22	1.28	1.35	1.37	1.35
MF-BVAR	0.96	1.10	1.18	1.25	**1.30**	**1.30**	**1.30**
CNB	**0.70**	**0.86**	**1.07**	**1.19**	1.32	1.38	1.44

Note: Bold indicates the lowest value of the RMSE for a particular horizon.

Looking at Table 2, there are several observations worth noting. First, all the models perform better than the naïve random walk forecast. Second, the DFM comes out as the best among the mixed-frequency model-based forecasts for the nowcast and the 1Q-ahead horizon. The DFM is competitive with the CNB for nowcasts (the difference in the RMSE being less than 0.1). Third, MF-BVAR performs best for horizons beyond 1Q ahead. MF-BVAR is competitive with the CNB at 2Q–3Q and performs best for horizons beyond the third quarter. Table 3 shows qualitatively similar results when the December 2012 vintage is used for evaluating the forecasts.

According to Arnoštová et al. (2010), the CNB framework performed much better than the DFM in terms of forecasting accuracy. However, this might stem from a lack of information contained in the time span examined, which ended in 2009. Our results suggest that extending the time span to 2012, i.e., including the information carried by the recent financial and economic crisis, improves the performance of the DFM substantially.

The relative performance of the two variants of MF-VAR and MIDAS is comparable for nowcasts and worse in the case of MIDAS if a longer forecasting horizon is considered. This is similar to the findings for nowcasting GDP in the euro area in Kuzin et al. (2011), who find that MIDAS forecasts better for nowcasting (up to 4–5 quarters) and MF-VAR outperforms MIDAS for longer horizons.

5. Density Nowcasts from MF-BVAR

Bayesian estimation of MF-VAR offers a straightforward way of constructing density nowcasts/forecasts. We restrict our attention to density nowcasts.

The motivation for extending our analysis to density nowcasting is twofold. First, we want to illustrate how density nowcasts of output are constructed in the context of Czech real-time vintage data. As suggested by some practitioners, density nowcasts allow uncertainty to be introduced into core forecasting models (usually DSGE-type models), which use nowcasts as initial conditions (e.g. Bache et al., 2010). Density nowcasting then represents the first step in developing such a procedure, the second step being soft conditioning of the forecasts on the nowcast densities. The second motivation is to examine how the uncertainty and precision of GDP nowcasts change with the release of new data during the forecasting period.

We start by evaluating density nowcasts. The measure we apply is based on the Kullback-Leibler Information Criterion (KLIC) – see Mitchell and Hall (2005). The KLIC for a model i is defined as follows:

$$KLIC_i = \int f_t(y_t) \ln \frac{f_t(y_t)}{f_{t,i}(y_t)} dy_t = E\left[\ln f_t(y_t) - \ln f_{t,i}(y_t)\right], \tag{10}$$

where $f_t(y_t)$ is the true density of a random variable and $f_{t,i}(y_t)$ is the density based on model i.

To compare the performance of density nowcasts from two models ($i = 1,2$), it is enough to compare the expected logarithmic score (as the logarithmic score of the true density in the KLIC in formula (10) is the same for both models):

$$E \ln S_i = E\left[\ln f_{t,i}(y_t)\right]. \tag{11}$$

The model with the higher expected logarithmic score gives on average a higher probability to events that have occurred ex post. The expected logarithmic score can be estimated by the average of $\ln f_{t,i}(y_t)$ over the evaluation sample. The resulting number is called the log score.

Figure 2: Log Score for Selected Indicators Over the Nowcasting Horizon
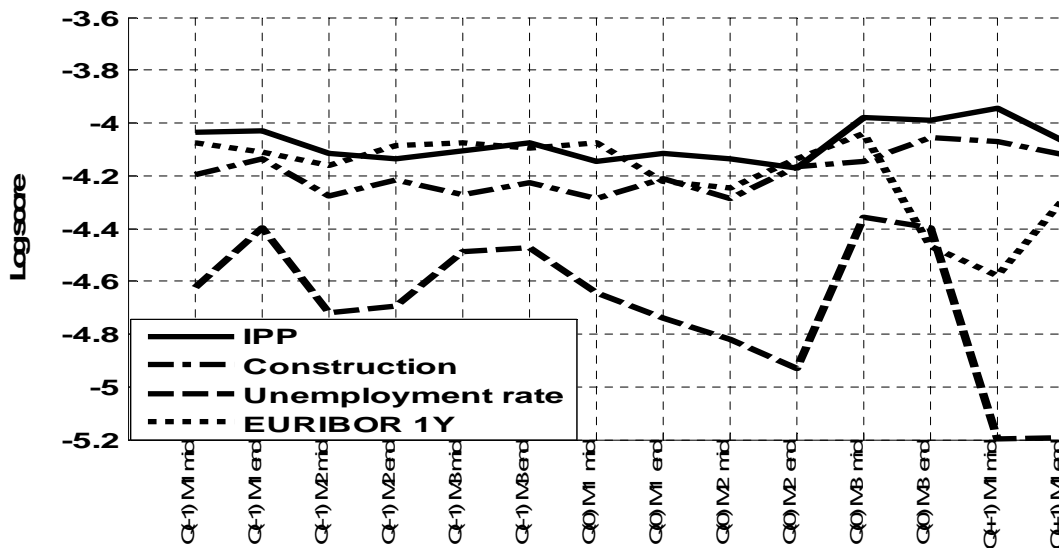
As an example, Figure 2 presents log scores for selected monthly indicators. The figure suggests which monthly indicators (bivariate VARs) provide more accurate density nowcasts. It turns out, for example, that industrial production is a more useful monthly indicator than the unemployment rate for all the nowcasting periods considered. Furthermore, Figure 2 suggests how the accuracy of the density nowcasts changes with the arrival of new data during the nowcasting period. Surprisingly, for some indicators the log score decreases at the end of the nowcasting period, when the most accurate information consistent with the ex-post observed GDP growth should be available.

Figure 3 shows the log score for the combined density nowcasts. The individual density nowcasts from bivariate MF-BVARs are combined linearly with equal weights. As a robustness check, linear combination with recursive log score weights is used (see Kascha and Ravazzolo, 2010, for a discussion of various weighting schemes for density combination). The results, however, are largely unaffected.

Figure 3: Log Score for the Combined Density Nowcast
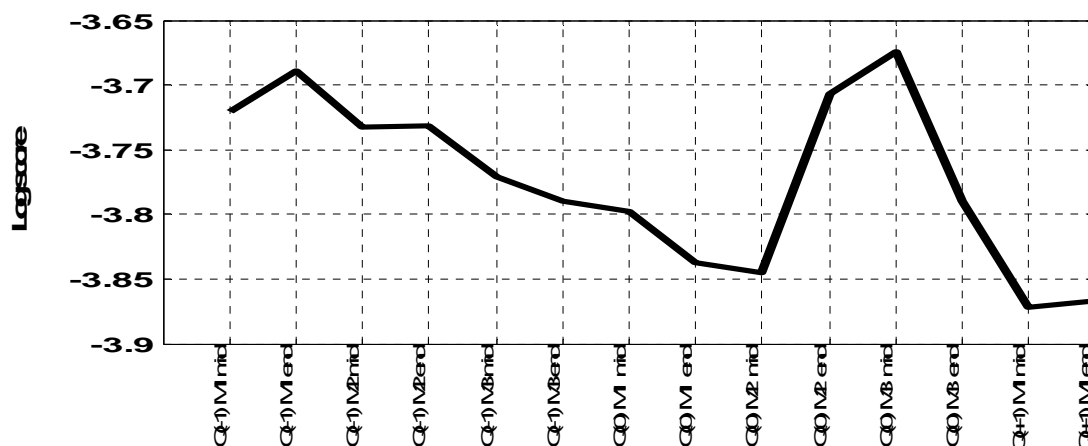
The log score for the combined nowcast densities is higher than the individual log scores presented in Figure 2. The magnitude of the change over the nowcasting period, however, is not large, i.e., the accuracy of the density nowcasts does not change much with the arrival of new information. So, the new information arriving seems to add as much new relevant information as noise.

Next, Figure 4 shows how the uncertainty related to the nowcasts decreases over the nowcasting period. The figure presents the distance of a particular quantile of the posterior distribution of the combined nowcast to the median of the distribution. The number for a particular nowcasting period represents the average over all quarters considered for nowcasting. The falling profiles for all the quantiles considered suggest decreasing uncertainty as a consequence of the arrival of new information during the nowcasting period.

Figure 4: Average Distance to the Median of the Combined Density Nowcast for Selected Quantiles
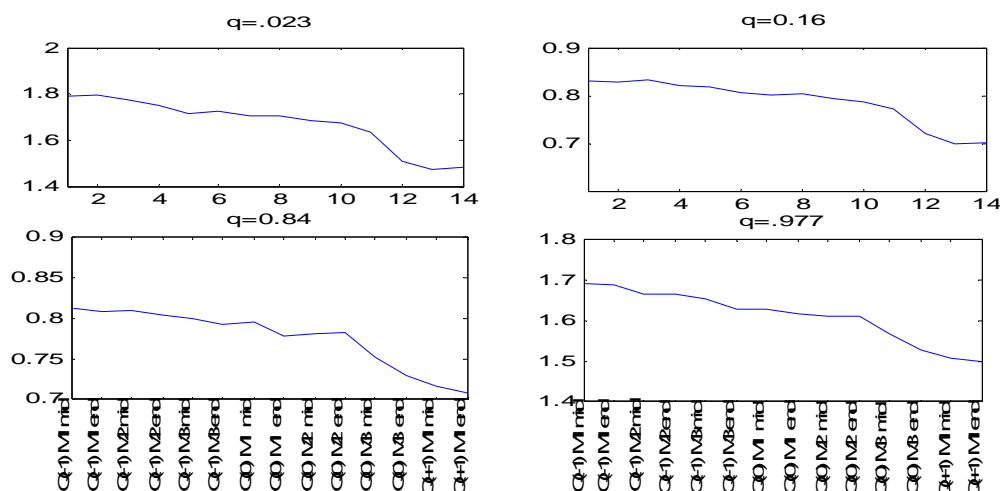
Finally, Figure 5 reports selected quantiles of the density nowcasts computed at the end of the relevant quarter (*Q(0) M3*) and the observed GDP growth. As above, the density nowcasts are produced by combining the density nowcasts from bivariate VARs and simply averaged. The combination based on log scores provides almost identical results.

Figure 5: Nowcasts and Observed GDP Growth, 2005Q1–20012Q3
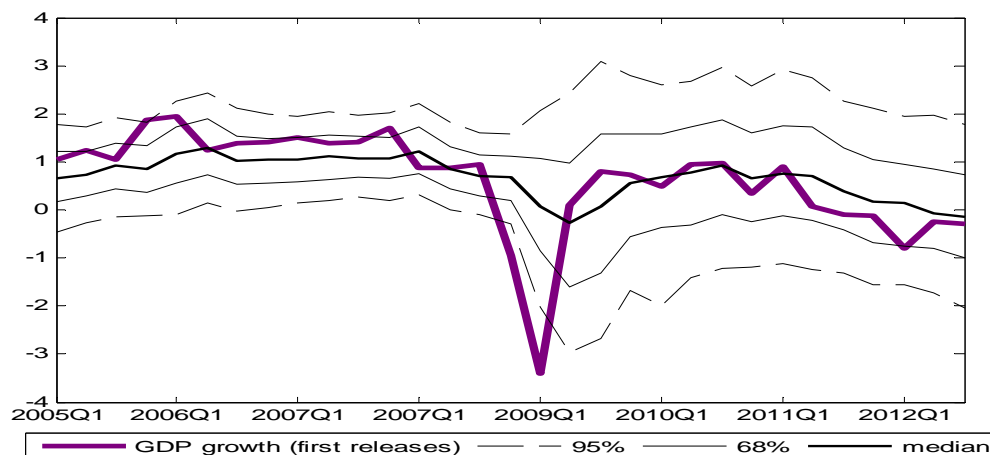
Two points are worth emphasizing. First, the uncertainty related to the nowcasts increased significantly during and after the 2008 crisis, which hit the Czech Republic in 2009. Second, the fall in GDP in 2009 is not captured by the 95% credible set of nowcasts even though foreign monthly indicators are included. This only reflects the severity of the negative shock to GDP during the 2009 recession.

6. Concluding Remarks

In this paper we employ three classes of mixed-frequency data models to examine the forecasting of Czech GDP in real time. Specifically, we use two variants of mixed-frequency vector autoregression estimated by the EM algorithm and the Kalman smoother (MF-VAR) and by Bayesian techniques (MF-BVAR), the mixed-data sampling model (MIDAS), and the dynamic factor model (DFM) and evaluate their precision against the CNB's macroeconomic forecasts.

The results suggest that for nowcasting and short-term forecasting the performance of the dynamic factor model is comparable to the macroeconomic forecasts published by the CNB. At longer horizons, MF-VARs compete successfully with the CNB's forecasts. Moreover, the Bayesian approach to the estimation of the MF-VAR model adds to the precision of the GDP forecasts. To summarize, mixed-frequency data models are an important complementary tool to the currently used forecasting approaches, which often draw heavily on expert judgment. As mixed-frequency models take into account a much broader set of time series than single-frequency models they can provide a similar level of forecasting quality as judgmental forecasts.

The models presented here might be useful for nowcasting and forecasting other variables as well, especially ones that have long publication delays. Future improvements to the models might lie in combining the forecasts from various models or combining forecast densities similarly to Aastveit et al. (2011). Alternatively, capturing possible nonlinear relationships between the indicators (e.g.

financial variables) and GDP might improve the predictions. Finally, note that the models that employ the Kalman filter (MF-VAR and DFM) can also be used to produce conditional forecasts in a relatively straightforward manner (Banbura et al., 2014).

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APPENDIX A: Combination of Individual Bivariate MF-VARs/MF-BVARs based on MSE

As a benchmark, the simple mean over the nowcasts/forecasts from the bivariate MF-VARs is considered. However, the performance of the models might be improved if the weights depend on the previous forecasting error of a particular model. In this section, we compare the results for the two weighting schemes. Note that the mean squared errors used to compute the weights for quarter t_q are taken for quarters $t_{q-2},...,t_{q-5}$ to account for the GDP publication lag.

The results using MSE weighting suggest that the improvements in the various weighting schemes are generally modest. Moreover, the performance varies for different horizons and different models. Selecting the top five models generally works best for MF-BVAR, while for MIDAS and MFVAR there are no clearly preferred weighting schemes.

Table A1: Nowcasting – Different Weighting Schemes (Evaluated Using First Releases)

	Q(-1) M1 mid	Q(-1) M1 end	Q(-1) M2 mid	Q(-1) M2 end	Q(-1) M3 mid	Q(-1) M3 end	Q(0) M1 mid	Q(0) M1 end	Q(0) M2 mid	Q(0) M2 end	Q(0) M3 mid	Q(0) M3 end	Q(+1) M1 mid	Q(+1) M1 end
MFVAR														
Simple Mean	1.03	1.03	1.04	1.02	1.01	1.00	1.00	1.00	1.00	0.99	0.79	0.80	0.79	0.80
Inverse MSE	**1.00**	**1.00**	**1.01**	0.98	**1.00**	**0.98**	**0.98**	**0.99**	**0.99**	**0.98**	0.77	0.78	0.78	0.78
Best model	1.11	1.15	1.03	1.07	1.04	1.12	1.10	1.04	**0.99**	1.12	0.85	0.84	0.83	0.65
Top 5 models	1.02	1.01	**1.01**	**0.97**	**1.00**	0.99	1.00	**0.99**	**0.99**	**0.98**	**0.70**	**0.72**	**0.72**	**0.73**
MF-BVAR														
Simple Mean	1.00	0.99	**0.99**	0.98	0.96	0.94	0.93	0.93	0.92	**0.91**	0.80	0.82	0.82	0.82
Inverse MSE	**0.98**	0.99	**0.99**	**0.95**	0.94	**0.91**	**0.92**	**0.90**	**0.91**	**0.91**	0.79	0.80	0.80	0.81
Best model	1.01	1.04	1.02	0.98	0.95	0.95	0.96	0.98	0.99	0.96	0.80	0.79	0.85	0.90
Top 5 models	**0.98**	**0.96**	1.00	0.98	**0.93**	**0.91**	**0.92**	0.91	0.93	0.95	**0.75**	**0.75**	**0.79**	**0.80**
MIDAS														
Simple Mean	1.22	1.19	1.18	**1.19**	1.20	1.20	1.11	1.20	1.09	1.08	0.82	0.79	0.79	0.82
Inverse MSE	**1.19**	1.19	1.14	1.32	**1.06**	**1.07**	**1.03**	**1.06**	**1.03**	**1.03**	0.78	0.78	0.78	0.78
Best model	1.25	**1.15**	**1.10**	1.40	1.18	**1.07**	1.14	1.19	1.32	1.04	**0.59**	0.87	0.90	1.27
Top 5 models	1.26	1.22	1.11	1.24	1.23	1.11	1.13	1.22	1.11	1.09	0.76	**0.75**	**0.73**	**0.81**

Table A2: Nowcasting – Different Weighting Schemes (Evaluated Using Dec 2012 Vintage)

	Q(-1) M1 mid	Q(-1) M1 end	Q(-1) M2 mid	Q(-1) M2 end	Q(-1) M3 mid	Q(-1) M3 end	Q(0) M1 mid	Q(0) M1 end	Q(0) M2 mid	Q(0) M2 end	Q(0) M3 mid	Q(0) M3 end	Q(+1) M1 mid	Q(+1) M1 end
MFVAR														
Simple Mean	1.21	1.21	1.21	1.20	1.15	1.15	1.15	1.15	1.15	1.15	0.93	0.93	0.93	0.93
Inverse MSE	**1.17**	**1.17**	1.18	1.16	1.14	**1.13**	**1.13**	1.14	1.14	1.13	0.91	0.92	0.92	0.92
Best model	1.24	1.26	1.18	1.20	**1.09**	1.18	1.17	**1.13**	**1.07**	1.18	0.98	0.97	0.96	**0.82**
Top 5 models	1.19	1.18	**1.17**	**1.15**	1.12	**1.13**	1.15	**1.13**	1.13	**1.11**	**0.85**	**0.87**	**0.88**	0.88
MF-BVAR														
Simple Mean	1.17	1.17	**1.16**	1.15	1.11	1.09	1.08	1.08	1.08	1.07	0.95	0.96	0.96	0.97
Inverse MSE	**1.15**	1.17	1.17	**1.12**	1.09	1.06	**1.07**	**1.04**	**1.07**	**1.06**	0.95	0.95	**0.95**	**0.96**
Best model	1.17	1.19	1.19	1.15	**1.05**	**1.04**	1.09	1.13	1.14	1.12	0.97	0.92	0.99	1.02
Top 5 models	**1.15**	**1.14**	1.17	1.15	1.06	1.07	**1.07**	1.07	1.09	1.12	**0.92**	**0.91**	0.95	0.96
MIDAS														
Simple Mean	1.41	1.35	1.37	**1.35**	1.32	1.35	1.20	1.32	1.16	1.18	0.89	0.89	0.89	0.89
Inverse MSE	**1.39**	1.37	1.31	1.46	**1.19**	1.23	**1.14**	**1.20**	**1.11**	1.14	0.88	0.90	0.89	**0.88**
Best model	1.45	**1.34**	**1.25**	1.53	1.29	**1.22**	1.18	1.30	1.31	**1.13**	**0.78**	1.00	1.02	1.36
Top 5 models	1.46	1.38	1.29	1.39	1.30	1.26	1.20	1.28	1.15	1.19	0.87	**0.85**	**0.85**	0.90

Table A3: Forecasting – Different Weighting Schemes (Evaluated Using First Releases)

	Nowcast	1Q-ahead	2Q-ahead	3Q-ahead	4Q-ahead	5Q-ahead	6Q-ahead
MFVAR							
Simple Mean	0.80	1.01	1.06	1.13	1.20	**1.18**	**1.19**
Inverse MSE	0.78	**1.00**	**1.01**	1.13	1.20	**1.18**	**1.19**
Best model	0.84	1.13	1.21	1.13	1.20	1.20	1.23
Top 5 models	**0.72**	**1.00**	1.06	**1.12**	1.19	1.19	1.21
MF-BVAR							
Simple Mean	0.82	0.95	1.03	1.10	1.15	1.14	1.15
Inverse MSE	0.80	0.93	**1.02**	1.10	1.15	1.14	1.15
Best model	0.79	0.98	1.13	1.12	1.18	1.16	1.17
Top 5 models	**0.75**	**0.91**	**1.02**	**1.09**	**1.14**	**1.12**	**1.13**
MIDAS							
Simple Mean	0.79	1.14	1.27	1.28	**1.29**	1.34	1.37
Inverse MSE	0.78	**1.05**	1.32	1.23	1.24	**1.28**	**1.31**
Best model	0.87	1.12	1.31	1.30	1.34	1.35	1.52
Top 5 models	**0.76**	1.13	**1.23**	**1.18**	1.31	1.43	1.43

Table A4: Forecasting –Different Weighting Schemes (Evaluated Using Dec 2012 Vintage)

	Nowcast	1Q-ahead	2Q-ahead	3Q-ahead	4Q-ahead	5Q-ahead	6Q-ahead
MFVAR							
Simple Mean	0.93	1.15	1.22	1.28	**1.35**	1.37	1.35
Inverse MSE	**0.92**	1.14	**1.16**	1.28	**1.35**	1.37	1.35
Best model	0.97	1.18	1.31	1.29	1.36	1.37	1.38
Top 5 models	0.87	**1.13**	1.20	**1.27**	**1.35**	**1.36**	**1.34**
MF-BVAR							
Simple Mean	0.96	1.10	1.18	1.25	1.30	1.30	1.30
Inverse MSE	0.95	1.07	1.18	1.25	1.30	1.30	1.30
Best model	0.92	1.07	1.26	1.28	1.34	1.33	1.31
Top 5 models	**0.91**	**1.05**	**1.17**	**1.23**	**1.29**	**1.28**	**1.26**
MIDAS							
Simple Mean	0.89	1.22	1.44	1.45	1.49	1.54	1.54
Inverse MSE	0.90	**1.15**	1.46	1.39	**1.43**	**1.48**	**1.48**
Best model	1.00	1.19	1.42	1.43	1.51	1.55	1.66
Top 5 models	**0.86**	1.18	**1.38**	**1.35**	1.50	1.62	1.60

APPENDIX B: Results Based on Forecasts That Use Revised Data

Using the last vintage data instead of the data available at the time of the forecast does not consistently lower the forecast errors. There is some evidence of a decline in errors for the DFM at short horizons and also for the MF-BVAR at medium horizons. Often, however, using last vintage data worsens the forecasting performance, although the differences in the RMSE are mostly rather small.

Figure B1: RMSE Error of Real-time Nowcasts Relative to Nowcasts Based on Revised Data
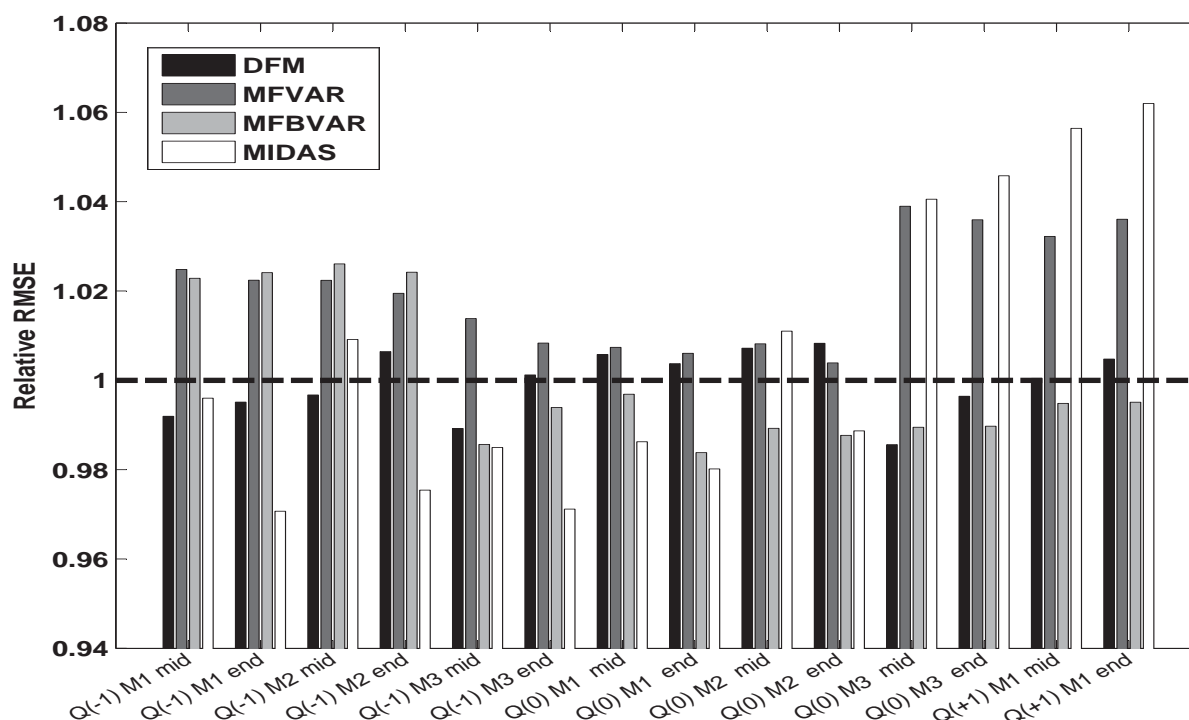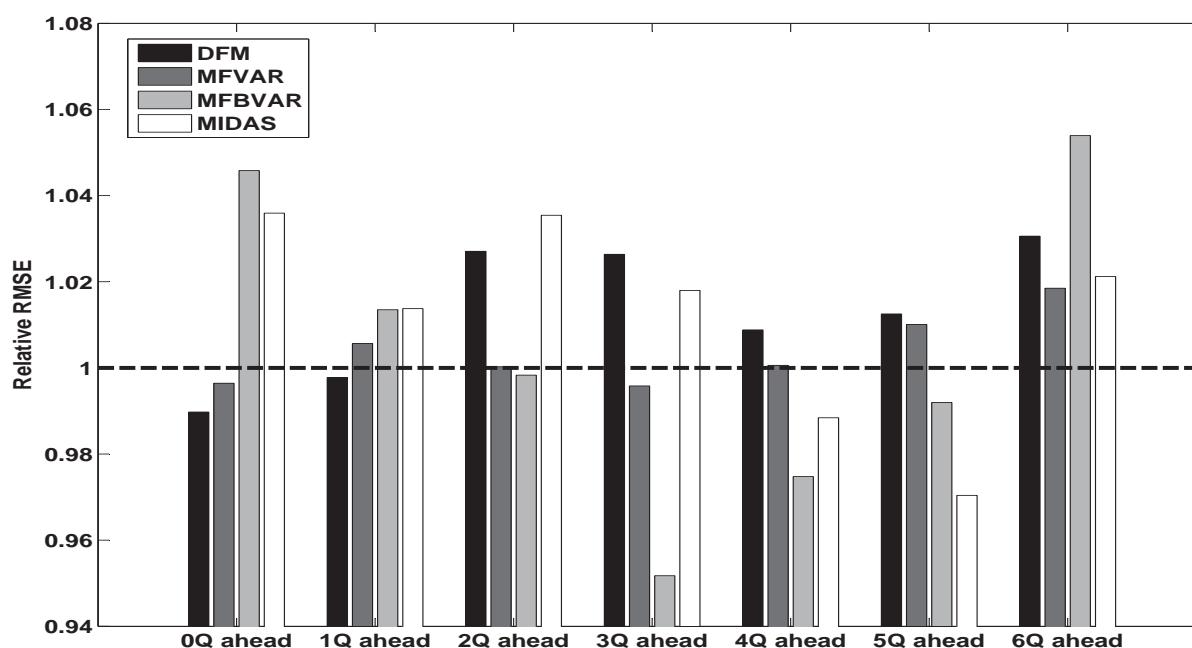

Figure B2: RMSE Error of Real-time Forecasts Relative to Forecasts Based on Revised Data

APPENDIX C: Alternative Polynomial Weights for MIDAS Models

We also evaluate a more general MIDAS model:

$$y_{t_q+1}^Q = \mu + \delta y_t^Q + \beta \sum_{j=0}^{p^Q} \sum_{i=0}^{N_M-1} w_{N_M-i+j*N_M}(\theta) X_{N_M-i,t_q-j}^M + u_{t_q+1} , \tag{C1}$$

where $w_k(\theta)$ denote the weights for the respective lags with a vector of parameters θ, and N_M denotes the number of months in the quarter. We consider two different polynomial schemes:

(i) a normalized beta polynomial scheme with a zero last lag:

$$w_k(\theta) = w_k(\theta_1, \theta_2) = \frac{x_k^{\theta_1-1}(1-x_k)^{\theta_2-1}}{\sum_{k=1}^{N} x_k^{\theta_1-1}(1-x_k)^{\theta_2-1}}, \text{ where } x_k = \frac{k-1}{N-1}, \tag{C2}$$

(ii) a normalized exponential Almon lag polynomial scheme:

$$w_k(\theta) = w_k(\theta_1, \theta_2) = \frac{\exp(\theta_1 k + \theta_2 k^2)}{\sum_{k=1}^{N} \exp(\theta_1 k + \theta_2 k^2)} . \tag{C3}$$

The index k covers all considered lags of the monthly indicator (in order from the most recent observations). The parameters μ, β, θ are estimated by nonlinear least squares.

The results of this sensitivity check generally suggest that the unrestricted MIDAS performs consistently better than the exponential and beta polynomial schemes, especially at shorter horizons.

Table C1: Nowcasting – Alternative MIDAS Polynomial Schemes

	Q(-1) M1 mid	Q(-1) M1 end	Q(-1) M2 mid	Q(-1) M2 end	Q(-1) M3 mid	Q(-1) M3 end	Q(0) M1 mid	Q(0) M1 end	Q(0) M2 mid	Q(0) M2 end	Q(0) M3 mid	Q(0) M3 end	Q(+1) M1 mid	Q(+1) M1 end
Evaluated using first releases of GDP														
Beta	1.22	**1.19**	1.22	1.21	**1.20**	**1.19**	1.13	1.21	1.12	1.11	0.86	0.84	0.84	0.86
Exp	**1.21**	**1.19**	1.22	1.20	1.24	**1.19**	1.14	1.23	1.13	1.11	0.86	0.84	0.84	0.86
UMIDAS	1.22	**1.19**	**1.18**	1.19	**1.20**	1.20	**1.11**	**1.20**	**1.09**	**1.08**	**0.82**	**0.79**	**0.79**	**0.82**
Evaluated using Dec 2012 vintage														
Beta	1.40	**1.35**	1.40	1.37	**1.32**	1.34	1.22	1.33	1.19	1.19	0.92	0.92	0.91	0.92
Exp	**1.39**	1.36	1.41	1.36	1.35	**1.33**	1.23	1.35	1.20	1.20	0.91	0.91	0.91	0.92
UMIDAS	1.41	**1.35**	**1.37**	**1.35**	**1.32**	1.35	**1.20**	**1.32**	**1.16**	**1.18**	**0.89**	**0.89**	**0.89**	**0.89**

For longer forecasting horizons the performance of all the MIDAS polynomials is largely comparable, with beta mostly having the smallest RMSE.

Table C2: Forecasting – Alternative MIDAS Polynomial Schemes

	Nowcast	1Q-ahead	2Q-ahead	3Q-ahead	4Q-ahead	5Q-ahead	6Q-ahead
Evaluated using first releases of GDP							
Beta	0.84	1.15	**1.26**	**1.28**	**1.28**	**1.34**	**1.35**
Exp	0.84	1.17	**1.26**	**1.28**	**1.28**	**1.34**	1.35
UMIDAS	**0.79**	**1.14**	1.27	**1.28**	1.29	**1.34**	1.37
Evaluated using Dec 2012 vintage							
Beta	0.92	1.23	**1.43**	**1.45**	**1.48**	**1.53**	1.53
Exp	0.91	1.25	**1.43**	1.46	**1.48**	1.54	**1.52**
UMIDAS	**0.89**	**1.22**	1.44	**1.45**	1.49	1.54	1.54

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